When David becomes Goliath: Why repo market frictions matter

Carlos Cañón[*a], Eddie Gerba[†b], and Jozef Baruník[‡c]

[a] *Bank of England & King's College London*

[b] *Bank of England & LSE*

[c] *Charles University*

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Abstract

Using proprietary gilt market and transaction-level gilt repo datasets, this paper identifies how funding market microstructure frictions affect system-wide market liquidity. Starting from the structure of the repo market, individual dealer constraints and intermediation frictions generate inefficiencies with welfare implications through three independent, albeit related, mechanisms. More broadly, we provide a new perspective on how financial imperfections in the money market, measured by market power and relationship trading, impact the real economy through shocks to individual dealer capacity.

Keywords: Market power, Relationship trading, Repo market, Bond market, Mispricing, Market liquidity.

JEL Codes: G14, G21, G22, G23.

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[*] carlos.canonsalazar@bankofengland.co.uk

[†] eddie.gerba@bankofengland.co.uk

[‡] barunik@fsv.cuni.cz

1 Introduction

It is well documented that repo markets play a crucial role for market functioning, financial stability, and the economy as a whole. At the micro-level, repos are an integral part of the banking industry's treasury, liquidity, and asset/liability management practices, as well as an essential element for managing open market operations by central banks (Cullen (2018)). On the macro side, and with the exponential growth of market-based liabilities over the past three decades, repos have become a better indicator of credit conditions affecting the economy than, for example, the money stock. The repo market is not only a key determinant of market-wide liquidity, but also plays a fundamental role in the transmission of monetary policy and the gearing of prudential policy (Adrian and Shin (2009), Adrian and Shin (2010), Keister (2019),Eisenschmidt et al. (2024); Huber (2023b)).

Consequently, repo market frictions have important implications for financial stability and the wider economy. For example, dealer constraints can lead to fragmentation and migration of intermediation to non-dealers, see Lewis et al. (2021). Similarly, market power and structural inefficiencies can reduce overall market liquidity or, in some cases, contribute to liquidity crises, see Syverson (2024). Market-wide frictions, in turn, affect the real economy through the funding channel, suboptimal allocation of credit resources, reduction of pension dividends or margin calls, thus limiting wealth creation and leaving certain risks in the system under/unpriced, etc.

The frictions that we examine in this paper arise from the market power of dealers and relationship trading with non-dealers in the repo market. We show how they give rise to three types of inefficiency which, although independent of each other, collectively generate welfare losses. The first arises from dealers' individual market power, which causes repo prices (spreads), as well as volumes, to deviate from their market efficient level, and dealers' individual relationship trading activity, which conditions the overall volume of repo contracts. The second inefficiency arises from the dispersion of dealers' individual market power, which reduces market liquidity and leads to productivity losses. The third arises from the transmission of market-wide shocks across dealers (so-called global factors), mainly in the reverse repo segment as we will show, which adds to the existing productivity loss. In

addition, we show how these inefficiencies lead to mispricing in the government bond (gilt) market, with further implications for the economy by altering the transmission of monetary policy, Treasury bond issuance (fiscal policy) and the availability of high-quality collateral for pension funds, insurers, and credit intermediaries. Finally, we show how bargaining power dynamics leads to fragmentation in repo versus reverse repo contracts, providing further empirical support for the "preferred habitat" argument (Vayanos and Vila (2021); Gourinchas et al. (2022)).

Using detailed transaction-level data from the UK repo market between 2016 and 2022, we highlight key facts from repo transactions between dealers and non-dealers, as well as between dealers. We document the differences between the bilateral OTC and inter-dealer segments and discuss variations across non-dealer sectors, such as hedge funds, asset managers, insurance companies, and pension funds. Additionally, using bond-level data from the UK sovereign bond market, we document mispricing (relative to a spline benchmark), as well as duration, liquidity, and volatility at different points of the yield curve.

The UK repo and bond markets are particularly well-suited for studying how frictions in funding markets spill over to other core markets, ultimately affecting market-wide metrics like liquidity. First, London is a global financial center, and financial institutions operating in diverse markets, such as derivatives or bond markets, have incentives to use the repo market to obtain liquidity or securities. Second, the major dealers in the repo market are also the market makers in the bond market. Consequently, our analysis focuses on the subset of dealers operating in both markets, and we only use repo transactions that use UK sovereign bonds as collateral. Finally, during our sample period, there were major events, such as Brexit, the Dash-for-Cash, and Covid-19, that stressed all financial markets and provided multiple sources of variation.

Following standard IO literature (Syverson (2024)), and using the bilateral OTC segment data, we compute dealer-level markup and markdown metrics. Additionally, following relationship lending literature (Brauning and Fecht (2017); Jurkatis et al. (2022)), we compute dealer/non-dealer-level relationship trading metrics. Lastly, following recent literature on dynamic networks (Barunik and Ellington (2020, 2024)), we compute market-wide dealer

global factors. For the bond market, following literature on mispricing (Lewis et al. (2021); Pelizzon et al. (2025); Hu et al. (2013)), we construct bond-level mispricing metrics and a market-wide metric of market liquidity.

With these metrics, we initially document how market power and relationship trading metrics shape repo transactions. Additionally, using the dealer global factors, we show evidence that dealers segment non-dealers based on their sector, such as hedge funds and asset managers versus pension funds and insurance companies. In the rest of the paper, we demonstrate two ways market power-related frictions (one associated with its level and another with inter-dealer dispersion) and another way related to dealer global factors spill over to the bond market. Lastly, we show that all three spillover channels remain significant for market-wide metrics, such as market liquidity.

Our main threat to identification arises from the fact that dealers and non-dealers select their counterparts in the repo market, potentially causing selection bias. To address this issue, we follow an instrumental variable approach. Specifically, we exploit the granularity of the transaction-level data to compute granular instrumental variables (GIVs, following Gabaix and Koijen (2024)) to isolate the effects of market power and relationship trading metrics on the outcome variables. For all regressions, we obtain valid, share-weighted instrumental variables for each endogenous variable. In some cases, we combine GIVs with other instruments to improve identification.

We contribute to the thin (but growing) literature on financial market frictions in three ways. First, we pin down the size of the frictions using market liquidity metrics and suggest a way to conceptualise it in aggregate or system-wide terms. [1] Second, we explicitly link industrial organisation features in financial markets to productivity (and the productivity frontier), which operates through the notion of market liquidity and collateral availability.

[1] One potentially helpful way to think about it could be in terms of an aggregate market liquidity gap, or the difference between actual system-wide market liquidity and the level at which markets operate efficiently in the absence of frictions and central bank intervention. Note that this is distinct from, though somewhat related to, the standard market liquidity gap in finance, which measures the mismatch between the supply and demand for a security, or the maturity of a security, or an institution's liquid assets and liabilities, i.e. an institution's liquidity gap. The frictions we describe in this paper can cause this mismatch, but they are measured at the aggregate system level. This concept of liquidity allows us to link microstructural phenomena to macroeconomic fluctuations in the business cycle. Further work should attempt to quantify this gap.

Finally, we examine open market interventions of central banks through the lens of industrial relations and bargaining power dynamics (as opposed to market-wide outcomes). The conceptual novelty, we believe, lies in linking micro and macro phenomena in financial markets by providing a microfoundation for financial market frictions in aggregate fluctuations.

In the wake of the mini-budget crisis, the COVID stress, including the 2020 dash for cash, and the US repo market stress in 2019, the global (Basel Markets Committee) discussion on market disruption tools has gained momentum, and many central banks are considering introducing them as central bank balance sheets shrink. The economic costs of such disruptions are high, and the moral hazard problems associated with ex-post central bank interventions are significant. It is therefore elementary to have a toolkit that can (potentially) prevent such events from occurring or minimise their damage by acting quickly. This paper provides a rationale for why these tools can serve a stabilisation purpose, in addition to the market-correcting objective.

The remainder of the paper is structured as follows. Section 2 outlines the literature context of our paper and our contribution. Sections 3 and 4 describe the data, stylised facts, hypotheses, and our identification approach. Section 5 provides a detailed discussion of the results, including an outline of the market power mechanisms driving the inefficiencies and deadweight losses. Section 6 is devoted to various policy implications of our findings, given the global debate on instruments to address market dysfunction. Finally, Section 7 concludes the paper. Additional details, such as the characterisation of the UK repo market, the theoretical underpinnings of our methodology, or the regression tables, can be found in the appendix, including an online appendix.

2 Literature context

Efficient repo markets are key to maintaining financial stability and ensuring the smooth transmission of monetary policy. However, excessive use can also be a source of systemic risk and a source (or forceful propagator) of distress (Bassi et al. (2024)). This delicate balance places it at the forefront of stabilisation concerns (Aikman et al. (2024)) and is the reason

why fiscal policymakers have recently paid considerable attention to its smooth functioning (Hauser and Logan (2022), Buiter et al. (2023), Eckhold et al. (2024)). We decouple this trade-off using the optics of industrial relations and market microstructure behaviour to understand when and where inefficiencies may arise.

In addition, repo markets are closely linked to the government bond market. In the UK, dealers in the repo and gilt markets overlap to a large extent. For preferred habitat investors and arbitrageurs, gilts provide both an investment opportunity and collateral for funding (or lending). Similarly, especially during the QE period, when high quality collateral was scarce, government bond collateral was highly sought after in both markets (gilt and reverse repo). One documented result of the close correlation is the liquidity regime dependent response of long-term government bond yields to monetary policy shocks. Constraints on the balance sheets of both dealers and hedge funds led to a large (small) response of bond yields in periods of high (low) market liquidity (Guimaraes et al. (2023)). Another result is that the (relative) collateral value of QE-targeted bonds in the repo market increased, dampening the term premium effects of asset purchases and increasing their local supply. It is therefore useful to consider both markets in combination (Jappelli et al. (2023)). In this paper, we go one step further and provide evidence for a new channel of gilt mispricing generated by market power inefficiencies in the repo market. This finding implies that industrial relations in one market have implications for the efficiency of the other market. This is granular evidence of the market-wide phenomena (such as fragmentation, specialisation, sharp (temporary) declines in repo volumes, pockets of liquidity or sharp fluctuations in collateral value) documented in the literature.

Although occasional disruptions in the money market remind us of its fundamental role for the economy, there is little literature attempting to link its microstructure (frictions) to the macroeconomy or even to system-wide market liquidity. An exception is DeFiore et al. (2024). The authors construct a general equilibrium model including secured and unsecured money markets and central bank facilities. They examine the macroeconomic effects of three alternative scenarios: 1) increased haircuts in the secured market; 2) reduced access to the unsecured money market; and 3) fear of increased deposit withdrawals. and show that

these can have significant effects on investment and output. More recently, Wu (2024) has developed a New Keynesian repo model with market segmentation, financial frictions and preference shocks. In their model, imperfect markets, driven by segmentation and preference shocks, hinder the transmission of conventional expansionary monetary policy and can cause economic recessions. To our knowledge, this is the first paper to seriously model financial market frictions in a macroeconomic framework. However, it does not include industrial relations and broader market microstructure features, as in our paper. While their paper focuses on investor preferences, we instead center on how bargaining power dynamics matter for market liquidity, collateral availability and price transmission across markets. Also, while the two aforementioned papers are purely theoretical, our aim here is to provide granular empirical evidence on the existence and role of microstructure inefficiencies for aggregate fluctuations. In this sense, we hope that our work can serve as a microfoundation for future models of financial market frictions. Finally, to the best of our knowledge, this is the first paper to use gilt (UK proprietary) data to reveal a fundamental point about the industrial organisation of financial markets.

The closest paper to ours is that of Eisenschmidt et al. (2024), who show how the market power of dealers in the European repo market impedes the pass-through of the ECB's policy rate. Based on the notion that most repo trades are conducted over-the-counter by a very small number of dealers, these dealers have significant market power. The result is an imperfect and heterogeneous pass-through from interdealer repo rates to OTC repo rates (similar to the findings in Huber (2023b)), with the interdealer repo rate in turn determined by the central bank's deposit facility rate and the value of collateral. While undoubtedly innovative and insightful, our paper goes beyond that study in four ways. First, we take a much broader perspective on market power by simultaneously examining the dynamics of bargaining power in the repo and reserve repo segments, both in prices and volumes, contrasting individual market power with global market factors and the cross-market consequences for the prices of sovereign bonds. Second, we link the microstructure phenomena to macroeconomic fluctuations through the lens of aggregate market liquidity and productivity. Third, we look beyond the specific transmission of monetary policy to identify the welfare implications of these inefficiencies. Fourth, and perhaps most fundamentally, we

examine market power and trading behaviour as inextricably linked to market (in)efficiency and system-wide stabilisation. Monetary and prudential policies are therefore interlinked in our framework. Thus, the expansion and contraction of the central bank's balance sheet has a monetary policy dimension in terms of regulating aggregate demand. At the same time, it ensures the stability of the financial system. Conversely, liquidity regulation ensures that the system has adequate liquidity buffers to function effectively and withstand exogenous shocks. Meanwhile, it also ensures that the transmission of monetary policy is smooth and effective.

Our intention is to uncover how microstructural frictions (or inefficiencies) in the repo market matter for system-wide market liquidity. We decompose the main question into two parts. First, from a positive perspective, we seek to identify the system-wide (or macroeconomic) implications of the microstructural frictions by focusing on the UK money market. Then, from a normative perspective, we tentatively explore why market dysfunction is relevant for aggregate financial and economic performance.

3 Method

3.1 Hypotheses

Dealers in the UK repo market may have market power relative to non-dealers due to their access to central counterparty clearing services. Thus, we expect the traditional deadweight loss to operate in the form of lower volumes and higher funding costs.[2] We also expect to find evidence of welfare losses associated with the dispersion of market power (across dealers), which is reflected in market-wide aggregate distortions.Boar and Midrigan (2019); Brooks et al. (2021); David and Venkateswaran (2019); Haltiwanger et al. (2018); Liang (2023); Weinberger (2020). Because the repo market is closely related to other core markets, Brunnermeier and Pedersen (2008), markups and markdowns in the repo market could spill over to individual collateral used in repo transactions and to market-wide measures of market liquidity. This paper provides empirical evidence for both mechanisms.

[2] Huber (2023a); Eisenschmidt et al. (2022) document the impact of market power for the US and EUR repo markets.

The effect of mark-ups and mark-downs in the repo market is mediated by several factors. First, there is ample evidence of relationship lending in various OTC markets, e.g. Jurkatis et al. (2022); Di Maggio et al. (2017); Hau et al. (2021); Afonso et al. (2014), yet it is unclear whether stronger relationships counterbalance dealers' market power. Second, market power could operate through quantities and prices, and it is empirically interesting to measure this. Third, market power could operate differently across financial sector segments, i.e. hedge funds, asset managers, insurance companies, and pension funds. Finally, since we know the identity of non-dealers, we test whether non-dealers active in both the repo and reverse repo segments receive different terms of trade vis-a-vis non-dealers active in only one segment.

The first hypothesis focuses on the impact of dealer-specific market power on the repo market. Concretely, we want to understand how market power operates at individual repo transaction level, and the role of other factors, e.g. relationship lending, sector specific differences, and common shock to main dealers, in attenuating the impact on quantities or prices.

Hypothesis 1. Dealer-specific market power creates deadweight losses that affect both repo prices and volumes.

The second hypothesis focuses on repo dealer-specific market power spillovers. From the repo segment, non-dealers could face difficulties in accessing arbitrage capital, which should increase mispricing, e.g. Hu et al. (2013), and deteriorate market liquidity. From the reverse repo segment, non-dealers could face difficulties in acquiring gilts in exchange for funding, contributing to search frictions in the gilt market and ultimately increasing mispricing, e.g. Duffie et al. (2015), also deteriorating market liquidity.

Hypothesis 2. Dealer-specific market power (markup and markdown) impacts individual gilts, bond-market liquidity, and (financial) market-wide liquidity/productivity.

The literature on misallocation due to market power emphasises that this specific welfare loss does not depend on repo dealers holding positive markups and markdowns, but is directly related to how market power is distributed across dealers, Syverson (2024).[3] The next

[3] Another way of framing it is that the welfare loss is proportional to the wedge between marginal revenue and marginal cost. We evaluate this interpretation empirically and the results hold.

hypothesis focuses on how this second source of welfare loss affects market-wide aggregates.

Hypothesis 3. There is a sizeable welfare loss due to the distribution/dispersion of market power across dealers (markups and markdowns), which affects market-wide liquidity/productivity.

As with the previous two mechanisms related to market power, we argue that common repo dealer shocks could also have similar spillovers.[4] The next hypothesis focuses on how common permanent and transitory shocks to repo dealers shape individual bonds, bond market makers, and market-wide liquidity. If collateralised funding markets are short-term in nature, we should expect common permanent shocks to repo dealers to have stronger spillovers to the bond market and to market-wide aggregates.

Hypothesis 4. Persistent (market-wide) shocks matter the most for aggregate liquidity/productivity

So far, the stated hypotheses describe three independent mechanisms that relate repo dealers to individual gilt-, bond market-, and (financial) market-wide liquidity. The final hypothesis focuses on their interaction. The first two mechanisms, associated with dealer-specific market power, are known to be interrelated but operate under very specific conditions, i.e. if all dealers have the same level of market power, then the second mechanism disappears. The last mechanism is more general, as it zooms in on common shocks, transitory and permanent, which are not only associated with market power and which can potentially be the main driver of spillovers.

Hypothesis 5. The three aforementioned mechanisms/effects are independent of each other, and therefore have an ambiguous impact on overall welfare.

[4] The OTC segmentation literature is closely related as it predicts how dealers will segment clients, e.g. based on their characteristics, trading patterns, etc.. The literature remains inconclusive on the determinants of dealer heterogeneity. Sambalaibat (2023) argues that the largest dealers in an OTC market will specialise in the most active non-dealers, and Lewis et al. (2021) shows empirically that this intuition can be extended to other asset classes. There are authors who assume away any dealer heterogeneity, e.g. Farboodi et al. (2022); Wang (2021), or who explain it on the basis of ex ante factors, e.g. Üslü (2019); Eisfeldt et al. (2022). In any case, assuming dealer heterogeneity, trade and prices will decline as core traders become more interconnected.

3.2 Identification

Market power The identification strategy for the analysis of the repo market poses several challenges. First, reverse causality is expected in relational trading.[5] Volumes and repo rates between dealers and non-dealers are determined at the dyadic level, as are the measures of relational trading. Thus, if the repo rate increases (relative to a risk-free rate), non-dealers would have incentives to change the frequency of trading and the funding dependence with that dealer. Second, there could also be reverse causality with market power. Markups and markdowns are constructed at the dealer level. If a dealer has to change the repo rate with an important counterparty, this will change its overall market power.

To address reverse causality on the proxies for market power and relationship trading metrics, we exploit the granularity of our data to construct granular instrumental variables (see Gabaix and Koijen (2024)). We recover idiosyncratic shocks at the level of individual dealers and non-dealers and use them to construct valid instruments for each variable. Essentially, we run a principal components factor model for each endogenous variable using the characteristics of the dealer/non-dealer dyad and extract the residuals. The constructed instruments are the size-weighted residuals of the regression of each endogenous variable on the factors, controlled for fixed effects.

For example, depth from the dealers' perspective is assumed to be driven by common and idiosyncratic shocks. The instrument is based on netting dealers' idiosyncratic variation in $Depth^D_{ND,t}$ from their common shock. We use variables that explain the formation of relationships with non-dealers but have little or no correlation with non-dealers' terms of trade, such as volumes and repo rates, to extract the common shock using principal component analysis. We retain the principal components that explain 90% of the total variation and use them to run the following r factor model,

$$Depth^D_{ND,t} = \sum_{r=1}^{R} \lambda^r_{dl} \eta_t + e_{dlt} \tag{1}$$

where η_t is the common shock and e_{dlt} is an idiosyncratic shock. The residuals from equation

[5] We will properly define these variables in the next section.

1, denoted by $\hat{e}_{dlt}$, are used to compute the GIV as the share-weighted average idiosyncratic shock:

$$z_t^{Depth^D} = \sum_{idl} S_{dl}\hat{e}_t \tag{2}$$

where S_{dl} is the dealer/non-dealer dl share of transactions. As an additional robustness check, we include additional terms in equation 1: λ_d, ξ_l and ϕ_m which are dealer, non-dealer, and month of year fixed effects. To account for non-linearities, we include the square of the granular instrument and call it $z_t^{Depth_2^D}$. We do the same for the other endogenous variables, so that we end up with eight GIVs, two for each endogenous variable $z^{Depth_t^D}$, $z_t^{Depth^{ND}}$, $z_t^{Intensity^{DND}}$, z_t^{LI} and $z_t^{Depth_2^D}$, $z_t^{Depth_2^{ND}}$, $z_t^{Intensity_2^{DND}}$, $z_t^{LI_2}$.

