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Abstract

We use transaction-level data to study trading and clearing relationships between dealers (ie, Gilt-edged Market Makers and clearing members) and their clients, and price discovery in the UK gilt cash and futures markets in 2016. Using a network approach we analyse the distribution of trading and clearing relationships between dealers and clients, the concentration of the associated volumes and how these change over time. We find that volumes in each market are concentrated in a few key dealers, that clients tend to have relationships with a limited number of dealers and that such relationships and volumes were resilient during most of 2016, including around the EU referendum and subsequent policy announcements. We also assess the systemic risk that could be caused by the inability of those dealers operating across the two markets to perform their roles as clearing member and market maker, finding that there may be some scope for spillover effects from potential disruption in the cash market to the futures market through this channel. Finally, we find that order flows (that we proxy using net volume traded) of clients in the UK gilt futures market can affect cash prices, suggesting that the futures market plays a role in price discovery in the cash market.

Key words: Gilt cash and futures markets, price discovery, network analysis, financial stability, resilience.

JEL classification: G10, G20.

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1. Introduction

The UK government bond (gilt) market is a core financial market. It plays a key role in supporting government financing, the provision of high-quality collateral and the transmission of monetary policy. The gilt futures market is used as an alternative way for getting exposure to the gilt cash market, for hedging purposes and for speculation on future gilt prices. These markets underpin several aspects of financial markets and, in turn, real economy financing, and therefore their resilience is very important for UK financial stability.

The UK gilt cash and futures markets have very different structures. The gilt cash market relies heavily on dealer intermediation, as it is an over-the-counter (OTC) market with designated market makers called Gilt-edged Market Makers (GEMMs). Gilt futures, instead, are traded on exchange using a central limit order book and cleared through a central counterparty (CCP). While the gilt cash market can be classified as a 'slow' market compared to the 'fast' futures market, they are both highly active and liquid markets (Anderson, Webber, Noss, Beale and Crowley-Reidy (2015)). However, trading activity and market structure in both markets can be associated to vulnerabilities, and it is key to analyse them in order to study risks to financial stability.[1,2]

In this paper, we use transaction-level data to study some of the links between the UK gilt cash and futures markets, and their resilience. In the first part of the paper, we analyse the two market structures in isolation and then their interlinkages (i.e., key market participants which feature across the two markets). We start by studying the relationships between dealers and clients in each market, and by assessing which institutions play a key role separately in each market and across the two. We assess the resilience of these relationships over time, and the impact of the systemic risk associated with the hypothetical 'exit' of key institutions across the two markets. In the second part, we analyse the role played by the futures market in price discovery in the cash market. Our analysis focuses on the time period from January 2016 to end-November 2016, therefore covering the significant price moves around the EU referendum and subsequent policy announcements.[3]

We create a new dataset by combining granular transaction level data uniquely available to public authorities: the UK Financial Conduct Authority (FCA) Zen data on the gilt cash and EMIR Trade Repository (TR) data on gilt futures. From data on transactions in the gilt cash market we are able to map trading activity between GEMMs and clients. Whereas from data on gilt futures we are able to map clearing activity between clearing members and clients. We are also able to map clients into different sectors (e.g., asset managers, hedge funds

[1] While government bond markets have always been deemed safe markets, they can also experience high levels of dysfunctionality and illiquidity. For instance, during the "dash for cash" associated to the spread of Covid-19 worldwide in March 2020 the UK gilt market and the US Treasury market experienced dysfunctionality, and only the intervention of central banks managed to stabilise trading activity in those markets (for instance, see Hauser (2020), Cunliffe (2020), Schrimpf, Shin, Sushko (2020) and Barth and Kahn (2020)).
[2] Vulnerabilities can also be associated to flash episodes of extreme price volatility, such as the "flash rally" witnessed in the US Treasury market on October 15, 2014 (see Bouveret, Breuer, Chen, Jones and Sasaki (2015) and Joint Staff Report (2015)) albeit that episode did not have long-lasting destabilising consequences requiring central bank intervention.
[3] On August 4, 2016 the MPC announced several policy measures including the purchase of UK gilts. See Bank of England cuts Bank Rate to 0.25% and introduces a package of measures designed to provide additional monetary stimulus.

and principal trading firms, insurance companies and pension funds, other banks and so on) and this allows us to analyse differences across different types of clients.