Dealer factors Finally, to identify trader factors, we use the generalised identification scheme of Pesaran and Shin (1998) adapted by Barunik and Ellington (2024) to approximate models with time-varying parameters, since a shock to one variable in the model does not necessarily occur in isolation. The use of time-varying frequency responses further identifies the persistence of shocks (Barunik and Ellington, 2024). As the global factors derived from the aggregate shock transmission of dealers and non-dealers are used to explain volumes and spreads in both markets at the dyadic level, there is no other type of endogeneity to be addressed in the regressions.

4 Empirics

4.1 Data

We use proprietary transaction-level data for the UK repo market between January 2016 and January 2022. As shown below, we focus on the largest subsample of transactions, those utilising gilts as collateral, to avoid dealing with asset classes that are illiquid relative to gilts, and to avoid biasing the formation of relationship trading based on ownership of illiquid assets. The dataset includes all repo and reverse repo transactions between dealers

and non-dealers, and between dealers and CCPs. A detailed description of the structural features of the UK repo market can be found in Annex A.

Table 1. Summary statistics for the repo market by type of transaction (repo vs. reverse repo) between dealers and non-dealers. Our sample only uses gilts as collateral. Volumes are in sterling and the interest rate spread is relative to the BoE reference rate.

	p50	mean	sd	min	max	N
	Repo					
Volume	3.12E+07	4.59E+07	4.41E+07	1.09E+06	2.74E+08	335601
Rate spread	-0.01	-0.01	0.09	-0.75	0.77	335601
Haircut	0.00	-0.92	5.84	-55.70	8.71	335601
	Reverse					
Volume	4.50E+07	6.51E+07	7.26E+07	1.11E+06	7.50E+08	350609
Rate spread	-0.08	-0.10	0.08	-0.79	0.64	350609
Haircut	0.00	0.16	1.72	-50.37	3.48	350609

Table 1 presents summary statistics on repo market data by type of transaction between dealers and non-dealers. The median transaction is £31 million at a repo rate of 1 bp below the BoE reference rate when dealers provide liquidity in exchange for collateral, and £45 million at a repo rate of 8 bp below the BoE reference rate when dealers receive liquidity in exchange for collateral. In both cases, the median haircut is zero.

Table 2. Summary statistics for the repo market by type of transaction (repo vs. reverse repo) between dealers and CCPs. Our sample only uses gilts as collateral. Volumes are in sterling and the interest rate spread is relative to the BoE reference rate.

	p50	mean	sd	min	max	N
	Repo					
Volume	2.34E+07	3.47E+07	3.85E+07	1.02E+06	3.30E+08	1149310
Rate spread	-0.06	-0.08	0.08	-0.95	0.65	1149310
Haircut	0.00	-0.27	2.97	-50.06	1.85	1149310
	Reverse					
Volume	2.27E+07	3.44E+07	4.11E+07	1.02E+06	5.00E+08	1103752
Rate spread	-0.06	-0.07	0.08	-0.95	0.56	1103752
Haircut	0.00	-0.01	0.36	-23.37	1.75	1103752

Table 2 presents summary statistics on repo market data by type of transaction between dealers and CCPs. The median transaction is £23 million with a repo rate of 6 bp below the BoE reference rate when dealers provide liquidity in exchange for collateral and £22 million with a repo rate of 6 bp below the BoE reference rate when dealers receive liquidity in exchange for collateral. As in the previous table, the median haircut is zero for both cases.[6]

To examine the impact of market power of repo dealers on the mispricing of gilts, we use ISIN-level metrics of mispricing, volatility, liquidity, residual maturity, and a set of bond-level characteristics. The mispricing metric is the difference between the bond yield and a daily benchmark yield constructed using all gilts available in the market at the time.

Table 3. Summary statistics of the gilts market by residual maturity. Mispricing is the difference between the yield and the benchmark yield, liquidity is the ask/bid spread, volatility is the high/low spread.

		p50	mean	sd	min	max	N
3yr - 7yr	Mispricing	-0.11	0.10	2.18	-4.92	6.61	7566
	Duration	5.28	5.32	1.22	2.86	7.66	7566
	Liquidity	0.03	0.04	0.02	0.01	0.26	7566
	Volatility	0.24	0.28	0.23	0.05	6.87	7566
8yr - 19yr	Mispricing	0.20	0.12	1.48	-5.24	4.74	10810
	Duration	9.94	10.69	2.60	6.73	18.55	10810
	Liquidity	0.05	0.06	0.04	0.01	0.54	10810
	Volatility	0.66	0.77	0.48	0.15	11.00	10810
20yr or more	Mispricing	0.03	-0.16	1.27	-5.19	3.46	14309
	Duration	22.56	22.90	4.95	14.64	37.31	14309
	Liquidity	0.11	0.12	0.06	0.03	0.57	14309
	Volatility	1.57	1.87	1.18	0.33	37.94	14309
Total	Mispricing	0.066	0.00	1.60	-5.24	6.61	32685
	Duration	13.40	14.79	8.27	2.86	37.31	32685
	Liquidity	0.07	0.08	0.06	0.01	0.57	32685
	Volatility	0.86	1.14	1.07	0.05	37.94	32685

Table 3 shows summary statistics for the gilt market. The median gilt has a positive mispricing of 7 pp. However, when zooming in on the three different residual maturity buckets, only short-end gilts have a negative mispricing of 11 pp. The measures of all

[6] Note that the deviation from the median figures reported in tables 1 and 2 is higher than the median. This means that there is a lot of variation between trades and a lot of variability around the median.

other bond characteristics (duration, liquidity and volatility) increase as residual maturity increases.

4.2 Main Variables

Market Power We use mark-ups and mark-downs as a proxy for market power. Dealers operate in the repo segment, providing liquidity in exchange for collateral, and in the reverse repo segment, absorbing liquidity also in exchange for collateral. As non-dealers operate with a small number of dealers, they exercise monopoly power in the repo segment and monopsony power in the reverse segment.

The markup in the repo segment is a function of the marginal cost of production, which is not observed in our data.[7] In the context of price competition with differentiated products, a firm's optimal pricing rule in a symmetric equilibrium is equal to the mark-up on the inverse of the elasticity of demand for liquidity. Our strategy is to back out the dealer-level markup using a simple structural model of supply and demand, following the standard demand estimation literature in empirical industrial organisation.

For the reverse repo segment, e.g. when dealers absorb liquidity in exchange for collateral, the market power proxy (markdown) is instead a function of the marginal revenue of liquidity, see Manning (2003), but again unobservable. Analogous to equation B.2, it's possible to use a one-to-one relationship between the markdown and the inverse elasticity of liquidity supply, see Yeh et al. (2022).

The estimation is done in two steps.[8] First, we set up supply and demand models for short-term funding and estimate the demand (supply) coefficients using our dataset of dealer/non-dealer transactions. We then use the coefficients to compute own-price elasticities and then apply the price-cost mark-up (or marginal revenue-price mark-down) formula derived from the model to back out product-level markups (markdowns) and compute a proxy for dealer-level market power.

[7] A common practice in reduced-form approaches, see Cañón et al. (2022), is to use dealers' balance sheet data and estimate their cost function, and thus obtain marginal cost. This approach is not feasible in our setup due to data availability.

[8] See Appendix B for details.

The optimal pricing rule allows us to derive a markup and a markdown for each dealer at each period t. In Appendix B we explain the procedure in detail.

$$MarkUp_{dt} \equiv \frac{r_{dt} - c_{dt}}{r_{dt}} = -\frac{1}{\eta_{dt}}, \qquad MarkDown_{dt} \equiv \frac{mrev_{dt} - r_{dt}}{r_{dt}} = \frac{1}{\nu_{dt}} \tag{3}$$

where r_{dt} is the average repo rate of dealer d at time t, c_{dt} is the marginal cost of dealer d at time t, $mrev_{dt}$ is the marginal revenue of liquidity of dealer d at time t. Finally, η_{dt} (ν_{dt}) is the elasticity of demand (supply).

Dealer Factors Dealer and non-dealer transaction volumes and interest rate spreads in the UK repo market (both for repo and reverse repo) can be affected by shocks between these market participants, which may form an asymmetric network of trading relationships between dealers. We are interested in measuring such a network, in particular, the extent to which dealers that drive most of the volume matter for the rest of the market. In addition, we want to identify such relationships formed by shocks of heterogeneous persistence, namely transitory and persistent shocks transmitted between dealers and non-dealers. More specifically, our global dealer factor will measure the percentage share of shocks from selected dealers that contribute to the overall market variation. In other words, we will measure the extent to which all dealers are influenced by selected dealers relative to the shock transmission across all dealers and non-dealers. Later, we will be interested in exploring how increasing the intensity of the global dealer factor affects volumes, spreads, gilt mispricing, and market-wide liquidity.

Formally, we consider a $N \times N$ dimensional system with $N = N^D + N^{ND}$ number of dealers (N^D) and non-dealers (N^{ND}) who can transmit shocks to each other throughout the system. To quantify the influence of shocks, we draw on the literature (Diebold and Yilmaz, 2012), which notes that variance decompositions are useful for tracking how shocks affect the future variation of variables within a system, and are therefore a natural choice for inferring shock transmission. Following Baruník and Křehlík (2018); Barunik and Ellington (2024), who further work with time dynamics as well as heterogeneous persistence of shocks, we will define the global dealer factors that vary smoothly over time and are inferred from shocks of

heterogeneous persistence. Specifically, these shocks will be of transitory (tr) or persistent (per) nature, and we will collect them in a time-varying variance decomposition matrix $\theta_{t,d}$ identified from the underlying TVP-VAR model at a given level of persistence $d \in \{tr, per\}$ as detailed in the appendix C.

Specifically, $\theta_{t,d}$ holds information about how much of the future variation of a variable j is due to a shock with persistence d to the variable k at a given time. This is important because the influence of shocks can evolve smoothly over time.

The impact of a selected set of dealers $Dsel$ on the rest of the dealers in the system, relative to all other shocks that may be transmitted between dealers and non-dealers, then forms our global dealer factor with a given persistence d as

$$\mathcal{G}lobal\mathcal{F}_{t,d}^{Dsel} = \sum_{\substack{j=1 \\ j\neq k \\ k\in Dsel}}^{N^D} \left[\widehat{\theta}_{t,d}\right]_{j,k} \Bigg/ \sum_{j,k=1}^{N^D+N^{ND}} \left[\widehat{\theta}_{t}\right]_{j,k}, \tag{4}$$

where $DSel$ is the set of selected dealers whose importance we want to measure. Note that $\widehat{\theta}_t = \widehat{\theta}_{t,tr} + \widehat{\theta}_{t,per}$ and therefore $\mathcal{G}lobal\mathcal{F}_{t,d}^{Dsel} \in [0,1]$ measures the contribution of shocks of a specific persistence of selected dealers relative to the total shocks in the system, and $\left[\widehat{\theta}_t\right]_{j,k}$ is a j,kth element of the time-varying decomposition matrix.

In the estimation, we construct a global factor containing 15 dealers and 7 non-dealer sectors (banks, central banks, asset managers, hedge funds, pension funds, etc.), working with a 22×22 matrix $\widehat{\theta}_t$ measuring the impact of dealers on dealers, dealers on non-dealers, non-dealers on dealers, and non-dealers on non-dealers over the whole period, estimated on volumes and spreads. We will select a number of dealers that account for a large proportion of all funding and we will be interested to see if there is a significant global factor that influences the whole market. The global factor for both repo and reverse repo markets, measured independently of volume and spread shocks, will measure the intensity with which a few selected dealers influence the rest of the market.

Other relevant covariates Dealers and non-dealers in the UK repo market are not randomly matched. In our sample, dealers have an average of nine non-dealer counterparties,

while non-dealers have an average of less than three dealers. Moreover, these trading relationships tend to be stable. These features are observed in other OTC markets, e.g. Zhou Yueshen and Zou (2023), and we need to include them in the analysis.

We measure relationship trading in two dimensions, e.g. depth and intensity. Our measure of depth, denoted $Depth^{D}_{ND,t}$ and in line with Afonso et al. (2014); Li (2021); Han et al. (2022), is calculated as the share of financing received/provided by dealer D to non-dealer ND out of all financing received/provided by all non-dealers in the previous month.[9]

$$Depth^{D}_{ND,t} = \frac{\sum_{t}^{t-20} volume^{D}_{ND,t}}{\sum_{t}^{t-20} \sum_{ND} volume^{D}_{ND,t}} \tag{5}$$

The equation 5 is a proxy for the strength of the trading relationship. A valuable feature of our dataset is that we are able to calculate each metric separately for different segments. In principle, there is nothing to prevent a dealer from having differentiated relationships in the repo and reverse repo segments. Indeed, we observe that some non-dealers only interact with dealers in certain market segments.

Trading relationships aren't just characterised by their depth. From the point of view of dealers, two non-dealers with the same depth may have a different impact on inventory constraints if one executes frequent small trades and the other very few large trades.[10] Recurring trades could be associated with proactive risk management strategies, while end-of-month/quarter trades could be associated with window-dressing strategies, see Anbil and Senyuz (2018); Gerba and Katsoulis (2024); Bassi et al. (2023).

Our measure of intensity, $Intensity_{DND,t}$, is computed as the number of transactions in the last 20 working days between dealer D and non-dealer ND. There are variations of this metric in the relationship trading literature for OTC markets, e.g.Brauning and Fecht (2017), but all use the frequency of transactions as the main input source. Higher intensity also implies more opportunities for dealers to learn private information from non-dealers, so

[9] Analogously, we could calculate the share of financing received/provided by non-dealer ND from dealer D out of all financing received/provided by all dealers in the previous month. The results are qualitatively the same using this alternative measure, and are available on request.

[10] Sambalaibat (2023) shows that OTC dealers segment based on the trading needs of their clients. Dealers at the core of the dealer network would serve the most active non-dealers.

while dealers may prefer to increase intensity, non-dealers may not want to if the trading relationship is sufficiently beneficial to them.

$$Intensity_{DND,t} = \sum_{t}^{t-20} (\mathbf{1}_{volume_{DND,t}>0}) \tag{6}$$

Our dataset is granular enough to construct the intensity metric separately for repo and reverse repo segments. This feature is convenient as we can measure the relationship of any given dealer non-dealer dyad in each repo segment.

4.3 Stylized facts

Table 4 shows the number of potential counterparts that could form a trading relationship. While we observe a fixed number of dealers, the number of non-dealers can change depending on the segment. For example, in the repo segment we have 3380 different non-dealers belonging to 727 different families, and in the reverse segment these numbers are 2004 and 682 respectively.[11] Our data is granular enough to identify non-dealers that operate in both segments simultaneously with the same dealer.

Table 4. Dealer, Non-Dealers and Family of Non-Dealers in our sample.

	Repo	Reverse Repo
Dealers	15	15
NDealers	3380	2004
Family of ND	727	682
Dyads D/ND	5803	3484
Dyads D/Family	2112	1767

Table 4 shows the number of dyads in our sample, which is the unit of analysis for our panel estimation. For the repo segment, we observe 2112 dealer/family non-dealer dyads, and for the reverse repo segment, this number decreases to 1767. If we zoom in on non-dealers

[11] By family we mean a financial institution that could offer different investment vehicles to end-investors. For example, BlackRock is an asset manager that could offer many individual funds to retail investors. In our data, individual non-dealers are each of these funds and BlackRock is the family. As we explain in the paper, our analysis is done at the family level.

that are active in both segments simultaneously, the number of dyads falls to 1048. Our analysis is at the non-dealer family level, so we drop the word "family" and use non-dealers.

Dealers hold more counterparts than non-dealers Table 5 shows the number of counterparts for dealers and non-dealers. It can be seen that, on average, a non-dealer has fewer counterparts than an average dealer. While for dealers this number fluctuates around ten counterparts, for non-dealers it does not reach three counterparts. This feature is not unexpected as it's also observed in other OTC markets.

Table 5. Average number of counterparts and average counterparty dependence

	Repo		Reverse	
	No Counter.	% Funding	No Counter.	% Funding
Non-Dealers	2.73	52.39%	2.93	60.04%
Dealers	9.46	41.95%	6.77	46.13%

OTC vs inter-dealer segments Dealers are active on a daily basis in both the OTC and inter-dealer markets. As emphasized above, the inter-dealer market accounts for a large proportion of daily volume, e.g. around 70%. There are also more fundamental differences. First, table 6 shows that while virtually all transactions in the inter-dealer segment are overnight, in the OTC segment this share does not reach 50% and the remaining share is made up of transactions with maturities of less than one week or one month.

Second, dealers' use of the inter-dealer market is closely related to their holdings. Table 6 shows that while dealers use on average three different gilts in the OTC segment, they use ten times as many in the inter-dealer segment.

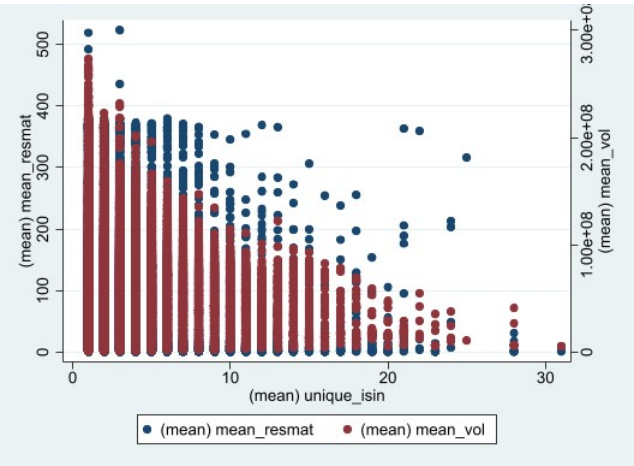
Table 6. % Overnight Funding

	OTC		CCP	
	Repo	Reverse	Repo	Reverse
Overnight Funding	31.59%	46.61%	99.06%	98.64%
Unique ISINs	2.42	2.11	25.19	22.25

In addition, Figure 1 shows a negative relationship between the number of unique gilts

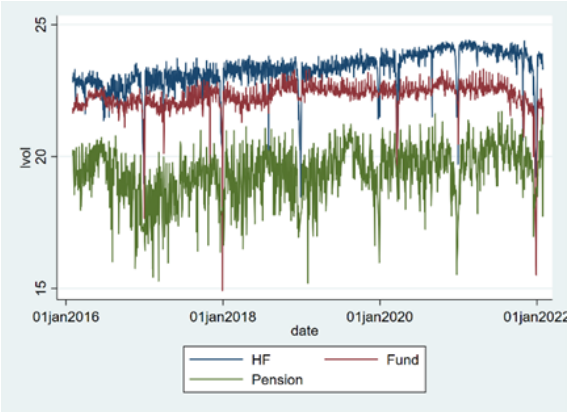
and the size and duration of repo transactions. Repo transactions are, on average, larger and longer when dealers operate with fewer gilts. We interpret this as evidence of inventory constraints.

Figure 1. Unique gilts vs Mean Volume & Mean ResMaturity at OTC segment

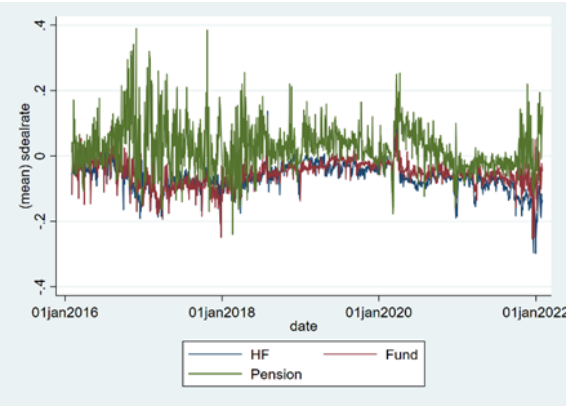


Sector heterogeneity in OTC segment The figures 2a - 2b show the historical volume and the repo spread. Hedge funds and other funds are the two most important sectors in the OTC segment, and the spread to the bank rate is usually negative. In contrast, pension funds have a smaller but still relevant presence, yet their spread is positive.