Our data allow us to analyse vulnerabilities associated to *trading activity* in an OTC market, such as the cash market, and to *clearing activity* in exchange traded derivatives, such as gilt futures. In order to understand risks to financial stability, it is important to study vulnerabilities due to the frictions faced by clients when accessing an OTC market, such as any limitations in the number of trading relationships with GEMMs, their costs and the concentration of trading volumes among GEMMs. Similarly, it is relevant for financial stability to study the vulnerabilities faced by clients when accessing clearing services in exchange traded derivatives, like gilt futures. The reliance of clients on a limited number of clearing members could create fragilities were key clearing members unable to perform their obligations (for example, in a crisis). Identifying key players across the two markets is important to understand systemic risk across the two markets.[4] Finally, the study of price discovery between the two markets is important to understand drivers in changes of gilt cash prices (and therefore yields) that are a key benchmark for financial markets. We also analyse linkages between changes in market structure and price discovery.

We model trading and clearing relationships between dealers (i.e., GEMMs and clearing members) and clients belonging to different sectors as networks. Network models have been widely used to study financial markets (see, for instance, Boss, Elsinger, Summer and Thurner (2004), Bargigli, Di Iasio, Infante, Lillo, Pierobon (2015)), and here we use bipartite networks where nodes belonging to one group (i.e., dealers) can only be connected to nodes belonging to another group (i.e., clients). By studying the first order properties (such as degrees, strengths and density) we find that in both markets clients rely on few key dealers. On average over our sample, the daily volume traded between the top 3 GEMMs and their clients is around 43% and 44% of the total volume traded, while that cleared by top 3 clearing members for their clients is around 81% of the total volume cleared. On average on a daily basis, clients trade with around 1 or 2 GEMMs and use a single clearing member.[5] Both daily trading and clearing relationships show some persistency over time. This is consistent with frictions faced by clients when trading in OTC markets, such as the gilt cash market (Duffie, Gârleanu and Pedersen (2005), Duffie, Gârleanu and Pedersen (2007), Hugonnier, Lester, Weill (2020)), and by frictions faced by clients when setting up clearing relationships (FSB (2008)). We also find that those firms that are both GEMMs and clearing members are key players across the two markets. This is not surprising given the key role played by each type of institution in each market, and highlights the necessity to further investigate the systemic risk associated to these institutions, which we do later in the paper.

We assess the resilience of the structure of the networks of trading and clearing relationships between dealers (GEMMs and clearing members) and clients using null models (Bargigli, Di Iasio, Infante, Lillo, Pierobon (2015), Squartini, Van Lelyveld, and Garlaschelli (2013)). Null models allow us to create randomised versions

[4] These are not the only risks to financial stability related to these two markets. For instance, other risks to financial stability relate to imbalances between demand and supply of liquidity in these markets and flash crashes in 'fast' futures markets.
[5] As these results are based on the daily observations of the networks, they do not account for 'dormant' relationships that are not used on a daily basis but that might be used in case needed (e.g., stress times).

of the real network that preserve some real properties (e.g., in- and out- degree or in- and out-strengths). We study the resilience of networks associated to gilt cash and futures markets by detecting changes in measures that compare the real networks with the randomised ones created by the null model. We find that the networks were relatively stable throughout 2016, including around key events – i.e., EU referendum, QE dates and macroeconomic announcements (i.e., inflation, unemployment and MPC announcements).

We study the systemic risk associated to those firms that are both GEMMs and clearing members that we found to be active across both markets by simulating the consequences of their hypothetical 'exit' from both markets, following an approach similar to Mallaburn, Roberts-Sklar and Silvestri (2019). We assess the impact of their exit on volumes traded and cleared and on clients' ability to access each market (i.e., the number of relationships between dealers and clients). We remove GEMMs and clearing members subsequently from each market according to their gross volume in each market. We find that on average the removal of top 3 GEMMs and clearing members leads to a reduction of around 30% and 80% in the volume in gilt cash and futures, respectively (consistently with the concentration of volume); and a reduction of 30% and 70% in the number of daily connections between dealers and clients. The cash market appears to be relatively more resilient to the exit of key players compared to gilt futures market. The failure of top GEMM-CMs is more likely to spill-over from the cash to futures markets, given that the top GEMMs typically account for around 40% of daily futures clearing volumes. During our considered time frame we find that both networks were broadly resilient overall.

Finally, we study price discovery between the two markets.[6] To the best of our knowledge we are the first to undertake this analysis for the UK gilt market. Following Brandt and Kavajecz (2004) and Brandt, Kavajecz and Underwood (2007) we test whether order flows (that we proxy using net volume traded) both in cash and futures markets are the way private information is incorporated into gilt cash prices. We are particularly interested in assessing whether order flows of clients in gilt futures affect gilt cash prices. In our regressions, we control for macroeconomic events[7,8] and roll-over of futures contracts, as well as for the liquidity of each market. We find that order flows corresponding to some of the client sectors in the gilt futures markets lead to statistically significant changes in gilt cash market prices. Particularly, order flows from hedge funds in the gilt futures market increase gilt cash prices, while order flows from asset managers, insurance companies and pension funds decrease gilt cash prices. We find that a less liquid futures market is related to higher cash market prices. We also analyse how gilt cash prices are related to the density of the network of trading relationships between dealers and clients in the cash market, and find that greater interconnectedness between dealers and clients appears to reduce gilt cash prices.

[6] Generally cash (or spot) markets and derivatives markets are related by arbitrage (see, for instance Brandt et al. (2007) and Mizrach and Neely (2008) for US Treasury cash and futures markets).

[7] Government bond prices are affected by macro-economic news, which are public information (see Brandt and Kavajecz (2004)).

[8] We consider the following macro-economic news in our analysis: public announcements of UK inflation (CPI/PPI) and unemployment (both from the ONS), and MPC announcements (from Bank of England).

The paper is structured as follows. Section 2 provides a summary of the existing academic literature that is related to this work. Section 3 describes the dataset used. Section 4 describes the methodology and the results of the analysis of the networks of relationships between dealers and clients associated to the gilt cash and futures markets. Section 5 and 6 describe the analysis of the resilience of these networks over time and to the exit of key players, respectively. Section 7 focuses on the analysis of price discovery between the two markets. Finally, section 8 concludes.

2. Related literature

Our paper is related to the existing literature on trading networks, on how trading relationships affect pricing mechanisms and on price discovery between cash and futures markets. It also contributes to the existing knowledge on gilt markets. In this section, we provide a summary of the key papers on each of the topics listed above that are particularly relevant for our work.

Recently, financial networks have been used to study financial markets. For instance, the structure of the sterling corporate bond market and its resilience to the exit of key players and around bond downgrades has been analysed by Mallaburn, Roberts-Sklar and Silvestri (2019) using a network approach. Financial networks have also been used to study more than one market at the time. Fontaine and Walton (2020) study the Canadian spot and repo markets, finding that the complexity of the networks of counterparties increases around news releases, and also assess the resilience of such networks to settlement fails. Bardoscia, Bianconi and Ferrara (2018) study counterparty exposures on interest rates, credit and foreign exchange derivatives contracts using a network with different layers, with each layer corresponding to a different contract (i.e., multilayer network). Similarly, using a multilayer network Bargigli, Di Iasio, Infante, Lillo and Pierobon (2015) analyse the secured and unsecured Italian interbank market. They also use null models to investigate higher order properties of the network (such as reciprocity, clustering and assortativity). Also Squartini, Van Lelyveld and Garlaschelli (2013) use null models to analyse the Dutch interbank network during the global financial crisis. Specifically, they find that null models measuring the "distance" between the real and a benchmark network are able to detect changes in the network around the crisis.

For the municipal bond markets, Li and Schurhoff (2018) find that the network has a core-periphery structure where clients face a "centrality premium" when trading with more central dealers as they are able to quickly match buyers and sellers compared to more peripheral dealers. Dealer trading relationships and their behaviour in the US corporate bond market has been studied by Di Maggio, Kermani and Song (2017), that show that core dealers charge lower spreads to other core dealers compared to less central dealers and clients, and that this was particularly true during the global financial crisis. Kondor and Pinter (2019) study how heterogeneous private information in the gilt cash market is impounded in gilt cash prices depending on the number of dealers used by clients (client's centrality in the network). They find that an average client has better performance when dealing with more dealers and this is higher during macroeconomic announcements in the gilt market**.**

Building on the work of Brandt and Kavajecz (2004) that studies price discovery in the US Treasury cash market, Brandt, Kavajecz and Underwood (2007) look at price discovery between the US Treasury cash and futures markets. They show that in US Treasury markets, price discovery in the cash market is related to order flows of different trader types in the futures market, and also to market liquidity and the prevailing financing rate (general collateral repo rate). Using an approach based on Hasbrouck (1995) and Harris, McInish and Wood (2002), Mizrach and Neely (2008) study price discovery in the US Treasury cash and futures markets showing the important role played by the futures market in price discovery. Similarly, using the approaches proposed by Hasbrouck (1995) and Gonzalo-Granger (1995), Campbell and Hendry (2007) study price discovery between cash and futures markets for the Canadian government bond market and the US Treasury market. They find that price discovery happens mostly in the futures market for both markets. However, over time changes to the trading system have increased price discovery in the US Treasury cash market. More recently, Fleming, Nguyen and Ruela (2020) study price discovery between US Treasury cash and futures markets around a change in tick size in both markets using the framework proposed by Hasbrouck (1995).[9]

The liquidity of the gilt futures market has been studied using order book data by Fullwood and Massacci (2018), finding that it was resilient during stress events, such as the EU referendum in 2016, and that such resilience does not come at the expense of reduced liquidity in normal times. Also the role played by different market participants in the gilt cash market has been studied. Benos and Zikes (2018) look at dealers, and analyse whether funding constraints affect dealers' ability to provide liquidity in the gilt cash market. They find that dealer balance sheet constraints and less interdealer activity have a negative impact on liquidity. Czech, Huang, Lou and Wang (2020) find that hedge funds and mutual funds contribute to price discovery in the gilt market in two different ways. While mutual funds are able to predict changes in short-term interest rates making use of macroeconomic news, hedge funds are also able to predict the order flows of other investors.