Existence of global dealer factors Figures 3a and 3b show the global dealer factors for both transaction volume and spread on both the repo and reverse repo segments, formed in response to transitory and persistent shocks. Note that we select 5 dealers that explain 40% of all funding in both the repo and reverse repo markets (note that these may be different), and we can see that the total contribution of this subset of dealers is between 8% and 18% (as the sum of transitory and persistent factors). Note that the global factor derived from spread shocks is more volatile.

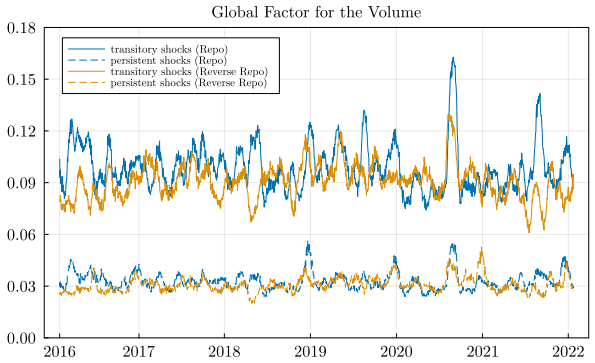


(a) Volume

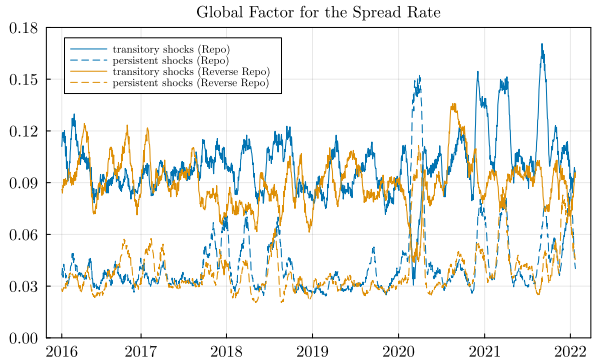


(b) Rate Spread

Figure 2. Log volume and repo rate spread using the non-dealer dataset with daily frequency. The spread is the difference between the repo rate and the reference rate.



(a) Volume



(b) Rate Spread

Figure 3. Global dealer factors derived from both transitory and persistent shocks to repo and reverse repo volumes and spreads.

5 Results

5.1 Market Power

We implement a simple structural model to identify dealer-level mark-ups and mark-downs using data from bilateral OTC repo market segments. The Appendix section B presents the model in detail. We follow a demand approach (Berry, 1994) and use the equality between predicted shares, given by equation (B.5) in the appendix, and observed market shares S_{dt} to transform the initial non-linear model into a linear one.

$$\ln S_{dt} - \ln S_{0t} = \mathbf{x}_d\boldsymbol{\beta} - \alpha r_{dt} + \gamma I_{dt} + \phi_t + \xi_d + \Delta\xi_{dt}. \tag{7}$$

where $\mathbf{x}_d$ is a (row) vector of observable product (dealer) characteristics that do not vary over time; r_{dt} is the average repo rate between dealer d and non-dealers at t; I_{dt} is the average frequency, across non-dealers, of dealer d's lending/borrowing relationships at t; ϕ_t accounts for time shocks common to all transactions observed in the market at t; ξ_d captures the mean valuation of unobserved dealer characteristics that do not vary over time; $\Delta\xi_{dt}$ are unobserved dealer characteristics that vary over time.

We have three potentially endogenous variables, e.g. repo rate, frequency and residual maturity, as they are under the control of individual dealers. Dealers d may have incentives to adjust these variables in response to changes in non-dealers' need for funding or securities, or changes in preferences for time-varying dealer characteristics, $\Delta\xi_{ft}$, that are unobserved by the econometrician. To correct for potential bias in our estimates, we exploit both the granularity and the panel structure of our data to generate instrumental variables: two granular IVs (GIVs) for frequency, two difference IVs (DIVs) for repo rate, and three DIVs for residual maturity.[12] Thus, the identification assumption is that our instrumental variables are not correlated with demand shocks after controlling for aggregate shocks at the market

[12] GIVs are computed as in Gabaix and Koijen (2024), and DIVs are computed as the difference of the dealer-level variable from the mean across dealers divided by the standard deviation across dealers. Repo rate DIVs are the unique ISINs in the OTC reverse repo segment and the unique ISINs in the interdealer reverse repo segment. Maturity DIVs are the average maturity in the interdealer repo segment, the percentage of overnight in the OTC repo segment and the average funding in the OTC reverse repo segment.

level and observed and unobserved characteristics at the dealer level.

We estimate the model (7) using two-stage least squares. We report the results of the estimation in table D.1. The top panel presents estimates with the reverse repo segment used to calculate the markdown, and the bottom panel presents estimates with the repo segment used to calculate the markup. Both panels have five columns: columns (1) and (3) show the estimates without correcting for endogeneity, columns (2) and (4) correct for endogeneity, and the last column eliminates the frequency variable from the column (4) specification as a robustness check. Finally, while the first two columns use the full sample, the last three columns eliminate the top 5% of non-dealers (according to their transaction volume) to ensure that dealers' bargaining power is not distorted. Our preferred specification is in column (4).

The estimates for the repo rate have the expected sign in each repo segment and are highly statistically significant. In the top panel, the positive sign implies that the supply of funds from non-dealers is upward sloping; in the bottom panel, the negative sign implies that the demand for liquidity from non-dealers is downward sloping. In particular, comparing columns (4) and (2), we confirm that excluding the top 5% of non-dealers increases the slope of demand and supply.

The estimates for frequency provide insight into the drivers of market power. Table D.1 shows that the market power of dealers decreases as the number of interactions between dealers and non-dealers in the last month increases. This characteristic is only statistically significant when we calculate the markdown, but the sign remains when we calculate the markup. This result supports the argument that market power of repo dealers is, at least, partly driven by adverse selection.

[Table D.1]

The market power of dealers may differ between the repo and reverse repo segments. To suggest otherwise is misleading, as we show in table D.2, where we estimate the demand model using data from both repo segments. In particular, the estimate for the repo rate (column (4)) is no longer statistically significant, and its level is a fraction of that obtained in table D.1.

5.2 Repo Market Impact

The market power of repo dealers should affect the terms of trade for non-dealers. Theoretically, we should expect dealers with higher market power to worsen terms of trade, i.e. to reduce volumes and increase repo rates and haircuts. On the other hand, if the main friction between dealers and non-dealers is asymmetric information, then dealers with higher market power will improve the terms of trade of non-dealers as counterparties know more about each other.[13]

Empirical work has largely been confined to the banking sector, see Altunbas et al. (2022); Carlson et al. (2022); Cruz-García et al. (2021); Cañón et al. (2022). Studies with transaction-level data, such as the data quality we have, tend to support the first view. Higher levels of market power negatively affect the borrower's terms of trade. Our study is the first attempt to examine this issue for the repo market.

Our preferred specification is below,

$$\begin{aligned}\Gamma_{Dlt} &= \beta_0 + \beta_1 marketPower_{D,t} + \beta_3 depth^{D}_{ND,t} + \beta_2 frequency_{DND,t} \\ &+ \beta_3 \log\, CB\, reserves_t + \beta_4 DF\, tot\, repo_t + \beta_5 DF\, tot\, reverse_t \\ &+ \beta_6 \mathbf{X}_{DND,t} + \beta_7 \mathbf{G}_{D,t} + \beta_8 \mathbf{H}_t + \lambda_d + \epsilon_l + \eta_t + \nu_{dlt} \qquad (8)\end{aligned}$$

where Γ_{Dt} can be the logarithmic volume between dealer D and non-dealer ND at time t ($lvol_{DND,t}$) or the repo rate spread over the reference rate for the same transaction ($rate_{DND,t}$). The explanatory variables are the market power proxy (i.e. markup or markdown) for dealer D at time t ($marketPower_{Dt}$), the depth metrics for dealer D ($depth^{D}_{ND,t}$) and the intensity of dealer D and non-dealer ND at time t ($frequency_{DND,t}$), and the dealer factors for each repo segment ($DF\, tot\, repo_t$ and $DF\, tot\, reverse_t$).[14] We include dealer-specific controls ($\mathbf{G}_{D,t}$) and time-specific controls ($\mathbf{H}_t$). Finally, we include dealer (non-dealer) fixed effects, non-dealer (dealer) fixed effects interacted with month fixed effects

[13] Our setup incorporates the interaction between adverse selection and imperfect competition. Crawford et al. (2018) argue that higher markups reduce the negative impact on prices associated with an increase in adverse selection.

[14] This specification does not distinguish between transitory and permanent shocks to repo dealers. We introduce the distinction later.

for the situation where dealers (non-dealers) provide liquidity to non-dealers (dealers).[15]

Some explanatory variables are potentially endogenous, i.e. the relationship trading proxies and market power. Relationship trading proxies vary at the dyadic level and it may be that changes in the terms of trade affect depth or intensity. Market power only varies at the trader level, but it could be that changes in the terms of trade of large non-dealers affect the market power of dealers. To correct for the potential estimation bias, we exploit the granularity of our dataset and the panel structure of our data to generate a granular IV for each variable. The identifying assumption is that our instruments are not correlated with demand shocks after controlling for market-level aggregate shocks and dealer-level observed and unobserved characteristics.

We estimate our preferred specification using two-stage least squares. In all tables, we distinguish estimates for repo transactions from those for reverse repo transactions. In addition, as our data is granular enough to identify pairs of dealers and non-dealers that engage in repo and reverse repo on the same day, we present results using all non-dealers and results using the subsample of non-dealers that engage in both segments simultaneously.

Tables D.3 - D.6 show the impact of market power and dealer factors in the repo market. The structure of the tables is always the same. In the top panel, we present estimates for funding, measured as the logarithm of volume, and in the bottom panel we present estimates for the repo spread in absolute value. In both panels we present estimates for the repo segment and for the reverse repo segment. In the tables D.4 and we distinguish dealer factors attributed to transitory shocks from permanent shocks.[16]

Dealers' deal with non-dealers in two ways, either by providing liquidity or by receiving liquidity in exchange for collateral. In both situations dealers are in an advantageous position, but we would expect market power to operate differently in each case. In repo transactions, when dealers are liquidity providers, we would expect dealers with higher market power to provide less funding. There is a large literature in banking showing that lenders with higher market power reduce lending, Altunbas et al. (2022); Carlson et al. (2022); Cruz-García et al. (2021); Cañón et al. (2022). In reverse repos, on the other hand, dealers have opposite

[15] Alternatively, we use dyad fixed effects and the results are very similar, qualitatively and quantitatively.
[16] In the online appendix, table A.2

incentives and we would expect qualitatively different results.

Table D.3 shows the estimates of our benchmark model 8 for the log volume. We obtain the expected sign of market power in the reverse repo segment, but the estimates lack significance. Dealers with higher market power reduce the (log) volume relative to the average loan (which is 35) by 0.55, which is about 1.6%. However, once we introduce dealer factors, the estimates are no longer significant. For the repo segment, the estimates are not statistically significant. Second, the relationship trading proxies, in both the repo and reverse repo segments, show that stronger and/or more intense relationships increase volume.[17]

The bottom panel of table D.3 shows the impact on the (absolute) spread between the repo rate and the bank rate. We consistently find that dealers with higher market power charge or pay higher spreads (which are negative on average). In the repo segment, this is consistent with dealers charging a repo rate below the reference rate to access gilts. In the reverse repo segment, dealers with higher market power also receive larger (negative) spreads. It's worth noting that the estimates for the relationship trading proxies are not statistically significant.

Returning to hypothesis 1, Table D.3 shows that dealer-specific market power produces the expected deadweight loss in the repo market, but only through repo rates, as volumes are mostly driven by relationship trading metrics.

Dealer factors, which capture shocks to repo dealers, also affect individual transactions. Table D.3 shows that as dealers become more interconnected, volumes increase and spreads narrow. These findings hold when we distinguish between temporary and permanent shocks to repo dealers, see table A.2.

[Tables D.3 - D.4 here]

Dealers tend to operate in both repo segments, as do a non-negligible fraction of non-

[17] We provide evidence of a non-monotonic relationship between the importance of non-dealers to dealers and the funding they receive. In tables A.5 - A.6 in the online appendix, we replace the relationship trading proxies with two dummies, e.g. 'Client' and 'Client Low'. We find that Client is equal to one if the non-dealer in a given pair is simultaneously above quantile 70 in all relationship trading metrics; on the other hand, a non-dealer is a Low Client if it is simultaneously below quantile 30. Consistently, both dummies are statistically significant, but while Client has a positive sign, Client Low has a negative sign.

dealers. As a robustness test, we repeat the same analysis, but only with dealer/non-dealer dyads operating simultaneously in both segments. Tables A.1 and A.2 in the online appendix show that the results are qualitatively unchanged. For market power, there are no major differences between estimates using all dyads and dyads active in both repo segments. The only difference is for the dealer factors, as once the main dealers become more interconnected, only transitory shocks increase repo volumes.

5.3 OTC Repo Segmentation

We observe qualitative differences between non-dealers from different sectors. Evidence from the UK and elsewhere, e.g. Czech and Pinter (2022), suggests that hedge funds and asset managers behave more procyclically than pension funds and insurance companies.

Tables D.5 - D.6 present our benchmark specification in equation 8 for two sectors, namely hedge funds & asset managers (HFs & AMs) and pension funds & insurance companies (PFs & ICs). Both tables are constructed in the same way. The top panel shows estimates for the repo segment and the bottom panel estimates for the reverse repo segment. Finally, each panel presents estimates for each sector.[18]

Focusing on volume, we highlight two features of market power. First, the market power of dealers does not affect HFs & AMs, but it does affect PFs & ICs.[19] This is consistent with the fact that these institutions are responsible for most of the daily transactions, and in our estimation of market power in table D.1 we show that market power decreases with the variable frequency, which captures monthly interactions. Second, the effect of market power is stronger (in absolute terms) in the reverse repo segment than in the repo segment. This implies that dealers with larger markdowns receive less funding from PFs & ICs in exchange for gilts.

In terms of relationship trading metrics, Table D.5 shows that HFs & AMs highly value relationships with dealers. Estimates of both proxies, i.e. depth and frequency, are

[18] In the online appendix, tables A.3 and A.4 extend tables D.5 and D.6 by splitting dealer factors into transitory and persistent shocks.

[19] In previous versions, we show that the volume of non-dealer banks is not affected by the market power of repo dealers. They are available on request.

statistically significant for non-dealers from this sector. PFs & ICs tend to operate less frequently and that's why Depth is the only relationship metric that is statistically significant.

We now proceed to test for market segmentation (or fragmentation). According to Sambalaibat (2023), there is evidence of segmentation if, as main dealers become more interconnected, certain non-dealer sectors also increase their funding from/to repo dealers. The common characteristic of these sectors is that they trade frequently and account for a large share of total volume.

We argue that dealers segment the repo and reverse repo segments if dealer factors have a homogeneous impact across non-dealer sectors.

Table D.5 shows that in the repo segment, as the main dealers become more interconnected, only PFs & ICs increase the funds they receive. In the reverse repo segment, as the main dealers become more interconnected, only HFs & AMs increase the funding they provide in exchange for gilts. We argue that this evidence support the segmentation (or fragmentation) hypothesis, as HFs & AMs are the most relevant institutions from the reverse repo segment and PFs & ICs are the most relevant institutions in the repo segment.

Table D.6 shows the impact on the repo spread by non-dealer sector. According to table D.4, transitory and permanent shocks affect all non-dealer sectors.

[Tables D.5 - D.6 here]

Tables D.5 - D.6 show that shocks to dealer interconnectedness have a differentiated impact on non-dealer segments. We interpret these results as evidence of OTC segmentation.

5.4 Bond-Level Mispricing

The market power of repo dealers generates two different welfare losses that could lead to mispricing in the bond market, for example Syverson (2024). Market power induces the traditional deadweight loss that reduces funding (access to gilts) through the repo (reverse repo) segment and distorts repo rates in favour of dealers. A second welfare loss is related

to the variation in mark-ups or mark-downs across dealers, which leads to misallocation of funds in the repo market, which in turn leads to arbitrage frictions in the bond market.

Our benchmark specification includes both the individual and collective impact of repo dealers on bond market mispricing.

$$\begin{aligned} y_{bt} &= \alpha_0 + \alpha_1 MarkUp_{bt} + \alpha_2 MarkDown_{bt} + \alpha_3 DF_t^{Repo} + \alpha_4 DF_t^{Rev} \\ &+ \beta_1 X_{bt} + \beta_2 \gamma_t + \beta_3 FE_b + \beta_4 FE_t + \epsilon_{bt} \end{aligned} \tag{9}$$

where y_{bt} is the difference between the yield on bond b at time t and a benchmark yield constructed using a spline-based method, see Anderson and Sleath (2001),[20]. $MarkUp_{bt}$ and $MarkDown_{bt}$ are the (volume-)weighted average market power of dealers trading bond b at time t in each of the repo segments, DF_t^{Repo} and DF_t^{Rev} are the repo dealer factors at time t in each repo segment, X_{bt} are bond-level time-varying characteristics such as bid-ask spread, volatility, duration, repo premium,[21] residual maturity and the Bank of England's free-float share. γ_t are market-level time-varying confounders such as the log of Bank of England reserves, a proxy for UK systemic risk, and individual period-specific dummy variables (March 2020 dash-for-cash in the UK, September 2019 US repo market stress period, and Brexit period). Finally, we include bond fixed effects, and month fixed effects.

Tables D.7 - D.7 present evidence on the impact of repo dealer market power on gilt mispricing. Table D.7 shows the estimates for different modifications of equation 9 using gilts at all maturities. The first column shows the impact of MarkUp and MarkDown using an OLS specification and the second column controls for endogeneity bias using GIVs. Both columns suggest a causal effect of repo dealer market power on the functioning of the bond market, i.e. as dealers using gilt b as collateral for repo transactions increase their individual market power, the pricing of gilt b will deviate more from the benchmark.

[20] Nymand-Andersen (2018) compares well-known methods using ECB data and finds that spline-based methods perform slightly better

[21] Measured as the difference between repo trades using bond b at time t and repo trades using the general collateral category.

The dispersion of market power between repo dealers can also lead to mispricing of individual gilts.[22] Columns three and four of table D.7 modify our benchmark specification of equation 9 by replacing the (weighted) average markup (markdown) with the (weighted) average standard deviation of the markup (markdown) in column (3), and by including the interaction between the markup (markdown) and its dispersion in column (4).

Table D.7 shows evidence that the dispersion of market power is positively correlated with gilt mispricing. The evidence is particularly strong, in a statistical sense, when repo dealers receive funding from non-dealers in exchange for gilts. We also find that the interaction between market power proxies and their dispersion is not significant, at least when we include gilts of all maturities, implying that the two welfare losses associated with market power act *independently* on gilt mispricing.[23]

Finally, column (5) of table D.7 shows evidence that mispricing increases with the wedge between the dealer's marginal revenue from funding and the dealer's marginal cost of providing funding. Notably, although both elements are unobserved, we can proxy the difference with MarkUp and MarkDown.

[Table D.7 here]

Table D.8 extends the previous table and presents estimates for gilts of different maturities.[24] Specifically, the first three columns correspond to the second column of table D.7, the second group of three columns corresponds to the third column of that table, the third group of three columns corresponds to the fourth column, and the last group of three columns corresponds to the fifth column.

Table D.8 shows that market power operates mainly through the reverse repo segment. In the first three columns, we observe a positive and significant impact of MarkDown for all

[22] Previous studies have raised awareness of the role of market power dispersion in explaining macroeconomic aggregates, see for example Syverson (2024).

[23] Later in the table D.8 we observe that the latter result does not hold for long-term gilts, as the interaction term is significant when dealers obtain funding from non-dealers in exchange for gilts.

[24] Short-term gilts have a residual maturity of between 3 and 7 years, medium-term gilts have a residual maturity of between 8 and 19 years and long-term gilts have a residual maturity of at least 20 years. We exclude gilts with less than three years to maturity because the model selection error is higher for the front segment of the yield curve. All results are robust to the inclusion of the latter and are available on request.

maturities, but for MarkUp it is only significant for medium-term gilts. Similarly, in columns (4) - (6) we observe a significant impact only for the markdown dispersion, and in columns (7) - (9) the interaction term is significant only for the markdown and for long-term maturities.

[Table D.8 here]

Repo dealers can collectively influence the functioning of the bond market by fragmenting the repo market. Returning to Sambalaibat (2023), if the largest dealers specialise in non-dealers based on their activity or importance, then as the main dealers become more interconnected, certain non-dealer sectors will have access to either more funding or more gilts. We argue that our dealer factors (DFs) capture new information relative to other market-level variables[25], have the advantage of distinguishing between transitory and permanent shocks and should therefore be included in the benchmark specification.

Tables D.9 - D.10 expand Tables D.7 - D.8 in order to distinguish transitory from permanent shocks. On the one hand, in both tables we observe that transitory and permanent shocks in the reverse repo segment increase gilt mispricing. On the other hand, also in both tables, we observe an opposite effect only for permanent shocks for the repo segment.

[Tables D.9 - D.10 here]

The qualitative difference between the repo and reverse repo segments corresponds, as we will show later, to the way in which the main dealers segment the repo market. We will argue that the main dealers in the repo segment specialise in pension funds and insurance companies, while in the reverse segment they specialise in hedge funds and asset managers. For example, as the main dealers in the reverse segment become more interconnected, hedge funds and asset managers will increase their funding to dealers and acquire gilts, and the pricing of gilts will deviate from the benchmark price. Conversely, as the repo segment's main dealers become more interconnected, pension funds and insurance companies will provide

[25]For example, the correlation between the DF from the reverse segment and CB market share is 0.3, the log of CB reserves is 0.22, and UK systemic risk is -0.01. Similar correlations are obtained with the DF from the repo segment

more funding in exchange for gilts, and the pricing of gilts will move closer to the benchmark price.

The "dash-for-cash" period permits to further test the role of repo dealer segmentation during periods of stress. According to Czech et al. (2021), in the Dash-for-Cash period, hedge funds were the only sector that increased their borrowing (in the repo segment), and all nonbank sectors (except money market funds) increased their lending to repo dealers (in the reverse repo segment). According to Czech et al. (2021), non-bank financial institutions also significantly increased their activity in the gilt market.

Table D.11 shows that DFs have different effects for different gilt maturities during periods of high liquidity stress and high bond market activity. If we combine gilts of different maturities, see columns (1)-(2), the impact of DFs during the Dash for Cash period is no different from other periods. However, when we evaluate the impact across different maturities, we observe that for medium-term gilts, the impact of DFs during the dash-for-cash period is much stronger than in normal periods. Notably, for long-term gilts, as the main dealers in the reverse repo segment become more interconnected, mispricing during dash-for-cash does not increase, but rather decreases. The latter effect correlates with the fact that hedge funds tend to trade short-and medium-term gilts, while pension funds and insurance companies prefer long-term gilts.

[Table D.11 here]

5.5 Market Liquidity Impact

We now turn to the question of whether the individual market power of repo dealers and the collective segmentation of the repo market have an impact on market-level aggregates.

This paper explores the linkages between the funding and bond markets, see Brunnermeier and Pedersen (2008), but so far we have focused the analysis at the bond (or gilt) level. We now move on to assess the impact on market liquidity, understood as in Hu et al. (2013). To this end, we aggregate equation 9 at the daily level.

Table shows evidence that both individual and collective repo dealer actions affect market liquidity. The first two columns, where we do not distinguish between transitory and permanent DF shocks, show that higher market power and dispersion of market power deteriorate market liquidity only in the reverse repo segment. The latter is an interesting result, as the literature that includes market power generally does not distinguish between repo segments.

Market liquidity also deteriorates as the main repo dealers become more interconnected. Higher levels of DFs in the reverse repo segment worsen market liquidity, which is consistent with previous tables, as we have previously shown evidence that, as DFs increase, arbitrage opportunities at the bond level also increase.

Table D.12 also shows that higher levels of DF in the repo segment also worsen market liquidity. This result seems to be inconsistent with previous results, as we show that DF reduces bond-level mispricing. Columns (4) - (9) resolve this inconsistency by distinguishing between transitory and permanent shocks to DF. We provide evidence that transitory shocks to the repo segment worsen market liquidity, while permanent shocks improve market liquidity. Overall, transitory shocks outweigh permanent shocks.

[Table D.12 here]

5.6 Overarching discussion

This paper pins down three mechanisms associated with repo dealers that spillover to the bond market and create dysfunctionalities at the bond level. Furthermore, we show that all three mechanisms have a market-wide impact by determining overall market liquidity. We are ex ante agnostic about how these mechanisms interact, as there currently is no theoretical literature to anchor to. Yet, we wish to test, as stated in Hypothesis 5, whether these three mechanisms interact, either additively, or off-setting.

Again, in Table D.12 we provide evidence that once we include them all in our benchmark specification, they individually and additively contribute to market liquidity.[26] As expected,

[26]The impact to other macro variables is certainly of interest but it's out of scope and we leave it for future

most qualitative results at the bond-level are also observed at the market-level, but noticeably we obtain two new insights. First, at the aggregate level, the level of market power is less important than its dispersion between dealers. Second, the difference between transitory and permanent shocks to repo dealers is very clear. While transitory shocks undoubtedly worsen market liquidity, permanent shocks on the repo (reverse) segment actually improve (worsen) market liquidity. We argue that the latter qualitative difference between repo segments is explained by our evidence of OTC segmentation, e.g. main dealer from the repo segment specialize in PFs & ICs, and those from the reverse segment specialize in HFs & AMs.

Returning to Hypothesis 5, we provide some evidence of interactions. Table D.12 shows that the interaction between the (weighted) average market power and its dispersion is statistically significant for the reverse segment. So why don't we observe it in both repo segments? The reverse segment is used by hedge funds and asset managers to obtain gilts from dealers, most of which are on-the-run and might have high demand.

Table 7 summarize the main takeaways.

Table 7. Hypotheses and Takeaways

Hypothesis	**True/False**	**Takeaway**
1	FALSE	Market power affects repo rate, and relationship trading affects volume
2	TRUE	Level of market power increases bond mispricing and worsens market liquidity
3	TRUE	Market power dispersion effect dominates the effect of market power level
4	FALSE	Transitory shocks in the reverse segment are the most relevant
5	FALSE	The three channels are not independent

6 Further considerations on market dysfunction tools

The turbulent market events surrounding the COVID pandemic and the LDI "mini-budget crisis" have prompted financial regulators and central banks to rethink the universe of threats

research.

to the smooth functioning of the repo market. While the Great Financial Crisis highlighted the dangers of highly leveraged participants borrowing in the repo market, other sources of friction were largely overlooked.[27] The problems (and subsequent solutions) have been viewed through the lens of the culprits of the previous crisis, rather than with the repo and bond markets in mind. Also, the absorptive capacity of dealers' balance sheets hasn't received enough attention Menand and Younger (2023). As a result, the possible sources of distress or impairment were very narrow Yadav (2021).

According to the US Inter-Agency Working Group for Treasury Market Surveillance (IAWG) in its 2021 Principles for the Treasury Market, good market functioning implies that there are minimal price distortions caused by technical factors, externalities or frictions between closely related markets. Our paper shows that some of these distortions are non-negligible **in normal times** and lead to sizeable gilt mispricing and productivity losses. Yet in times of stress, these inefficiencies multiply. These have significant welfare costs for the economy because the repo and bond markets together are essential for government financing, for access to short-term funding, for obtaining high quality collateral, and for establishing a benchmark yield curve that underpins financing for households, businesses, and the public sector. Viewed through the lens of an overall market liquidity gap, this can become large and, by itself, cause economic recessions. Therefore, the public and private sectors must work together, through supervision, to enhance market resilience so to minimise these welfare costs and reduce the likelihood of severe disruptions. In addition, central banks need to develop an appropriate toolkit to mitigate (Logan (2023)) core market disruptions when they occur.

The BIS Markets Commission 2022 report (Hauser and Logan (2022)) states that the principle for central bank intervention aimed at restoring market functioning is that of a backstop.[28] The report recognises that the central bank has to strike a delicate and difficult balance: "...This means that, on the one hand, in situations where market disruptions are

[27] Basel 3 and 3.1 have largely focused on reducing leverage in the banking sector and internalising some of the costs of excessive borrowing. Similarly, macroprudential policy has largely been institution-focused rather than market-focused.

[28] The ESRB report Buiter et al. (2023) calls it a penalty term aimed at mitigating moral hazard. The idea is to ensure that pricing is at a level that would be unattractive in normal times. For lending facilities, the interest rate and the haircut should imply costs that would be high in normal times. For purchase facilities, the central bank should reassess the terms on an ongoing basis and offer to purchase at prices below those prevailing in normal financial market conditions.

likely to have a material adverse impact on the real economy, central banks should consider using their ability to expand their balance sheets and provide liquidity to mitigate this impact. On the other hand, it means that, under normal market conditions, central banks should aim not to (i) interfere with price discovery or market determination of resource allocation; or (ii) substitute for the primary obligation of market participants to manage their own risks, reinforced by appropriate macro- and micro-prudential regulation and supervision" (p. 3, par. 1, Hauser and Logan (2022)). We argue that the regulator needs to take additional account of microstructure frictions if it is to ensure that the market operates at the efficiency frontier and minimises the aggregate liquidity losses. Potential ways to do this include increasing the number of designated dealers in the repo and gilt markets, increasing their (balance sheet) intermediation capacity (as outlined in Logan (2023), increasing the capital of the main trading firms (non-dealers), as intermediation has increasingly migrated to this segment (Gerba and Katsoulis (2024)), encourage further fragmentation in reverse repo, see Ballensiefen et al. (2023), or push for a higher share of clearing through CCPs for both secondary markets (as argued in Duffie (2020) or Mancini et al. (2016)). In our view, this will also reduce the need for *ad hoc* central bank intervention, thus reducing the likelihood of a scenario of scarce collateral, or even one of central bank market making dominance. The extension of existing central bank lending facilities to non-banks, as exemplified by the Bank of England's Contingent NBFI Repo Facility (CNRF), will alleviate intermediation pressures in times of stress, but won't mitigate the underlying frictions (see BoE (2025) for further details of the program). Similar to the industrial policy for manufacturing and services, our recommendations have a structural objective for the financial market.

7 Concluding remarks

Using a proprietary gilt market dataset, we identify how market microstructure frictions impact system-wide market liquidity, and we provide new perspective on how financial imperfections in the money market, measured by market power and relationship trading, affect the real economy through shocks to individual dealer capacity.

We contribute to the thin (but growing) literature on financial market frictions in three ways. First, we pin down the size of the frictions using market liquidity metrics and suggest a way to conceptualise it in aggregate or system-wide terms. Second, we explicitly link industrial organisation features in financial markets to productivity (and the productivity frontier), which operates through the notion of market liquidity and collateral availability. Finally, we examine central bank open market interventions through the lens of industrial relations and bargaining power dynamics (as opposed to market-wide outcomes). The conceptual novelty, we believe, lies in linking micro and macro phenomena in financial markets by providing a microfoundation for financial market frictions in aggregate fluctuations.

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Appendix

A The UK Repo Market

A.1 Overview

Next, we wish to describe the UK repo market, both in terms of the institutional set-up and the participants.[29] We follow the description laid out in Gerba and Katsoulis (2024).

A repo transaction involves selling a security and agreeing to buy it back at a later date for a pre-agreed price. The security acts as collateral in the case the seller cannot buy it back and offers counterparty risk protection to the buyer who can sell it in order to limit losses. The difference between the sell price and the repurchase price determines the interest rate paid by the seller to borrow cash and is known as the **repo rate**, or price of the contract. The buyer can demand collateral haircuts to further reduce the risk of losses in case of a counterparty default by overcollateralising the loan. The transaction is called **repo** from the cash borrower's perspective and **reverse repo** from the cash lender's perspective. When a pre-specified security is exchanged as collateral, the transaction is known as **special repo**. On the other hand, when any security satisfying certain criteria, such as specific credit rating, is accepted the transaction is known as **general repo**. In special repo trades, the rate is typically *lower* compared to general repo, or even negative as demand is driven by cash lenders who are willing to pay interest to obtain the security (e.g. for collateral management purposes). In general repo, the rate is typically higher and positive as demand is driven by cash borrowers who seek funding.

A.2 Role of the repo market

Figure 4, coming from Clark et al. (2021), depicts where repos fit into the overall financial market chain (or system) . It's evident how relevant Repo is for participants of any modern

[29] It's important to point out the UK's institutional peculiarities in the repo market, as it differentiates significantly from that of the US or the Euro Area.

c

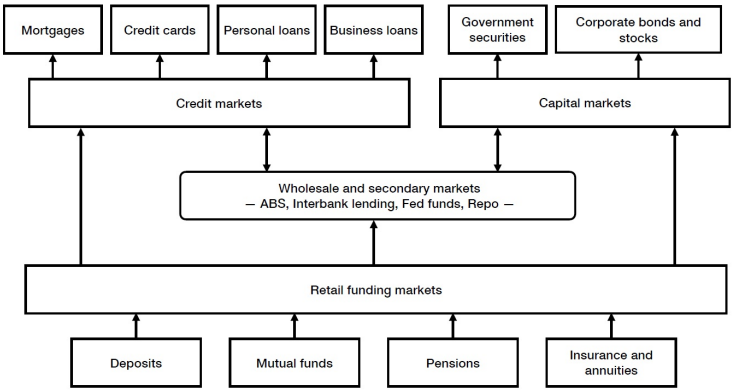


Figure 4

financial industry, e.g. banks and non-banks, since it's a core source of liquidity and collateral. For example, hedge funds could use the repo to fund long bond positions, or obtain collateral to implement short bond positions.

A.3 UK microstructure

The UK repo market is dominated by bank dealers that intermediate transactions mostly backed by UK government bonds, or **gilts** (Kotidis and van Horen, 2018). A wide range of other institutions also participate in the repo market including non-dealer banks, money market funds, central counterparties and corporates that invest cash through reverse repos. Hedge funds, pension funds, asset managers and insurance companies, on the other hand, borrow cash through repos to finance their investments (Bicu et al., 2017; Huser et al., 2021). The market includes transactions that occur between bank dealers (i.e. interdealer segment), which are mostly cleared through CCPs, and transactions that occur between dealers and clients that are mostly traded *bilaterally* or OTC (Kotidis and van Horen, 2018).

Figure 5 summarizes the stylized structure of the market in which dealers intervene.

In Figure 6a, we plot the evolution of the UK gilts repo market using SMMD, splitting total monthly volume by general collateral (GC) and special collateral (SC) trades. As can be seen, since 2016 there has been an increase in market activity, mainly SC trades,

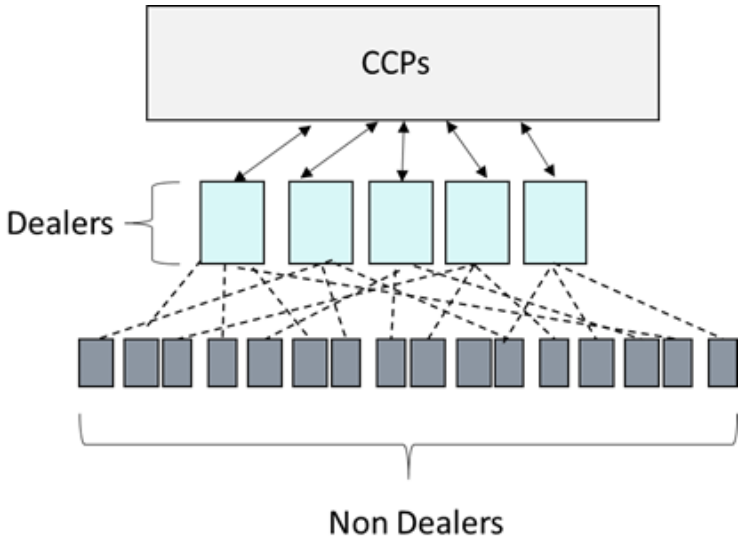
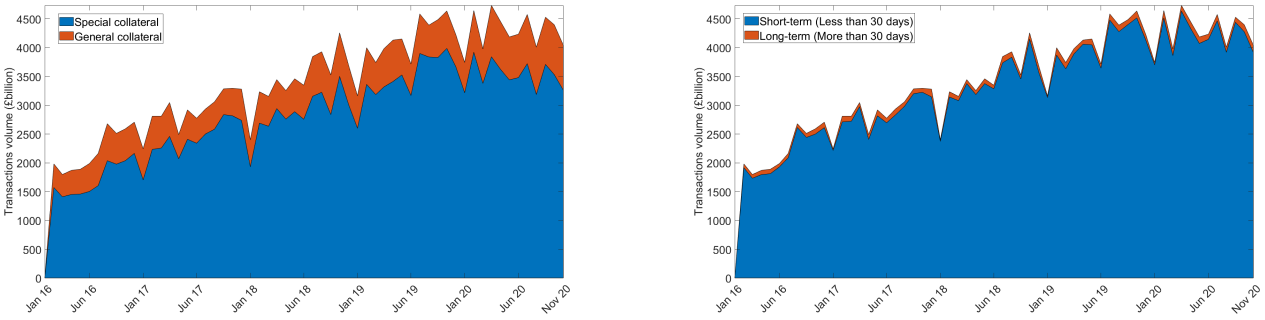


Figure 5. Repo Market Structure

which constitute 95% of transactions and 83% of total transactions volume. In Figure 6b we decompose total transactions volume by maturity buckets, less than or equal to 30 days, and more than 30 days. The graph shows that the majority of trades have a maturity of less than 30 days (97% of transactions and total volume). In Figure 7 we decompose total volume by participants' headquarters region. As is to be expected, UK-domiciled banks dominate the market in terms of traded volumes (32% of transactions and 40% of total volume), followed by US-domiciled banks (36% of transactions and 33% of total volume), EU-domiciled banks (24% of transactions and 20% of total volume), and Asia-domiciled banks (8% of transactions and 7% of total volume). Overall, on a monthly basis transaction volumes have doubled from £2 trillion in 2016 to £4 trillion in November 2020 which highlights the significance of repos as a key funding market in the UK.

To give perspective, we also report the gilts repo and reverse repo *holdings* separated across maturity and region, as share of the total market. As can be seen, short-term holdings constitute 54% of the total, indicating that while they represent the vast majority of transactions since they roll-over much more frequently, they are roughly equal to long-term repo and reverse repo holdings. Expressed differently, while in terms of flows (or volumes), short-term clearly dominates long-term, in terms of stocks (or holdings), the two are relatively



(a) By collateral type (SMMD) **(b)** B bucket (SMMD)

Figure 6. Monthly gilts repo and reverse repo transaction volumes

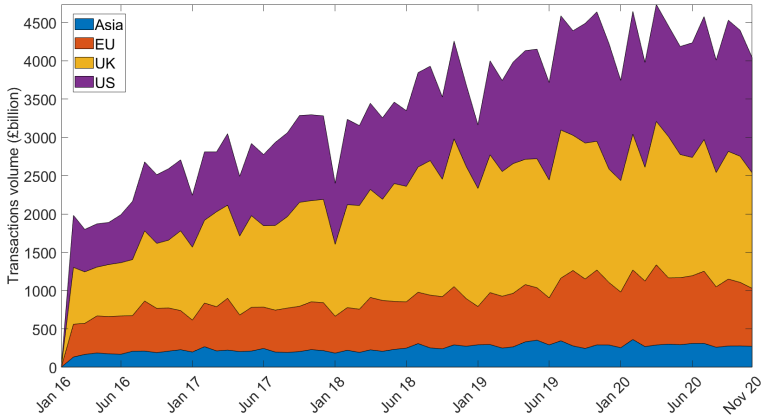


Figure 7. Monthly gilts repo and reverse repo transaction volumes by region (SMMD)

equal. Furthermore, UK banks hold 45% of the total volume, followed by US banks with 35%, EU banks with 14% and Asian banks with 6%.

In Panel A of Table **??**, descriptive statistics for daily and quarterly transaction volumes from SMMD are provided. On a daily frequency, the average general repo transaction volume across institutions is £1,542.68 million, while the average general reverse repo transaction volume is £469.48 million. On a quarterly frequency, the corresponding mean volumes are £51,328.04 million and £10,654.75 million. Special collateral transaction volumes follow a similar pattern, with daily average repo volumes being £2,333.68 million and reverse repo volumes being £1,728.02 million. On a quarterly frequency they average £91,351.56 million and £78,072.54 million. Overall, the higher volumes in repo compared to reverse repo transactions corroborates previous findings that banks and dealers are net borrowers in the UK repo market (Huser et al., 2021).

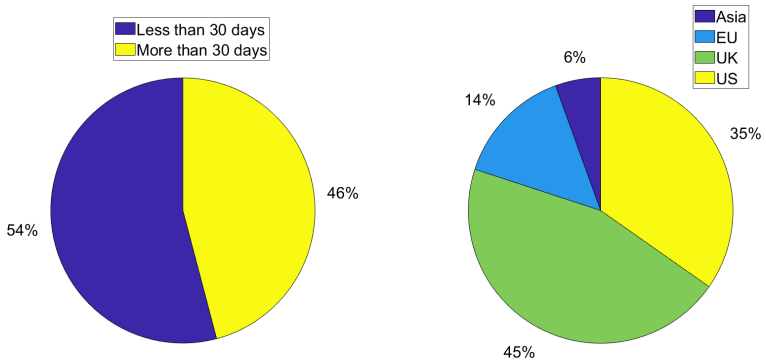


Figure 8. Gilts repo and reverse repo holdings volumes by maturity bucket and region (SMMD)

B A stylized structural model for markups and markdowns

We implement a simple structural model to retrieve dealer-level markups and markdown using data from bilateral OTC repo market segments. At the repo segment, we calculate the markup as dealers are the only providers of liquidity to non-dealers. At the reverse repo segment, we calculate the markdown as dealers are the only buyers of liquidity from non-dealers.

Below, we explain in detail the case of markups. Markdowns have an analogous specification and we comment briefly on the main differences.[30]

Supply side. Suppose that there are D dealers in the Repo market, indexed by $d = 1, \ldots, D$ each of which supplies liquidity or collateral through market making services. For the sake of simplicity, we assume that dealers are single-product firms; that is, each dealer supplies repo/reverse repo with fixed characteristics (e.g., interest rate, maturity and haircut) to non-dealers looking for liquidity/collateral in the bilateral OTC market. Accordingly, datawise, we aggregate all transactions made by a given dealer in a single product indexed by the same index of the dealer; the characteristics of that product correspond to averages of

[30] We argue repo dealers have both product and factor market power. Our approach is an approximation for markup and markdown estimation as we do not jointly estimate them. Following Syverson (2024) , a profit maximizing dealer first-order conditions show a combination of both metrics is equal to the ratio of elasticity of output wrt liquidity, and dealer's expenditure on liquidity expressed as a share of revenue. Our approach responds data limitation.

the observed lending terms across non-dealers that transacted from the same dealer in period t.[31] The variable profit of dealer d derived from its transactions in the repo market is given by:

$$\Pi_{dt} = (r_{dt} - c_{dt}) M_t s_d(\mathbf{r}_d),$$

where r_{dt} is weighted average interest rate given by d at time t, c_{dt} is the dealer's marginal cost, s_{dt} is the market share of dealer d at time t, $\mathbf{r}_t$ is the $F \times 1$ vector of interest rates of all dealers in the market, and M_t is the size of the repo market, which we take as all of the money borrowed by dealers and non-dealers in the repo market from any firm providing wholesale liquidity at time t.[32] We assume that dealers compete in setting interest rates and that a pure-strategy Bertrand-Nash equilibrium in prices exist. Therefore, the interest rate of the lending supplied by dealer d must satisfy the first order condition:

$$s_d(\mathbf{r}_t) + (r_{dt} - c_{dt}) \frac{\partial s_d(\mathbf{r}_t)}{\partial r_{dt}} = 0.$$

We have, therefore, a system of D equations, one for each of the dealers (products) existing in the market. Solving dealer d's equation for its interest rate-cost margin yields, for $d = 1, \ldots, D$:

$$r_{dt} - c_{dt} = \frac{1}{-\frac{\partial s_d(\mathbf{r}_t)}{\partial r_{dt}}} s_d(\mathbf{r}_t). \tag{B.1}$$

This optimal pricing rule allows us to back out a MarkUp index for each dealer at each period t. Dividing the two sides of equation (B.1) by d's interest rate yields:

$$MarkUp_{dt} \equiv \frac{r_{dt} - c_{dt}}{r_{dt}} = \frac{1}{\eta_{dt}}, \qquad \text{with} \qquad \eta_{dt} = -\frac{\partial s_d(\mathbf{r}_t)}{\partial r_{dt}} \frac{r_{dt}}{s_d(\mathbf{r}_t)}, \tag{B.2}$$

being the positive own price elasticity of demand. The Lerner index being a function of the

[31] This is a restrictive assumption relative to how the market works in reality, in which a given dealer/non-dealer pair may agree on several transactions in the same day, each of them characterized by a particular volume, a given interest rate, a given maturity, and a given collateral. Products provided by the same dealer to the same non-dealer may, therefore, be heterogeneous; we, therefore, obtain an average measure of the true market power of each dealer, which can vary across non-dealers.

[32] For simplicity, we assume that dealers expect the full repayment of each loan from borrowers and that they actually do the full repayment of their loans; this implies that there is no loss of profits due to default. For a model that explicitly accounts for default, see Crawford et al. (2018).

the demand elasticity implies that we do not need to observe the marginal costs of dealers to estimate the Lerner index, but to have a good estimate of the own price elasticity of demand.

The case of markdown is similar. Dealer d maximize profit $\Pi^f_{dt} = (mrev_{dt} - r_{dt})M^f_t s^f_d(\mathbf{r}_d)$, where $mrev_{dt}$ is the marginal revenue from aggregate funding obtained from non-dealers, and r_{dt} is the average repo rate from such funding. The remaining variables are as with the MarkUp but superscript f refers to the factor market (e.g. reverse repo segment) where dealer d has market power. Following a similar first order condition argument the markdown is inversely related to the elasticity of supply (ν_{dt}).

$$MarkDown_{dt} \equiv \frac{mrev_{dt} - r_{dt}}{r_{dt}} = \frac{1}{\nu_{dt}}, \qquad \text{with} \qquad \nu_{dt} = \frac{\partial s^f_d(\mathbf{r}_t)}{\partial r_{dt}} \frac{r_{dt}}{s^f_d(\mathbf{r}_t)}, \tag{B.3}$$

Demand model. The demand model presented in this section is in the spirit of the empirical industrial organization literature (in particular, Berry (1994) and Nevo (2000)). Non-dealers, indexed by $l = 1, 2, \ldots, ND$ face a multiple-choice decision among d dealers in each period. Assume that the conditional indirect utility of non-dealer l from choosing to borrow money from dealer d at time t is given by:

$$u_{ldt} = \mathbf{x}_d \boldsymbol{\beta} - \alpha r_{dt} + \gamma I_{dt} + \phi_t + \xi_d + \Delta\xi_{dt} + \varepsilon_{ldt} \tag{B.4}$$

where $\mathbf{x}_d$ is a (row) vector of observable product (dealer) characteristics that do not vary with time; r_{dt} is the mean interest rate of the lending granted by dealer d to non-dealers at t; I_{dt} is the mean intensity, across non-dealers, of dealer d's lending relationships at t; ϕ_t accounts for time shocks that are common to all of the transactions observed at t in the market; ξ_d captures the mean valuation of the unobserved dealer characteristics that do not vary with time; $\Delta\xi_{dt}$ are unobserved dealer characteristics that vary with time; and ε_{ldt} is an additively separable mean-zero random shock that captures idiosyncratic non-dealer preferences.[33]

We assume that non-dealers' choice set includes an "outside good", which may capture all other liquidity sources not considered in this analysis. Normalizing its mean utility to

[33]There is no practical distinction between MarkUp and MarkDown specification. Noticeably, the main difference is the expected sign of α, e.g. negative for MarkUp and positive for MarkDown.

zero, the indirect utility derived by non-dealer l from the outside option writes as $u_{l0t} = \varepsilon_{l0t}$. Another key assumption of this model is that non-dealers choose at most one product (i.e., dealer) at each period t. The product (dealer) chosen is the one giving the highest utility. For given unobserved demand shocks, $\boldsymbol{\varepsilon}_{ldt}$, bank l will choose product d if:

$$u_{ldt} \geqslant u_{lkt}, \ \forall\, k = 0, 1, \ldots, D.$$

Assuming that the shocks to utility ε_{ldt} are independent of the product characteristics and of each other (i.i.d.), and drawn from a Type 1 Extreme Value distribution, the market share of dealer d at time t is given by:

$$s_d(\mathbf{X}, \mathbf{r}_t) = \frac{\exp(\mathbf{x}_d\boldsymbol{\beta} - \alpha r_{dt} + \gamma I_{dt} + \phi_t + \xi_d + \Delta\xi_{dt})}{1 + \sum_k \exp(\mathbf{x}_k\boldsymbol{\beta} - \alpha r_{kt} + \gamma I_{kt} + \phi_t + \xi_k + \Delta\xi_{kt})}, \tag{B.5}$$

where $\mathbf{X}$ is the matrix of observed characteristics of all of the included dealers, that do not vary with time.

Elasticities. The non-dealer-level own- and cross-price demand elasticities are given by:

$$\eta_{ldkt} = \frac{\partial s_{dt}}{\partial r_{kt}} \frac{r_{kt}}{s_{dt}} = \begin{cases} -\alpha(1 - s_{dt}) r_{dt} & \text{id} \quad d = k, \\ \alpha s_{kt} r_{kt} & \text{if} \quad d \neq k. \end{cases} \tag{B.6}$$

The non-dealer-level own- and cross-price supply elasticities are given by:

$$\nu_{ldkt} = \frac{\partial s^f_{dt}}{\partial r_{kt}} \frac{r_{kt}}{s^f_{dt}} = \begin{cases} \alpha(1 - s^f_{dt}) r_{dt} & \text{id} \quad d = k, \\ \alpha s^f_{kt} r_{kt} & \text{if} \quad d \neq k. \end{cases} \tag{B.7}$$

Estimation and results. We follow Berry (1994) and use the equality between predicted shares, given by equation (B.5), and observed market shares S_{dt} to transform our non-linear model in a linear one. Formally, the model we obtain is given by:

$$\ln S_{dt} - \ln S_{0t} = \mathbf{x}_d\boldsymbol{\beta} - \alpha r_{dt} + \gamma SI_{dt} + \phi_t + \xi_d + \Delta\xi_{dt}. \tag{B.8}$$

Notice that our demand model allows for unobserved factors at the time ϕ_t and fund levels ξ_d. We account for those unobservables by including time and fund dummies, respectively. The latter capture also all of the observed fund attributes that do not vary with time $\mathbf{x}_d\boldsymbol{\beta}$. We do not account for dealer-time unobserved factors, $\Delta\xi_{dt}$; thus, we leave it as the error term of the model.

C Global Dealer Factors: Estimation

C.1 Overview of the time-varying parameter VAR model

Since the behaviour of dealers and non-dealers is highly dynamic, we approximate it with time-varying parameter vector autoregression (TVP-VAR) model:

$$x_{t,T} = \phi_0\left(\frac{t}{T}\right) + \phi_1\left(\frac{t}{T}\right)x_{t-1,T} + \ldots + \phi_p\left(\frac{t}{T}\right)x_{t-p,T} + \epsilon_t, \tag{C.1}$$

estimated from $(N^D + N^{ND})$ dimensional vector of volume of the Repo or Reverse Repo dealers and non-dealers $x_{t,T} = \left(Vol^D_{1,t,T}, \ldots, Vol^D_{N^D,t,T}, Vol^{ND}_{1,t,T} \ldots, Vol^{ND}_{N^{ND},t,T}\right)'$ in one system, or from $(N^D + N^{ND})$ dimensional vector of rate spread of the Repo or Reverse Repo dealers and non-dealers $x_{t,T} = \left(Rate^D_{1,t,T}, \ldots, Rate^D_{N^D,t,T}, Rate^{ND}_{1,t,T} \ldots, Rate^{ND}_{N^{ND},t,T}\right)'$ in day $t = 1, \ldots, T$ following the methodology of Barunik and Ellington (2024). Note the variable $x_{t,T}$ is triangular array of observations $(x_{t,T}; t = 1, \ldots, T)$ with sample size T that can be interpreted as a locally stationary approximation around a fixed point t/T. As a consequence, the process can change its properties smoothly over time.

An important feature of such local approximation is the possibility to represent a locally stationary process $x_{t,T}$ as a time-varying vector moving average:

$$x_{t,T} = \sum_{h=-\infty}^{+\infty} \alpha_{t,T}(h)\,\epsilon_{t-h}, \tag{C.2}$$

where coefficients $\alpha_{t,T}(h)$ can be approximated under certain smoothness assumptions a $\alpha_{t,T}(h) \approx \alpha(t/T, h)$, see Dahlhaus (1996). The innovations ϵ_t are independent random

variables with zero mean and finite variation. The original process $x_{t,T}$ can be represented as a linear combination of uncorrelated innovations with time-varying impulse response (TV-IRF) functions $\alpha_{t,T}(h)$. The information contained in the impulse response functions allows the contribution of shocks in the system to be measured. Thus, their transformations over time determine the interconnectedness of dealers and non-dealers.

We further transform local impulse responses in the system into local impulse transfer functions using Fourier transformations. This allows us to identify the persistence dynamics of interconnectedness based on the heterogeneous persistence of shocks in the system. A dynamic representation of the variance decomposition of shocks from dealer (or non-dealers) j to dealer (or non-dealers) k then establishes a dynamic horizon-specific adjacency matrix, which is central to our measures.

Specifically, the element of such a matrix that captures how shocks propagate from a dealer (or non-dealers) j to a dealer (or non-dealers) k at a given time and horizon[34] $d_i \in \mathcal{H} = \{\text{Tr}, \text{Per}\}$, is formally defined as:

$$\left[\theta^d_{t,T}\right]_{j,k} = \frac{\widehat{\sigma}^{-1}_{kk} \sum_{\omega \in d_i} \left(\left[\widehat{\alpha}_{t,T}(\omega) \widehat{\Sigma}_{t,T} \right]_{j,k} \right)^2}{\sum_{\omega \in \mathcal{H}} \left[\widehat{\alpha}_{t,T}(\omega) \widehat{\Sigma}_{t,T} \widehat{\alpha}^{\top}_{t,T}(\omega) \right]_{j,j}}, \tag{C.3}$$

where $\widehat{\alpha}_{t,T}(\omega) = \sum_{h=0}^{H-1} \sum_h \widehat{\alpha}_{t,T}(h) e^{-i\omega h}$ is an impulse transfer function estimated from Fourier frequencies ω of impulse responses covering a given horizon d_i frequencies.[35] Since the rows of the dynamic adjacency matrix do not necessarily sum to one, we normalise the element in each row by the corresponding row sum: $\left[\widetilde{\theta}^d_{t,T}\right]_{j,k} = \left[\theta^d_{t,T}\right]_{j,k} \Big/ \sum_{k=1}^{N} \left[\theta^d_{t,T}\right]_{j,k}$. Equation (C.3) fully defines a dynamic horizon-specific link between banks. Note that in the paper we denote $\left[\widehat{\theta}_{t,d}\right]_{j,k} = \left[\widetilde{\theta}^d_{t,T}\right]_{j,k}$ to ease the notation burden.

To obtain the time-varying coefficient estimates $\widehat{\phi}_{1,t,T}, ..., \widehat{\phi}_{p,t,T}$ and the time-varying covariance matrix $\widehat{\Sigma}_{t,T}$ we estimate the approximating model in Equation (C.1) using Quasi-Bayesian Local-Likelihood (QBLL) methods (Petrova, 2019). We provide a detailed

[34] In the empirical investigation, 20 business days divides the transitory and persistent horizons.
[35] Note that $i = \sqrt{-1}$.

discussion of the estimation algorithm in Appendix C.2.

For the estimation we use a kernel weighting function, which gives larger weights to those observations surrounding the period whose coefficient and covariance matrices are of interest. Using conjugate priors, the (quasi) posterior distribution of the parameters of the model are available analytically. This alleviates the need to use a Markov Chain Monte Carlo (MCMC) simulation algorithm and permits the use of parallel computing.

Finally, the variance decompositions of the forecast errors from the VMA(∞) representation require a truncation of the infinite horizon with a H horizon approximation. As $H \to \infty$ the error disappears (Lütkepohl, 2005). We note here that H serves as an approximating factor and has no interpretation in the time-domain. We obtain horizon specific measures using Fourier transforms and set our truncation horizon H=100; the results are qualitatively similar for $H \in \{50, 100, 200\}$. In computing our measures, we also diagonalise the covariance matrix because our objective is to focus on the connections controlled for possible contemporaneous correlation in residuals of the system. The $\alpha(u, d)$ matrix embeds the causal nature of connections, and the covariance matrix $\Sigma(u)$ contains contemporaneous covariances within the off-diagonal elements.

C.2 Estimation of the time-varying parameter VAR model

Let x_t be an $N \times 1$ vector generated by a stable time-varying parameter (TVP) heteroskedastic VAR model with p lags:

$$x_{t,T} = \phi_1(t/T)x_{t-1,T} + \ldots + \phi_p(t/T)x_{t-p,T} + \epsilon_{t,T}, \tag{C.4}$$

where $\epsilon_{t,T} = \Sigma^{-1/2}(t/T)\beta_{t,T}, \beta_{t,T} \sim NID(0, I_M)$ and $\phi(t/T) = (\phi_1(t/T), \ldots, \phi_p(t/T))^\top$ are the time varying autoregressive coefficients.

Note that all roots of the polynomial $\chi(z) = \det\left(I_N - \sum_{p=1}^{L} z^p x_{p,t}\right)$ lie outside the unit circle, and Σ_t^{-1} is a positive definite time-varying covariance matrix. Stacking the time-varying intercepts and autoregressive matrices in the vector $\phi_{t,T}$ with $\overline{x}_t^\top = (\mathrm{I}_N \otimes x_t)$, $x_t =$

$\left(1, x_{t-1}^{\top}, \ldots, x_{t-p}^{\top}\right)$ and denoting the Kronecker product by $\otimes$, the model can be written as:

$$x_{t,T} = \overline{x}_{t,T}^{\top}\phi_{t,T} + \Sigma_{t/T}^{-\frac{1}{2}}\beta_{t,T} \tag{C.5}$$

We obtain the time-varying parameters of the model by employing the Quasi-Bayesian Local-Likelihood (QBLL) approach of Petrova (2019). The estimation of Equation (C.4) requires re-weighting the likelihood function. The weighting function gives higher proportions to observations surrounding the time period whose parameter values are of interest. The local likelihood function at time period k is given by:

$$\begin{aligned} &\mathrm{L}_k\left(x|\theta_k, \Sigma_k, \overline{x}\right) \propto \\ &|\Sigma_k|^{\mathrm{trace}(D_k)/2} \exp\left\{-\frac{1}{2}(x - \overline{x}^{\top}\phi_k)^{\top}\left(\Sigma_k \otimes D_k\right)(x - \overline{x}^{\top}\phi_k)\right\} \end{aligned} \tag{C.6}$$

The D_k is a diagonal matrix whose elements hold the weights:

$$D_k = \mathrm{diag}(\varrho_{k1}, \ldots, \varrho_{kT}) \tag{C.7}$$

$$\varrho_{kt} = \phi_{T,k} w_{kt} / \sum_{t=1}^{T} w_{kt} \tag{C.8}$$

$$w_{kt} = (1/\sqrt{2\pi}) \exp((-1/2)((k-t)/H)^2), \quad \text{for } k, t \in \{1, \ldots, T\} \tag{C.9}$$

$$\zeta_{Tk} = \left(\left(\sum_{t=1}^{T} w_{kt}\right)^2\right)^{-1} \tag{C.10}$$

where ϱ_{kt} is a normalised kernel function. w_{kt} uses a Normal kernel weighting function. ζ_{Tk} gives the rate of convergence and behaves like the bandwidth parameter H in (C.9). The kernel function puts a greater weight on the observations surrounding the parameter estimates at time k relative to more distant observations.

We use a Normal-Wishart prior distribution for $\phi_k|\,\Sigma_k$ for $k \in \{1, \ldots, T\}$:

$$\phi_k|\Sigma_k \backsim \mathcal{N}\left(\phi_{0k}, \left(\Sigma_k \otimes \Xi_{0k}\right)^{-1}\right) \tag{C.11}$$

$$\Sigma_k \backsim \mathcal{W}\left(\alpha_{0k}, \Gamma_{0k}\right) \tag{C.12}$$

where ϕ_{0k} is a vector of prior means, Ξ_{0k} is a positive definite matrix, α_{0k} is a scale parameter of the Wishart distribution ($\mathcal{W}$), and Γ_{0k} is a positive definite matrix.

The prior and weighted likelihood function implies a Normal-Wishart quasi posterior distribution for $\phi_k|\ \Sigma_k$ for $k = \{1, \ldots, T\}$. Formally, let $A = (\overline{x}_1^\top, \ldots, \overline{x}_T^\top)^\top$ and $Y = (x_1, \ldots, x_T)^\top$, then:

$$\phi_k|\Sigma_k, A, Y \backsim \mathcal{N}\left(\widetilde{\theta}_k, \left(\Sigma_k \otimes \widetilde{\Xi}_k\right)^{-1}\right) \tag{C.13}$$

$$\Sigma_k \backsim \mathcal{W}\left(\widetilde{\alpha}_k, \widetilde{\Gamma}_k^{-1}\right) \tag{C.14}$$

with quasi posterior parameters:

$$\widetilde{\phi}_k = \left(I_N \otimes \widetilde{\Xi}_k^{-1}\right)\left[\left(I_N \otimes A^\top D_k A\right)\hat{\phi}_k + \left(I_N \otimes \Xi_{0k}\right)\phi_{0k}\right] \tag{C.15}$$

$$\widetilde{\Xi}_k = \widetilde{\Xi}_{0k} + A^\top D_k A \tag{C.16}$$

$$\widetilde{\alpha}_k = \alpha_{0k} + \sum_{t=1}^{T} \varrho_{kt} \tag{C.17}$$

$$\widetilde{\Gamma}_k = \Gamma_{0k} + Y' D_k Y + \Phi_{0k}\Gamma_{0k}\Phi_{0k}^\top - \widetilde{\Phi}_k\widetilde{\Gamma}_k\widetilde{\Phi}_k^\top \tag{C.18}$$

where $\widehat{\phi}_k = \left(I_N \otimes A^\top D_k A\right)^{-1}\left(I_N \otimes A^\top D_k\right) y$ is the local likelihood estimator for ϕ_k. The matrices Φ_{0k}, $\widetilde{\Phi}_k$ are conformable matrices from the vector of prior means, ϕ_{0k}, and a draw from the quasi posterior distribution, $\widetilde{\phi}_k$, respectively.

The motivation for employing these methods are threefold. First, we are able to estimate large systems that conventional Bayesian estimation methods do not permit. This is typically because the state-space representation of an N-dimensional TVP VAR (p) requires an additional $N(3/2 + N(p + 1/2))$ state equations for every additional variable. Conventional Markov Chain Monte Carlo (MCMC) methods fail to estimate larger models, which in general confine one to (usually) fewer than 6 variables in the system. Second, the standard approach is fully parametric and requires a law of motion. This can distort inference if the true law of motion is misspecified. Third, the methods used here permit direct estimation of the VAR's time-varying covariance matrix, which has an inverse-Wishart density and is symmetric positive definite at every point in time.

In estimating the model, we use p=2 and a Minnesota Normal-Wishart prior with a shrinkage value $\varphi = 0.05$ and centre the coefficient on the first lag of each variable to 0.1 in each respective equation. The prior for the Wishart parameters are set following Kadiyala and Karlsson (1997). For each point in time, we run 100 simulations of the model to generate the (quasi) posterior distribution of parameter estimates. Note we experiment with various lag lengths, $p = \{2, 3, 4, 5\}$; shrinkage values, $\varphi = \{0.01, 0.25, 0.5\}$; and values to centre the coefficient on the first lag of each variable, $\{0, 0.05, 0.2, 0.5\}$. Network measures from these experiments are qualitatively similar. Notably, adding lags to the VAR and increasing the persistence in the prior value of the first lagged dependent variable in each equation increases computation time.

D Tables

Table D.1. Demand Estimation: Repo and Reverse Repo Segments

	Reverse Repo Data				
Repo Rate	-1.238***	0.794***	-1.649***	1.25***	1.412***
	0.081	0.082	0.139	0.130	0.125
Residual Maturity	-0.018***	-0.001	-0.003***	0.014***	0.015***
	0.001	0.002	0.001	0.003	0.003
Frequency	0.030***	-0.335***	0.046***	-0.227***	
	0.001	0.019	0.001	0.034	
Collateral Market Value	-0.00***	-0.000***	-0.000***	-0.000***	-0.000***
	0.000	0.000	0.000	0.000	0.000
Sample	All	All	Restricted	Restricted	Restricted
Control function	no	yes	no	yes	yes
Month FE	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes
Obs	9,052,185	9,052,185	7,822,333	7,822,333	7,822,333
R2	0.1117	0.1363	0.1266	0.1594	0.1355
	Repo Data				
Repo Rate	1.240***	-0.369***	0.992***	-0.641***	-1.438***
	0.087	0.115	0.139	0.183	0.183
Residual Maturity	0.010***	0.022***	0.012***	0.009***	0.010***
	0.000	0.002	0.000	0.003	0.003
Frequency	0.052***	-0.592***	0.068***	-0.071	
	0.001	0.029	0.002	0.054	
Collateral Market Value	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	0.000	0.000	0.000	0.000	0.000
Sample	All	All	Restricted	Restricted	Restricted
Control function	no	yes	no	yes	yes
Month FE	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes
Obs	8,522,642	8,522,642	7,281,915	7,281,915	7,281,915
R2	0.1094	0.1216	0.1187	0.1252	0.099

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results of the regressions of demand estimation, as discussed in Section 4, for the period 2016 to 2022. Definitions, sources and frequency of all independent variables are presented in Section 4. The top panel present results using the reverse repo data, and the bottom panel presents the results using repo data.

Table D.2. Demand Estimation with Jointly Repo and Reverse Repo Segments

	Repo and Reverse Repo Data				
Repo Rate	-0.094	0.086	-0.209***	-0.118	0.129
	0.067	0.075	0.089	0.100	0.096
Residual Maturity	0.003***	0.010***	0.010***	0.013***	0.014***
	0.000	0.001	0.000	0.002	0.002
Frequency	0.045***	-0.752***	0.0914***	-0.369***	
	0.001	0.022	0.001	0.033	
Collateral Market Value	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	0.000	0.000	0.000	0.000	0.000
Sample	All	All	Restricted	Restricted	Restricted
Control function	no	yes	no	yes	yes
Month FE	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes
Obs	12,024,349	12,024,349	10,882,728	10,882,728	10,882,728
R2	0.0847	0.0931	0.0881	0.0901	0.0501

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results of the regressions of demand estimation, as discussed in Section 4, for the period 2016 to 2022. Definitions, sources and frequency of all independent variables are presented in Section 4. This tables uses all repo transactions without distinguishing between repo and reverse repo.

Table D.3. OTC impact: volume and spread

	Log volume			
	Repo		Reverse	
Market Power	-0.207	-0.187	-0.552**	-0.320
	[0.130]	[0.132]	[0.260]	[0.263]
Depth	0.721***	0.719***	0.938***	0.925***
	[0.238]	[0.238]	[0.300]	[0.300]
Frequency	0.008***	0.008***	0.012***	0.012***
	[0.001]	[0.001]	[0.002]	[0.002]
Log CB Reserves	-0.866***	-0.858***	1.809***	1.650***
	[0.164]	[0.170]	[0.239]	[0.239]
DF tot repo		1.753***		2.331***
		[0.534]		[0.498]
DF tot reverse		-0.298		2.021***
		[0.522]		[0.480]
Dealer FE	Yes	Yes	No	No
NonDealer FE	No	No	Yes	Yes
NonDealer*Week FE	Yes	Yes	No	No
Dealer*Week FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	92,314	92,314	115,555	115,555
R-squared	0.597	0.597	0.483	0.484
	Repo rate spread			
	Repo		Reverse	
Market Power	0.037***	0.035***	0.537***	0.527***
	[0.013]	[0.013]	[0.020]	[0.020]
Depth	-0.003	-0.003	0.008	0.009
	[0.012]	[0.012]	[0.009]	[0.009]
Frequency	-0.000	-0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Log CB Reserves	0.028***	0.029***	0.056***	0.063***
	[0.008]	[0.009]	[0.008]	[0.008]
DF tot repo		-0.123***		-0.091***
		[0.027]		[0.019]
DF tot reverse		-0.012		-0.091***
		[0.032]		[0.020]
Dealer FE	Yes	Yes	No	No
NonDealer FE	No	No	Yes	Yes
NonDealer*Week FE	Yes	Yes	No	No
Dealer*Week FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	92,314	92,314	115,555	115,555
R-squared	0.087	0.088	0.128	0.129

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results of the regressions of repo market impact, as discussed in Section 5, for the period 2016 to 2022. Definitions, sources and frequency of all independent variables are presented in Section 4. Panels report the results for the dependent variables as follows: the top panel uses log of volume, and the bottom panel uses the absolute value of repo spread to the reference rate determined by Bank of England. . Clustered standard errors on dealer / non-dealer dyads.

Table D.4. OTC impact by Frequency: volume and spread

	Log volume			
	Repo		Reverse	
Market Power	-0.204	-0.184	-0.378	-0.420
	[0.136]	[0.124]	[0.260]	[0.264]
Depth	0.719***	0.717***	0.927***	0.933***
	[0.238]	[0.238]	[0.301]	[0.300]
Frequency	0.008***	0.008***	0.012***	0.012***
	[0.001]	[0.001]	[0.002]	[0.002]
Log CB Reserves	-0.898***	-0.666***	1.358***	1.783***
	[0.185]	[0.190]	[0.238]	[0.238]
DF tran repo	1.837***		4.349***	
	[0.634]		[0.741]	
DF tran reverse	-1.037		2.227***	
	[0.917]		[0.651]	
DF per repo		3.944**		-1.031
		[1.562]		[1.259]
DF per reverse		-0.511		4.290***
		[1.070]		[1.193]
Dealer FE	Yes	Yes	No	No
NonDealer FE	No	No	Yes	Yes
NonDealer*Week FE	Yes	Yes	No	No
Dealer*Week FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	92,314	92,314	115,555	115,555
R-squared	0.597	0.597	0.484	0.483
	Repo rate spread			
	Repo		Reverse	
Market Power	0.034**	0.039***	0.532***	0.528***
	[0.013]	[0.013]	[0.020]	[0.020]
Depth	-0.003	-0.003	0.008	0.009
	[0.012]	[0.012]	[0.009]	[0.009]
Frequency	-0.000	-0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Log CB Reserves	0.048***	0.029***	0.069***	0.052***
	[0.009]	[0.010]	[0.009]	[0.008]
DF tran repo	-0.259***		-0.134***	
	[0.038]		[0.025]	
DF tran reverse	-0.073**		-0.066***	
	[0.037]		[0.025]	
DF per repo		0.021		-0.030
		[0.064]		[0.041]
DF per reverse		0.064		-0.239***
		[0.079]		[0.047]
Dealer FE	Yes	Yes	No	No
NonDealer FE	No	No	Yes	Yes
NonDealer*Week FE	Yes	Yes	No	No
Dealer*Week FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	92,314	92,314	115,555	115,555
R-squared	0.090	0.087	0.129	0.129

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results of the regressions of repo market impact by frequency of shocks to dealer, as discussed in Section 5, for the period 2016 to 2022. Definitions, sources and frequency of all independent variables are presented in Section 4. Panels report the results for the dependent variables as follows: the top panel uses log of volume, and the bottom panel uses the absolute value of repo spread to the reference rate determined by Bank of England. . Clustered standard errors on dealer / non-dealer dyads.

Table D.5. OTC impact by sector: Volume

Repo segment	AMs & HFs		PFs & ICs	
Market Power	0.056	0.043	-0.461*	-0.451*
	[0.114]	[0.116]	[0.247]	[0.259]
Depth	0.624**	0.624**	0.970***	0.949***
	[0.246]	[0.246]	[0.356]	[0.350]
Frequency	0.009***	0.009***	0.002	0.002
	[0.001]	[0.001]	[0.002]	[0.002]
Log CB Reserves	-1.389***	-1.363***	-1.053**	-0.972**
	[0.180]	[0.183]	[0.473]	[0.433]
DF tot repo		0.127		3.984**
		[0.550]		[1.687]
DF tot reverse		-0.553		-0.441
		[0.507]		[2.149]
Dealer FE	Yes	Yes	Yes	Yes
NonDealer*Week FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	68,781	68,781	11,955	11,955
R-squared	0.632	0.632	0.503	0.504
Reverse segment	AMs & HFs		PFs & ICs	
Market Power	-0.287	-0.082	-1.611***	-1.645***
	[0.258]	[0.260]	[0.544]	[0.562]
Depth	0.526	0.512	2.138**	2.138**
	[0.326]	[0.327]	[0.859]	[0.858]
Frequency	0.014***	0.014***	-0.002	-0.002
	[0.002]	[0.002]	[0.003]	[0.003]
Log CB Reserves	1.207***	1.055***	0.079	0.139
	[0.228]	[0.222]	[0.900]	[0.908]
DF tot repo		2.123***		0.469
		[0.488]		[2.770]
DF tot reverse		1.785***		-1.347
		[0.471]		[2.389]
NonDealer FE	Yes	Yes	Yes	Yes
Dealer*Week FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	85,643	85,643	9,867	9,867
R-squared	0.454	0.455	0.364	0.364

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results of the regressions of repo market volume impact by non-dealer sector, as discussed in Section 5, for the period 2016 to 2022. Definitions, sources and frequency of all independent variables are presented in Section 4. Panels report the results for the dependent variables as follows: the top panel uses repo segment transactions, and the bottom panel uses reverse repo segment transactions. Clustered standard errors on dealer / non-dealer dyads.

Table D.6. OTC impact by sector: Spread

Repo segment	HFs & AMs		PFs & Ics	
Market Power	0.118***	0.115***	-0.207***	-0.206***
	[0.008]	[0.008]	[0.028]	[0.027]
Depth	0.002	0.002	0.000	0.003
	[0.010]	[0.010]	[0.016]	[0.015]
Frequency	-0.000	-0.000	-0.000	-0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Log CB Reserves	0.015*	0.020**	-0.061**	-0.079**
	[0.009]	[0.009]	[0.029]	[0.031]
DF tot repo		-0.072***		-0.523***
		[0.020]		[0.098]
DF tot reverse		-0.062***		0.169**
		[0.023]		[0.078]
Dealer FE	Yes	Yes	Yes	Yes
NonDealer*Week FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	68,781	68,781	11,955	11,955
R-squared	0.053	0.054	0.297	0.308
Reverse segment	HFs & AMs		PFs & Ics	
Market Power	0.570***	0.559***	0.183***	0.180***
	[0.022]	[0.022]	[0.023]	[0.023]
Depth	0.007	0.007	0.022	0.024
	[0.012]	[0.012]	[0.017]	[0.017]
Frequency	0.000	0.000	-0.000	-0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Log CB Reserves	0.072***	0.081***	0.043***	0.046***
	[0.008]	[0.009]	[0.016]	[0.016]
DF tot repo		-0.099***		-0.136***
		[0.022]		[0.039]
DF tot reverse		-0.111***		-0.034
		[0.023]		[0.038]
NonDealer FE	Yes	Yes	Yes	Yes
Dealer*Week FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	85,643	85,643	9,867	9,867
R-squared	0.141	0.142	0.155	0.158

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results of the regressions of repo market rate spread impact by non-dealer sector, as discussed in Section 5, for the period 2016 to 2022. Definitions, sources and frequency of all independent variables are presented in Section 4. Panels report the results for the dependent variables as follows: the top panel uses repo segment transactions, and the bottom panel uses reverse repo segment transactions. Clustered standard errors on dealer / non-dealer dyads.

Table D.7. Mispricing: All sample

	(1)	(2)	(3)	(4)	(5)
MarkUp	0.198**	0.520***		0.191*	
	[0.092]	[0.148]		[0.103]	
MarkUP Dispersion			0.212	0.732	
			[0.286]	[2.366]	
MarkUP*MarkUP Dispersion				-0.454	
				[1.840]	
MarkDown	0.771***	0.645***		0.731***	
	[0.182]	[0.183]		[0.186]	
MarkDown Dispersion			1.382***	-4.099	
			[0.259]	[3.603]	
MarkDown*MarkDown Dispersion				4.323	
				[2.876]	
MarkDown - MarkUp					0.384***
					[0.129]
DF tot repo	-0.821*	-0.818*	-0.818*	-0.824*	-0.820*
	[0.431]	[0.425]	[0.466]	[0.425]	[0.466]
DF tot reverse	1.922**	1.954***	1.823**	1.929**	1.806**
	[0.759]	[0.752]	[0.821]	[0.756]	[0.815]
CB Market Share	-0.235***	-0.231***	-0.252***	-0.232***	-0.257***
	[0.079]	[0.079]	[0.077]	[0.078]	[0.077]
Log CB Reserves	-0.318***	-0.355***	-0.142	-0.315***	-0.142
	[0.122]	[0.123]	[0.126]	[0.121]	[0.126]
Bond*Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Mat Bucket FE	Yes	Yes	Yes	Yes	Yes
GIVs	No	Yes	No	No	No
Observations	32,585	32,585	32,585	32,585	32,585
R-squared	0.035	0.035	0.031	0.037	0.031

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results of the regressions of bond-level mispricing, as discussed in Section 5, for the period 2016 to 2022. Definitions, sources and frequency of all independent variables are presented in Section 4. The dependent variable is the absolute value of the spread between the bond-level yield and the predicted yield based on a spline. We use Driscoll-Kraay standard errors with 20 working days lag.

Table D.8. Mispricing: All sample by maturity

	(1) - (3)			(4) - (6)			(7) - (9)			(10) - (12)		
	Short	Medium	Long	Short	Medium	Long	Short	Medium	Long	Short	Medium	Long
MarkUp	0.058	1.247***	0.105				0.074	0.665***	-0.027			
	[0.218]	[0.256]	[0.178]				[0.173]	[0.229]	[0.133]			
MarkUP Dispersion				0.439	0.195	0.279	-8.611	3.557	0.737			
				[0.500]	[0.438]	[0.358]	[5.780]	[4.708]	[2.951]			
MarkUP*MarkUP Dispersion							7.082	-2.811	-0.377			
							[4.510]	[3.759]	[2.332]			
MarkDown	1.060***	0.605**	0.518**				1.126***	1.109***	0.304			
	[0.242]	[0.270]	[0.235]				[0.181]	[0.248]	[0.226]			
MarkDown Dispersion				0.221	1.261***	1.508***	6.344	-3.876	-13.385***			
				[0.607]	[0.422]	[0.400]	[6.883]	[5.145]	[4.512]			
MarkDown*MarkDown Dispersion							-4.862	3.748	12.130***			
							[5.449]	[4.029]	[3.683]			
MarkDown - MarkUp										-0.068	0.491**	0.472***
										[0.200]	[0.192]	[0.162]
DF tot repo	-0.650	-1.405*	-0.952*	-0.647	-1.434*	-0.941*	-0.655	-1.390*	-0.957*	-0.645	-1.434*	-0.949*
	[0.648]	[0.769]	[0.517]	[0.698]	[0.857]	[0.518]	[0.645]	[0.763]	[0.510]	[0.700]	[0.856]	[0.515]
DF tot reverse	0.845	3.363***	1.821**	0.728	3.193***	1.720*	0.850	3.331***	1.787**	0.728	3.163***	1.700*
	[1.018]	[1.078]	[0.892]	[1.088]	[1.215]	[0.893]	[1.014]	[1.069]	[0.888]	[1.090]	[1.209]	[0.883]
CB Market Share	0.734***	-0.668***	-0.543***	0.629***	-0.675***	-0.536***	0.745***	-0.651***	-0.543***	0.628***	-0.690***	-0.542***
	[0.173]	[0.107]	[0.181]	[0.173]	[0.111]	[0.181]	[0.174]	[0.108]	[0.181]	[0.173]	[0.110]	[0.181]
Log CB Reserves	-0.792***	-0.730***	0.046	-0.607***	-0.430	0.156	-0.806***	-0.718***	0.093	-0.609***	-0.436	0.163
	[0.224]	[0.234]	[0.175]	[0.217]	[0.270]	[0.163]	[0.225]	[0.233]	[0.167]	[0.217]	[0.269]	[0.163]
Bond*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mat Bucket FE	No	No	No	No	No	No	No	No	No	No	No	No
GIVs	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No
Observations	7,536	10,770	14,274	7,536	10,770	14,274	7,536	10,770	14,274	7,536	10,770	14,274
R-squared	0.103	0.119	0.014	0.092	0.104	0.015	0.104	0.122	0.017	0.092	0.104	0.015

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results of the regressions of bond-level mispricing by maturity of the bond, as discussed in Section 5, for the period 2016 to 2022. Definitions, sources and frequency of all independent variables are presented in Section 4. The dependent variable is the absolute value of the spread between the bond yield and the predicted yield based on a spline. We use Driscoll-Kraay standard errors with 20 working days lag.

Table D.9. Mispricing: All sample by frequency

	(1) - (2)		(3) - (4)		(5) - (6)		(7) - (8)	
MarkUp	0.523***	0.522***			0.189*	0.197*		
	[0.150]	[0.144]			[0.103]	[0.102]		
MarkUP Dispersion			0.227	0.200	0.766	0.822		
			[0.288]	[0.284]	[2.388]	[2.354]		
MarkUP*MarkUP Dispersion					-0.466	-0.530		
					[1.863]	[1.822]		
MarkDown	0.638***	0.653***			0.733***	0.737***		
	[0.186]	[0.181]			[0.191]	[0.179]		
MarkDown Dispersion			1.362***	1.397***	-4.155	-4.043		
			[0.258]	[0.256]	[3.596]	[3.605]		
MarkDown*MarkDown Dispersion					4.362	4.295		
					[2.872]	[2.880]		
MarkDown - MarkUp							0.384***	0.387***
							[0.132]	[0.126]
DF tran repo	-0.785		-1.084		-0.823		-1.086	
	[0.643]		[0.681]		[0.637]		[0.680]	
DF tran reverse	2.080**		1.644*		2.026**		1.631*	
	[0.895]		[0.950]		[0.897]		[0.948]	
DF per repo		-3.008**		-2.600*		-2.974**		-2.589*
		[1.235]		[1.377]		[1.237]		[1.373]
DF per reverse		4.151**		3.971**		4.124**		3.939**
		[1.711]		[1.955]		[1.725]		[1.939]
CB Market Share	-0.230***	-0.228***	-0.250***	-0.249***	-0.232***	-0.230***	-0.255***	-0.255***
	[0.079]	[0.079]	[0.077]	[0.077]	[0.078]	[0.079]	[0.077]	[0.078]
Log CB Reserves	-0.358***	-0.389***	-0.101	-0.149	-0.313**	-0.348***	-0.101	-0.151
	[0.134]	[0.128]	[0.148]	[0.149]	[0.133]	[0.128]	[0.148]	[0.149]
Bond*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mat Bucket FE	Yes	Yes	Yes	No	Yes	No	Yes	No
GIVs	Yes	Yes	No	No	No	No	No	No
Observations	32,585	32,585	32,585	32,585	32,585	32,585	32,585	32,585
R-squared	0.033	0.035	0.030	0.031	0.035	0.037	0.029	0.031

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results of the regressions of bond-level mispricing by frequency of shock on dealers, as discussed in Section 5, for the period 2016 to 2022. Definitions, sources and frequency of all independent variables are presented in Section 4. The dependent variable is the absolute value of the spread between the bond yield and the predicted yield based on a spline. We use Driscoll-Kraay standard errors with 20 working days lag.

Table D.10. Mispricing: All sample by frequency and maturity

	(1) - (6)						(7) - (12)					
	Short		Medium		Long		Short		Medium		Long	
MarkUp	0.043	0.066	1.223***	1.217***	0.126	0.109	0.064	0.079	0.642***	0.660***	-0.015	-0.017
	[0.218]	[0.214]	[0.261]	[0.250]	[0.179]	[0.177]	[0.172]	[0.175]	[0.233]	[0.224]	[0.132]	[0.133]
MarkUP Dispersion							-8.775	-8.262	3.852	4.116	0.756	0.787
							[5.720]	[5.775]	[4.624]	[4.948]	[3.003]	[2.968]
MarkUP*MarkUP Dispersion							7.212	6.804	-3.058	-3.297	-0.375	-0.408
							[4.463]	[4.498]	[3.685]	[3.976]	[2.381]	[2.345]
MarkDown	1.056***	1.072***	0.550**	0.623**	0.517**	0.524**	1.115***	1.150***	1.072***	1.102***	0.320	0.317
	[0.248]	[0.244]	[0.277]	[0.265]	[0.234]	[0.238]	[0.181]	[0.174]	[0.251]	[0.242]	[0.230]	[0.226]
MarkDown Dispersion							6.050	6.508	-4.679	-3.797	-13.116***	-12.994***
							[6.852]	[6.805]	[5.245]	[5.175]	[4.490]	[4.553]
MarkDown*MarkDown Dispersion							-4.642	-4.952	4.352	3.662	11.915***	11.842***
							[5.431]	[5.379]	[4.111]	[4.048]	[3.660]	[3.716]
DF tran repo	-0.496		-2.529**		-0.512		-0.469		-2.491**		-0.557	
	[0.947]		[1.098]		[0.736]		[0.941]		[1.080]		[0.720]	
DF tran reverse	0.208		2.409		3.185***		0.265		2.392		3.117***	
	[1.284]		[1.498]		[1.095]		[1.289]		[1.487]		[1.091]	
DF per repo		-3.157**		-4.053**		-2.687*		-3.197**		-4.019**		-2.643**
		[1.366]		[1.880]		[1.371]		[1.351]		[1.869]		[1.347]
DF per reverse		4.022**		7.608***		2.404		4.009**		7.541***		2.361
		[1.819]		[2.329]		[1.985]		[1.800]		[2.308]		[1.976]
CB Market Share	0.734***	0.738***	-0.677***	-0.654***	-0.537***	-0.533***	0.744***	0.750***	-0.659***	-0.637***	-0.539***	-0.534***
	[0.172]	[0.173]	[0.107]	[0.109]	[0.182]	[0.181]	[0.174]	[0.174]	[0.108]	[0.109]	[0.181]	[0.181]
Log CB Reserves	-0.721***	-0.900***	-0.564**	-0.670**	-0.060	-0.026	-0.740***	-0.919***	-0.557**	-0.658**	-0.007	0.021
	[0.240]	[0.230]	[0.269]	[0.275]	[0.198]	[0.175]	[0.240]	[0.230]	[0.267]	[0.274]	[0.189]	[0.167]
Bond*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mat Bucket FE	No	No	No	No	No	No	No	No	No	No	No	No
Observations	7,536	7,536	10,770	10,770	14,274	14,274	7,536	7,536	10,770	10,770	14,274	14,274
R-squared	0.102	0.106	0.115	0.120	0.015	0.013	0.102	0.107	0.119	0.123	0.017	0.016

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results of the regressions of bond-level mispricing by bond residual maturity and frequency of shock on dealers, as discussed in Section 5, for the period 2016 to 2022. Definitions, sources and frequency of all independent variables are presented in Section 4. The dependent variable is the absolute value of the spread between the bond yield and the predicted yield based on a spline. We use Driscoll-Kraay standard errors with 20 working days lag.

Table D.11. Mispricing: Dash-for-cash

	(1) - (2)		(3) - (4)		(5) - (6)		(7) - (8)	
	All		Short		Medium		Long	
MarkUp	0.198**	0.197**	0.131	0.140	0.630***	0.642***	-0.019	-0.019
	[0.092]	[0.092]	[0.171]	[0.172]	[0.214]	[0.215]	[0.118]	[0.119]
MarkDown	0.771***	0.769***	1.086***	1.093***	1.170***	1.181***	0.401*	0.392*
	[0.182]	[0.183]	[0.178]	[0.178]	[0.245]	[0.244]	[0.223]	[0.225]
DF tot repo	-0.821*	-0.820*	-0.652	-0.659	-1.386*	-1.383*	-0.949*	-0.951*
	[0.431]	[0.431]	[0.645]	[0.644]	[0.767]	[0.766]	[0.515]	[0.515]
Dum Dash * DF tot repo		-4.861		8.384*		-47.031***		8.519*
		[3.973]		[4.616]		[12.508]		[4.558]
DF tot reverse	1.922**	1.923**	0.857	0.846	3.337***	3.322***	1.777**	1.781**
	[0.759]	[0.759]	[1.011]	[1.011]	[1.076]	[1.076]	[0.892]	[0.892]
Dum Dash * DF tot reverse		0.389		15.109		115.883***		-33.136***
		[10.754]		[12.581]		[21.776]		[11.828]
CB Market Share	-0.235***	-0.235***	0.743***	0.745***	-0.657***	-0.658***	-0.541***	-0.540***
	[0.079]	[0.079]	[0.174]	[0.174]	[0.108]	[0.108]	[0.181]	[0.181]
Log CB Reserves	-0.318***	-0.317***	-0.808***	-0.811***	-0.725***	-0.727***	0.092	0.093
	[0.122]	[0.122]	[0.224]	[0.223]	[0.234]	[0.233]	[0.169]	[0.169]
Dum Dash	-0.160***	0.693	-0.280***	-4.012***	-0.168	-7.964***	-0.071	3.093***
	[0.061]	[1.029]	[0.087]	[1.408]	[0.112]	[2.299]	[0.078]	[1.138]
Bond*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,585	32,585	7,536	7,536	10,770	10,770	14,274	14,274
R-squared	0.035	0.035	0.103	0.103	0.122	0.122	0.014	0.014

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results of the regressions of bond-level mispricing including a dummy for the dash-for-cash period and interaction with dealer factors, as discussed in Section 5, for the period 2016 to 2022. Definitions, sources and frequency of all independent variables are presented in Section 4. The dependent variable is the absolute value of the spread between the bond yield and the predicted yield based on a spline. We use Driscoll-Kraay standard errors with 20 working days lag.

Table D.12. Aggregate Effect on Market Liquidity

	(1) - (3)			(4) - (6)			(7) - (9)		
MarkUp	4.539		0.983	5.519		0.947	4.911		0.844
	[4.125]		[2.350]	[4.274]		[2.352]	[4.090]		[2.337]
MarkUP Dispersion		-4.427	-59.229		-3.389	-60.236		-5.155	-58.373
		[3.587]	[53.540]		[3.540]	[54.056]		[3.651]	[53.726]
MarkUp*MarkUp Dispersion			42.946			44.507			41.924
			[39.849]			[40.290]			[40.072]
MarkDown	-2.872		0.884	-3.776		1.173	-3.262		1.091
	[4.223]		[2.304]	[4.383]		[2.306]	[4.169]		[2.299]
MarkDown Dispersion		11.048**	-81.863**		12.458**	-77.307*		11.351**	-82.390**
		[4.866]	[37.919]		[4.903]	[39.858]		[4.874]	[36.748]
MarkDown*MarkDown Dispersion			67.143**			64.114**			67.709**
			[29.028]			[30.885]			[28.206]
DF tot repo	1.496***	1.659***	1.338***						
	[0.569]	[0.556]	[0.499]						
DF tot reverse	4.712***	5.024***	4.233***						
	[1.051]	[1.192]	[0.937]						
DF tran repo				4.483***	4.397***	4.342***			
				[1.042]	[1.099]	[0.962]			
DF tran reverse				5.729***	5.230***	5.345***			
				[1.274]	[1.298]	[1.136]			
DF per repo							-3.985**	-4.309**	-3.815**
							[1.733]	[1.793]	[1.545]
DF per reverse							7.616***	9.252***	6.727***
							[2.346]	[2.700]	[2.107]
CB Market Share	2.855***	3.156***	2.823***	2.725**	3.048***	2.604***	2.910**	3.200***	2.854***
	[1.076]	[1.129]	[1.008]	[1.065]	[1.128]	[0.985]	[1.136]	[1.176]	[1.052]
Log CB Reserves	-1.497***	-1.363***	-1.580***	-1.468***	-1.308***	-1.556***	-1.414***	-1.285***	-1.503***
	[0.390]	[0.376]	[0.405]	[0.379]	[0.367]	[0.394]	[0.391]	[0.376]	[0.407]
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GIVs	Yes	No	No	Yes	No	No	Yes	No	No
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	852	852	852	852	852	852	852	852	852
R-squared	0.232	0.223	0.240	0.231	0.222	0.242	0.226	0.219	0.236

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results of the regressions of market liquitidy, as discussed in Section 5, for the period 2016 to 2022. Definitions, sources and frequency of all independent variables are presented in Section 4. The dependent variable is market liquidity metrics from Hu et al. (2013) We use robust standard errors.

Online Appendix

A Additional Tables

Table A.1. OTC impact: simultaneous dyads

	Log volume			
	Repo		Reverse	
Market Power	-0.136	-0.108	-0.300	-0.195
	[0.130]	[0.132]	[0.259]	[0.253]
Depth	0.510**	0.511**	0.585***	0.582***
	[0.247]	[0.247]	[0.194]	[0.193]
Frequency	0.009***	0.009***	0.009***	0.009***
	[0.001]	[0.001]	[0.001]	[0.001]
Log CB Reserves	-0.103	-0.155	-0.097	-0.153
	[0.222]	[0.217]	[0.167]	[0.169]
DF tot repo		0.506		0.948*
		[0.488]		[0.537]
DF tot reverse		0.602		0.768
		[0.567]		[0.499]
Dealer FE	Yes	Yes	No	No
NonDealer FE	No	No	Yes	Yes
NonDealer*Week FE	Yes	Yes	No	No
Dealer*Week FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	52,396	52,396	52,597	52,597
R-squared	0.624	0.624	0.596	0.596
	Repo rate spread			
	Repo		Reverse	
Market Power	0.107***	0.104***	0.586***	0.575***
	[0.007]	[0.007]	[0.023]	[0.022]
Depth	0.016	0.015	0.023*	0.026*
	[0.014]	[0.014]	[0.014]	[0.014]
Frequency	-0.000	-0.000	-0.000	-0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Log CB Reserves	0.007	0.012	0.050***	0.057***
	[0.014]	[0.013]	[0.011]	[0.012]
DF tot repo		-0.068***		-0.090***
		[0.022]		[0.027]
DF tot reverse		-0.042		-0.142***
		[0.033]		[0.033]
Dealer FE	Yes	Yes	No	No
NonDealer FE	No	No	Yes	Yes
NonDealer*Week FE	Yes	Yes	No	No
Dealer*Week FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	52,459	52,396	52,670	52,597
R-squared	0.113	0.111	0.140	0.142

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results of the regressions of repo market impact for simultaneous dyads, as discussed in Section 5, for the period 2016 to 2022. Definitions, sources and frequency of all independent variables are presented in Section 4. Panels report the results for the dependent variables as follows: the top panel uses log of volume, and the bottom panel uses the absolute value of repo spread to the reference rate determined by Bank of England. Clustered standard errors on dealer / non-dealer dyads.

Table A.2. OTC impact by frequency: simultaneous dyads

	Log volume			
	Repo		Reverse	
Market Power	-0.119	-0.121	-0.188	-0.301
	[0.132]	[0.131]	[0.259]	[0.249]
Depth	0.512**	0.508**	0.583***	0.585***
	[0.247]	[0.247]	[0.191]	[0.194]
Frequency	0.009***	0.009***	0.009***	0.009***
	[0.001]	[0.001]	[0.001]	[0.001]
Log CB Reserves	-0.193	-0.044	-0.328*	-0.148
	[0.214]	[0.243]	[0.170]	[0.188]
DF tran repo	0.466		2.065***	
	[0.627]		[0.648]	
DF tran reverse	0.796		1.452**	
	[0.719]		[0.727]	
DF per repo		1.128		-1.062
		[1.196]		[1.390]
DF per reverse		0.396		0.583
		[1.267]		[1.053]
Dealer FE	Yes	Yes	No	No
NonDealer FE	No	No	Yes	Yes
NonDealer*Week FE	Yes	Yes	No	No
Dealer*Week FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	52,396	52,396	52,597	52,597
R-squared	0.624	0.624	0.596	0.596
	Repo rate spread			
	Repo		Reverse	
Market Power	0.103***	0.107***	0.581***	0.577***
	[0.007]	[0.007]	[0.023]	[0.022]
Depth	0.014	0.015	0.025*	0.026*
	[0.014]	[0.014]	[0.014]	[0.014]
Frequency	-0.000	-0.000	-0.000	-0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Log CB Reserves	0.029**	0.009	0.065***	0.046***
	[0.012]	[0.013]	[0.013]	[0.011]
DF tran repo	-0.158***		-0.134***	
	[0.030]		[0.037]	
DF tran reverse	-0.119***		-0.126***	
	[0.037]		[0.041]	
DF per repo		0.047		0.019
		[0.059]		[0.062]
DF per reverse		0.032		-0.328***
		[0.076]		[0.073]
Dealer FE	Yes	Yes	No	No
NonDealer FE	No	No	Yes	Yes
NonDealer*Week FE	Yes	Yes	No	No
Dealer*Week FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	52,396	52,396	52,597	52,597
R-squared	0.112	0.110	0.142	0.142

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results of the regressions of repo market impact for simultaneous dyads by frequency of shock to dealers, as discussed in Section 5, for the period 2016 to 2022. Definitions, sources and frequency of all independent variables are presented in Section 4. Panels report the results for the dependent variables as follows: the top panel uses log of volume, and the bottom panel uses the absolute value of repo spread to the reference rate determined by Bank of England. Clustered standard errors on dealer / non-dealer dyads.

Table A.3. OTC impact by sector and Frequency: Volume

Repo segment	HFs & AMs		PFs & Ics	
Market Power	0.053	0.032	-0.518*	-0.373
	[0.116]	[0.114]	[0.266]	[0.234]
Depth	0.623**	0.623**	0.963***	0.964***
	[0.246]	[0.246]	[0.349]	[0.352]
Frequency	0.009***	0.009***	0.002	0.001
	[0.001]	[0.001]	[0.002]	[0.002]
Log CB Reserves	-1.372***	-1.339***	-0.703*	-0.120
	[0.190]	[0.199]	[0.382]	[0.403]
DF tran repo	-0.046		0.353	
	[0.693]		[1.908]	
DF tran reverse	-0.221		-4.697	
	[0.693]		[4.115]	
DF per repo		1.455		17.607***
		[1.251]		[6.582]
DF per reverse		-2.284**		-0.264
		[1.045]		[3.844]
Dealer FE	Yes	Yes	Yes	Yes
NonDealer*Week FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	68,781	68,781	11,955	11,955
R-squared	0.632	0.632	0.504	0.507
Reverse segment	HFs & AMs		PFs & Ics	
Market Power	-0.128	-0.176	-1.717***	-1.468***
	[0.258]	[0.261]	[0.556]	[0.553]
Depth	0.514	0.521	2.154**	2.051**
	[0.327]	[0.326]	[0.864]	[0.845]
Frequency	0.014***	0.014***	-0.002	-0.001
	[0.002]	[0.002]	[0.003]	[0.003]
Log CB Reserves	0.789***	1.161***	0.682	0.715
	[0.211]	[0.219]	[0.927]	[0.834]
DF tran repo	4.021***		-4.707	
	[0.726]		[3.290]	
DF tran reverse	2.038***		-5.110*	
	[0.653]		[2.788]	
DF per repo		-1.172		12.144*
		[1.378]		[7.272]
DF per reverse		3.705***		1.996
		[1.215]		[7.428]
NonDealer FE	Yes	Yes	Yes	Yes
Dealer*Week FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	85,643	85,643	9,867	9,867
R-squared	0.455	0.454	0.364	0.367

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results of the regressions of repo market volume impact by non-dealer sector and frequency of shocks to dealers, as discussed in Section 5, for the period 2016 to 2022. Definitions, sources and frequency of all independent variables are presented in Section 4. Panels report the results for the dependent variables as follows: the top panel uses repo segment transactions, and the bottom panel uses reverse repo segment transactions. Clustered standard errors on dealer / non-dealer dyads.

Table A.4. OTC impact by sector and Frequency: Spread

Repo segment	HFs & AMs		PFs & Ics	
Market Power	0.115***	0.118***	-0.205***	-0.205***
	[0.008]	[0.008]	[0.027]	[0.029]
Depth	0.001	0.002	0.005	0.001
	[0.010]	[0.010]	[0.015]	[0.015]
Frequency	-0.000	-0.000	-0.000	-0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Log CB Reserves	0.034***	0.016*	-0.040	-0.076**
	[0.009]	[0.010]	[0.029]	[0.032]
DF tran repo	-0.147***		-0.921***	
	[0.026]		[0.164]	
DF tran reverse	-0.119***		0.218**	
	[0.031]		[0.097]	
DF per repo		0.024		-0.323*
		[0.053]		[0.189]
DF per reverse		-0.025		0.298
		[0.052]		[0.236]
Dealer FE	Yes	Yes	Yes	Yes
NonDealer*Week FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	68,781	68,781	11,955	11,955
R-squared	0.055	0.053	0.314	0.298
Reverse segment	HFs & AMs		PFs & Ics	
Market Power	0.564***	0.559***	0.182***	0.180***
	[0.022]	[0.022]	[0.023]	[0.023]
Depth	0.007	0.007	0.023	0.024
	[0.012]	[0.012]	[0.017]	[0.017]
Frequency	0.000	0.000	-0.000	-0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Log CB Reserves	0.087***	0.069***	0.056***	0.035**
	[0.010]	[0.009]	[0.016]	[0.015]
DF tran repo	-0.139***		-0.208***	
	[0.030]		[0.061]	
DF tran reverse	-0.082***		0.000	
	[0.029]		[0.043]	
DF per repo		-0.045		-0.131
		[0.051]		[0.090]
DF per reverse		-0.282***		-0.130
		[0.056]		[0.121]
NonDealer FE	Yes	Yes	Yes	Yes
Dealer*Week FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	85,643	85,643	9,867	9,867
R-squared	0.142	0.142	0.158	0.156

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results of the regressions of repo rate spread (in absolute value) impact by non-dealer sector and frequency of shocks to dealers, as discussed in Section 5, for the period 2016 to 2022. Definitions, sources and frequency of all independent variables are presented in Section 4. Panels report the results for the dependent variables as follows: the top panel uses repo segment transactions, and the bottom panel uses reverse repo segment transactions. Clustered standard errors on dealer / non-dealer dyads.

Table A.5. OTC impact by frequency: High Client vs Low Client

	Log volume			
	Repo		Reverse	
Market Power	-0.224*	-0.206*	-0.776***	-0.792***
	[0.121]	[0.116]	[0.272]	[0.273]
Client High	0.785***	0.781***	1.559***	1.564***
	[0.252]	[0.252]	[0.193]	[0.194]
Client Low	-1.091***	-1.096***	-0.013	-0.005
	[0.284]	[0.284]	[0.317]	[0.320]
Log CB Reserves	-0.608***	-0.326*	1.487***	1.843***
	[0.182]	[0.189]	[0.245]	[0.248]
DF tran repo	2.045***		3.854***	
	[0.630]		[0.748]	
DF tran reverse	-0.161		2.004***	
	[0.978]		[0.701]	
DF per repo		3.412**		-1.482
		[1.445]		[1.330]
DF per reverse		0.420		4.741***
		[1.210]		[1.321]
Dealer FE	Yes	Yes	No	No
NonDealer FE	No	No	Yes	Yes
NonDealer*Week FE	Yes	Yes	No	No
Dealer*Week FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	92,314	92,314	115,555	115,555
R-squared	0.568	0.568	0.420	0.419
	Repo rate spread			
	Repo		Reverse	
Market Power	0.035***	0.040***	0.530***	0.527***
	[0.013]	[0.013]	[0.020]	[0.020]
Client High	-0.016	-0.015	0.007	0.006
	[0.011]	[0.011]	[0.006]	[0.006]
Client Low	-0.012	-0.012	0.001	0.001
	[0.011]	[0.011]	[0.006]	[0.006]
Log CB Reserves	0.046***	0.025***	0.070***	0.053***
	[0.008]	[0.009]	[0.009]	[0.008]
DF tran repo	-0.263***		-0.136***	
	[0.039]		[0.025]	
DF tran reverse	-0.086**		-0.066***	
	[0.038]		[0.025]	
DF per repo		0.022		-0.031
		[0.067]		[0.041]
DF per reverse		0.058		-0.236***
		[0.082]		[0.047]
Dealer FE	Yes	Yes	No	No
NonDealer FE	No	No	Yes	Yes
NonDealer*Week FE	Yes	Yes	No	No
Dealer*Week FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	92,314	92,314	115,555	115,555
R-squared	0.075	0.072	0.129	0.129

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results of the regressions of repo market impact by frequency of shocks to repo dealers, replacing relationship trading metrics with dummy variables "High Client" and "Low Client", as discussed in Section 5, for the period 2016 to 2022. Definitions, sources and frequency of all independent variables are presented in Section 4. Panels report the results for the dependent variables as follows: the top panel uses log of volume, and the bottom panel uses the absolute value of repo spread to the reference rate determined by Bank of England. Clustered standard errors on dealer / non-dealer dyads.

Table A.6. OTC impact by frequency, Simultaneous Dyads: High Clients vs Low Clients

	Log volume			
	Repo		Reverse	
Market Power	-0.342**	-0.356**	-0.488*	-0.606**
	[0.151]	[0.149]	[0.286]	[0.271]
Client High	0.996***	0.992***	0.919***	0.915***
	[0.147]	[0.147]	[0.087]	[0.087]
Client Low	-0.796***	-0.799***	-0.359***	-0.360***
	[0.185]	[0.186]	[0.116]	[0.116]
Log CB Reserves	0.232	0.434*	-0.103	0.021
	[0.202]	[0.234]	[0.188]	[0.204]
DF tran repo	0.591		2.018***	
	[0.668]		[0.686]	
DF tran reverse	1.905**		0.842	
	[0.812]		[0.735]	
DF per repo		0.603		-1.155
		[1.184]		[1.470]
DF per reverse		0.925		-0.033
		[1.535]		[1.194]
Dealer FE	Yes	Yes	No	No
NonDealer FE	No	No	Yes	Yes
NonDealer*Week FE	Yes	Yes	No	No
Dealer*Week FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	52,396	52,396	52,597	52,597
R-squared	0.585	0.585	0.574	0.575
	Repo rate spread			
	Repo		Reverse	
Market Power	0.106***	0.110***	0.581***	0.577***
	[0.007]	[0.007]	[0.023]	[0.022]
Client High	-0.001	-0.001	0.005	0.005
	[0.004]	[0.004]	[0.008]	[0.008]
Client Low	0.011	0.011	0.002	0.002
	[0.008]	[0.008]	[0.006]	[0.006]
Log CB Reserves	0.026**	0.006	0.067***	0.048***
	[0.011]	[0.012]	[0.014]	[0.012]
DF tran repo	-0.159***		-0.134***	
	[0.031]		[0.037]	
DF tran reverse	-0.125***		-0.126***	
	[0.040]		[0.042]	
DF per repo		0.053		0.024
		[0.061]		[0.063]
DF per reverse		0.020		-0.328***
		[0.084]		[0.072]
Dealer FE	Yes	Yes	No	No
NonDealer FE	No	No	Yes	Yes
NonDealer*Week FE	Yes	Yes	No	No
Dealer*Week FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	52,396	52,396	52,597	52,597
R-squared	0.104	0.101	0.141	0.141

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results of the regressions of repo market impact by frequency of shocks to repo dealers and simultaneous dyads, replacing relationship trading metrics with dummy variables "High Client" and "Low Client", as discussed in Section 5, for the period 2016 to 2022. Definitions, sources and frequency of all independent variables are presented in Section 4. Panels report the results for the dependent variables as follows: the top panel uses log of volume, and the bottom panel uses the absolute value of repo spread to the reference rate determined by Bank of England. Clustered standard errors on dealer / non-dealer dyads.

Table A.7. OTC impact by sector, by frequency: High Client and Low Client

	Log Volume				Rate spread			
Repo segment	HFs & AMs		PFs & Ics		HFs & AMs		PFs & Ics	
Market Power	-0.165	-0.186	-0.312	-0.150	0.117***	0.120***	-0.206***	-0.206***
	[0.137]	[0.134]	[0.333]	[0.307]	[0.008]	[0.008]	[0.029]	[0.030]
Client High	0.948***	0.944***	-1.458**	-1.546**	0.004	0.004	-0.034	-0.039
	[0.187]	[0.188]	[0.622]	[0.662]	[0.005]	[0.005]	[0.040]	[0.037]
Client Low	-0.995***	-1.000***	-2.547***	-2.591***	0.016**	0.016**	-0.024	-0.028
	[0.254]	[0.255]	[0.668]	[0.690]	[0.007]	[0.007]	[0.027]	[0.027]
Log CB Reserves	-0.968***	-0.843***	-0.801	-0.285	0.032***	0.015	-0.047	-0.085***
	[0.198]	[0.205]	[0.575]	[0.538]	[0.008]	[0.009]	[0.029]	[0.030]
DF tran repo	0.357		2.727		-0.148***		-0.885***	
	[0.712]		[2.394]		[0.027]		[0.186]	
DF tran reverse	0.724		-6.533		-0.118***		0.172	
	[0.784]		[4.355]		[0.032]		[0.115]	
DF per repo		1.183		17.654**		0.029		-0.292
		[1.212]		[7.800]		[0.054]		[0.194]
DF per reverse		-1.091		-0.129		-0.029		0.292
		[1.216]		[3.644]		[0.053]		[0.235]
Dealer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NonDealer*Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	68,781	68,781	11,955	11,955	68,781	68,781	11,955	11,955
R-squared	0.588	0.588	0.336	0.326	0.043	0.040	0.289	0.265
	Log Volume				Rate spread			
Reverse segment	HFs & AMs		PFs & Ics		HFs & AMs		PFs & Ics	
Market Power	-0.382	-0.393	-1.746***	-1.503**	0.563***	0.558***	0.187***	0.185***
	[0.279]	[0.279]	[0.643]	[0.651]	[0.022]	[0.022]	[0.025]	[0.024]
Client High	1.350***	1.351***	0.418	0.405	0.009	0.008	-0.009	-0.009
	[0.136]	[0.136]	[0.705]	[0.693]	[0.007]	[0.007]	[0.011]	[0.011]
Client Low	-0.315	-0.314	-0.398	-0.498	0.008	0.008	-0.012	-0.013
	[0.262]	[0.262]	[0.857]	[0.811]	[0.006]	[0.006]	[0.010]	[0.010]
Log CB Reserves	0.853***	1.156***	0.424	0.476	0.089***	0.070***	0.057***	0.037**
	[0.233]	[0.241]	[0.910]	[0.915]	[0.010]	[0.009]	[0.017]	[0.017]
DF tran repo	3.747***		-4.909		-0.137***		-0.190***	
	[0.748]		[3.757]		[0.030]		[0.061]	
DF tran reverse	1.475**		-4.587*		-0.088***		0.006	
	[0.677]		[2.651]		[0.030]		[0.044]	
DF per repo		-1.400		12.365*		-0.040		-0.129
		[1.452]		[7.278]		[0.051]		[0.093]
DF per reverse		4.203***		1.966		-0.282***		-0.124
		[1.249]		[7.071]		[0.056]		[0.126]
NonDealer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dealer*Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	85,643	85,643	9,867	9,867	85,643	85,643	9,867	9,867
R-squared	0.402	0.401	0.362	0.364	0.138	0.139	0.138	0.135

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results of the regressions of repo market impact by frequency of shocks to repo dealers and non-dealer sectors, replacing relationship trading metrics with dummy variables "High Client" and "Low Client", as discussed in Section 5, for the period 2016 to 2022. Definitions, sources and frequency of all independent variables are presented in Section 4. Panels report the results for the dependent variables as follows: the top panel uses log of volume, and the bottom panel uses the absolute value of repo spread to the reference rate determined by Bank of England. Clustered standard errors on dealer / non-dealer dyads.

Table A.8. Mispricing: One-day mispricing lag

	All		Short		Medium		Long	
MarkUp	0.248*	0.270*	0.385	0.393	0.194	0.219	0.100	0.127
	[0.143]	[0.144]	[0.267]	[0.264]	[0.256]	[0.254]	[0.158]	[0.158]
MarkDown	-0.175	-0.147	0.542	0.558	-0.168	-0.149	-0.436*	-0.400
	[0.200]	[0.193]	[0.353]	[0.351]	[0.244]	[0.238]	[0.255]	[0.245]
DF tran repo	-0.134		-0.500		-0.170		0.051	
	[1.304]		[1.169]		[1.484]		[1.547]	
DF tran reverse	0.122		0.517		0.389		0.090	
	[1.382]		[1.355]		[1.515]		[1.752]	
DF per repo		-1.782		-0.400		-1.595		-3.073
		[1.567]		[1.674]		[1.630]		[1.949]
DF per reverse		0.091		-0.504		-0.533		0.803
		[1.865]		[2.082]		[2.089]		[2.133]
CB Market Share	-0.045	-0.044	0.231*	0.225*	-0.046	-0.053	-0.031	-0.020
	[0.048]	[0.049]	[0.126]	[0.127]	[0.067]	[0.068]	[0.083]	[0.086]
Log CB Reserves	0.010	-0.157	-0.581**	-0.626***	0.041	-0.115	0.364	0.101
	[0.318]	[0.242]	[0.254]	[0.212]	[0.349]	[0.264]	[0.378]	[0.305]
Bond*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,532	21,532	5,222	5,222	7,507	7,507	8,799	8,799
R-squared	0.041	0.042	0.024	0.024	0.031	0.032	0.056	0.059

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results of the regressions of bond-level one-day-ahead mispricing, as discussed in Section 5, for the period 2016 to 2022. Definitions, sources and frequency of all independent variables are presented in Section 4. The dependent variable is the absolute value of the spread between the bond-level yield and the predicted yield based on a spline. We use Driscoll-Kraay standard errors with 20 working days lag.

Table A.9. Mispricing benchmark: Three-day mispricing lag

	All		Short		Medium		Long	
MarkUp	0.441**	0.486***	0.180	0.242	0.595*	0.625*	0.221	0.242
	[0.191]	[0.187]	[0.370]	[0.363]	[0.337]	[0.331]	[0.183]	[0.179]
MarkDown	0.135	0.191	1.124*	1.222**	0.245	0.290	-0.257	-0.228
	[0.300]	[0.294]	[0.573]	[0.571]	[0.339]	[0.334]	[0.323]	[0.314]
DF tran repo	-1.543		-3.857***		-1.416		-0.127	
	[1.589]		[1.372]		[1.796]		[1.781]	
DF tran reverse	-0.834		-1.804		-0.008		-0.598	
	[1.777]		[2.105]		[1.870]		[2.018]	
DF per repo		-1.868		-2.630		-1.698		-1.796
		[2.317]		[2.773]		[2.337]		[2.663]
DF per reverse		2.084		4.308		1.367		1.199
		[2.524]		[3.247]		[2.841]		[2.863]
CB Market Share	-0.096*	-0.099*	-0.070	-0.094	-0.158**	-0.157**	-0.020	-0.019
	[0.055]	[0.055]	[0.136]	[0.134]	[0.069]	[0.070]	[0.093]	[0.094]
Log CB Reserves	-0.013	-0.293	-0.301	-0.852**	-0.076	-0.289	0.358	0.173
	[0.356]	[0.339]	[0.398]	[0.383]	[0.402]	[0.366]	[0.364]	[0.353]
Bond*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,089	15,089	3,639	3,639	5,269	5,269	6,174	6,174
R-squared	0.038	0.037	0.057	0.052	0.032	0.032	0.042	0.043

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results of the regressions of bond-level three-days-ahead mispricing, as discussed in Section 5, for the period 2016 to 2022. Definitions, sources and frequency of all independent variables are presented in Section 4. The dependent variable is the absolute value of the spread between the bond-level yield and the predicted yield based on a spline. We use Driscoll-Kraay standard errors with 20 working days lag.

Table A.10. Mispricing benchmark: Five-day mispricing lag

	All		Short		Medium		Long	
MarkUp	0.159	0.230	0.084	0.110	0.228	0.282	0.084	0.154
	[0.179]	[0.180]	[0.362]	[0.369]	[0.299]	[0.307]	[0.214]	[0.211]
MarkDown	0.113	0.198	0.459	0.508	0.419	0.524*	-0.245	-0.155
	[0.249]	[0.251]	[0.493]	[0.489]	[0.313]	[0.314]	[0.265]	[0.267]
DF tran repo	-2.613*		-2.406		-3.527**		-2.022	
	[1.559]		[1.732]		[1.796]		[1.713]	
DF tran reverse	-1.711		-0.096		-0.749		-2.504	
	[1.909]		[2.431]		[2.076]		[2.097]	
DF per repo		-1.396		-0.125		-1.551		-1.836
		[2.609]		[3.449]		[2.782]		[2.551]
DF per reverse		1.916		0.996		1.958		1.412
		[3.164]		[4.410]		[3.495]		[2.923]
CB Market Share	-0.052	-0.065	-0.043	-0.059	-0.038	-0.036	0.022	0.011
	[0.069]	[0.070]	[0.133]	[0.137]	[0.082]	[0.084]	[0.116]	[0.114]
Log CB Reserves	0.084	-0.276	-0.576	-0.733*	-0.028	-0.396	0.532	0.104
	[0.387]	[0.363]	[0.443]	[0.428]	[0.428]	[0.386]	[0.403]	[0.380]
Bond*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,547	15,547	3,759	3,759	5,457	5,457	6,326	6,326
R-squared	0.161	0.158	0.078	0.075	0.107	0.103	0.261	0.259

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results of the regressions of bond-level five-days-ahead mispricing, as discussed in Section 5, for the period 2016 to 2022. Definitions, sources and frequency of all independent variables are presented in Section 4. The dependent variable is the absolute value of the spread between the bond-level yield and the predicted yield based on a spline. We use Driscoll-Kraay standard errors with 20 working days lag.

Table A.11. Mispricing: Dash-for-Cash by frequency

	(1) - (4) Short				(5) - (8) Medium				(9) - (12) Long			
MarkUp	0.120	0.130	0.133	0.136	0.601***	0.607***	0.619***	0.628***	-0.007	-0.009	-0.009	-0.009
	[0.169]	[0.170]	[0.173]	[0.174]	[0.218]	[0.219]	[0.211]	[0.211]	[0.117]	[0.117]	[0.119]	[0.119]
MarkDown	1.076***	1.084***	1.109***	1.111***	1.139***	1.153***	1.161***	1.169***	0.415*	0.409*	0.410*	0.402*
	[0.178]	[0.178]	[0.173]	[0.172]	[0.248]	[0.247]	[0.239]	[0.238]	[0.226]	[0.227]	[0.223]	[0.224]
DF tran repo	-0.477	-0.503			-2.501**	-2.524**			-0.577	-0.563		
	[0.942]	[0.938]			[1.084]	[1.083]			[0.724]	[0.725]		
Dum Dash * DF tran repo		10.026*				8.157				-9.136***		
		[6.034]				[11.498]				[2.336]		
DF tran reverse	0.251	0.228			2.385	2.364			3.088***	3.098***		
	[1.288]	[1.286]			[1.495]	[1.496]			[1.094]	[1.094]		
Dum Dash * DF tran reverse		5.233				38.077***				1.524		
		[13.890]				[9.466]				[4.681]		
DF per repo			-3.189**	-3.180**			-4.006**	-3.977**			-2.574*	-2.612*
			[1.352]	[1.354]			[1.879]	[1.884]			[1.374]	[1.376]
Dum Dash * DF per repo				-12.393				-52.292***				22.775***
				[7.752]				[12.023]				[4.639]
DF per reverse			4.029**	4.024**			7.556***	7.523***			2.316	2.351
			[1.799]	[1.803]			[2.321]	[2.328]			[2.004]	[2.005]
Dum Dash * DF per reverse				-15.434				-58.753***				0.433
				[19.758]				[17.547]				[4.573]
CB Market Share	0.742***	0.745***	0.748***	0.748***	-0.665***	-0.666***	-0.643***	-0.644***	-0.536***	-0.535***	-0.531***	-0.530***
	[0.173]	[0.173]	[0.174]	[0.174]	[0.108]	[0.108]	[0.109]	[0.109]	[0.182]	[0.182]	[0.181]	[0.181]
Log CB Reserves	-0.741***	-0.741***	-0.919***	-0.920***	-0.563**	-0.564**	-0.662**	-0.663**	-0.006	-0.006	0.024	0.022
	[0.240]	[0.240]	[0.230]	[0.230]	[0.267]	[0.267]	[0.274]	[0.274]	[0.191]	[0.191]	[0.170]	[0.170]
Dum Dash	-0.285***	-0.968*	-0.218**	3.023	-0.220*	-2.434***	-0.101	12.982***	-0.049	0.270	0.009	-3.312***
	[0.096]	[0.534]	[0.090]	[2.377]	[0.130]	[0.403]	[0.110]	[2.095]	[0.070]	[0.240]	[0.079]	[0.869]
Bond*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,536	7,536	7,536	7,536	10,770	10,770	10,770	10,770	14,274	14,274	14,274	14,274
R-squared	0.102	0.102	0.106	0.106	0.118	0.118	0.122	0.123	0.015	0.015	0.013	0.013

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results of the regressions of bond-level mispricing, by frequency of shocks to dealers, including a dummy for the dash-for-cash period and interaction with dealer factors, as discussed in Section 5, for the period 2016 to 2022. Definitions, sources and frequency of all independent variables are presented in Section 4. The dependent variable is the absolute value of the spread between the bond yield and the predicted yield based on a spline. We use Driscoll-Kraay standard errors with 20 working days lag.