3. Data

We construct a novel dataset containing granular information on transactions in UK gilt cash and futures, covering the time period from January to November 2016.

[9] Here, we have focussed on the literature on price discovery in government bond (cash) markets only and between government bond cash and futures markets. However, the literature has also investigated price discovery in other cash and futures markets.

Gilts are traded over the counter through designated market makers called Gilt-edged Market Makers (GEMMs). GEMMS are required to provide liquidity on demand and in all conditions.[10] Gilts are listed on the London Stock Exchange (LSE), and trading activity occurs via electronic platforms (e.g. Tradeweb) or bilaterally by voice or some other method of electronic communications. GEMMs manage their inventory through the interdealer market (bilaterally or anonymously through inter-dealer brokers (IDBs)).[11] The gilt cash data comes from the FCA Zen database of market transactions. From our data we can analyse the trading network corresponding to executed transactions between any two counterparties in the market.

In this paper, we focus on long gilt futures. They are traded on the Intercontinental Exchange (ICE) Futures, on a central limit order book and are centrally cleared by ICE Clear Europe. We obtain the gilt futures data from EMIR Trade Repository (TR) Data, using a dataset compiled across four trade repositories – namely, The Depository Trust & Clearing Corporation (DTCC) Derivative Repository, UnaVista, Regis-TR and ICE Trade Vault Europe. The transaction reporting for exchange traded derivatives like gilt futures provides us with a view on the clearing network corresponding to executed transactions between any two counterparties, so includes transactions between clients and clearing members and clearing members and the CCP.

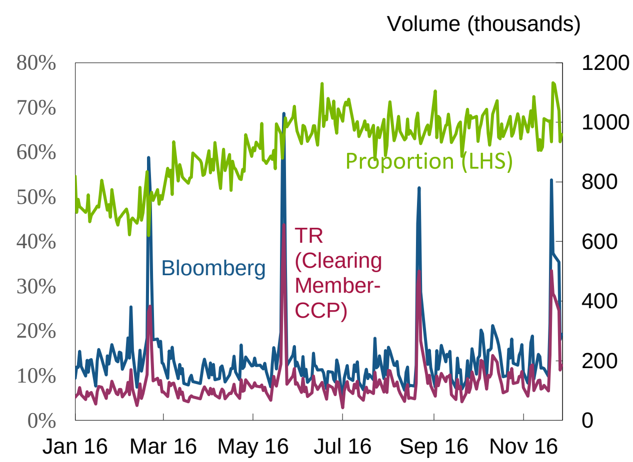
From the Zen data, we exclude trades conducted between the Bank of England (BoE) and the Debt Management Office (DMO) as part of auctions and quantitative easing transactions. We clean the data by dropping trades that are implausibly large or small, or have prices very far from the end-of-day prices recorded by Bloomberg. We also drop trades executed on an agency basis (i.e. we only include principal trades). Finally, we remove duplicates by matching trades which have been reported by both counterparties, and dropping one of them. From the Trade Repository data, we similarly remove misreported or duplicate reported trades, and conduct a range of plausibility checks on reported prices, volumes, price multipliers, and other selected variables compared to official Bloomberg data.[12] We drop any trades that cannot be identified as gilt futures or with missing reported values.[13]

In order to assess the coverage of our respective datasets, we can compare them to publicly available information via Bloomberg for long gilt futures market activity, and the Debt Management Office (DMO) statistics for gilt cash market turnover (see Figures 1 and 2). We find that on average we capture the majority (60%) of trading activity in long gilt futures on a daily basis when comparing to official Bloomberg statistics, with an increasing proportion of coverage through the year (green line in Figure 1). The differences are likely due to data quality issues, which have since improved as reporting standards have progressed through time.[14] In cash markets, the combined DMO estimate for trading turnover over 2016 was £25.9 billion. The average

[10] The GEMMs are obliged to provide liquidity in the secondary gilt market by making "on demand and in all conditions, continuous and effective two-way prices" – see "A guide to the roles of the DMO and Primary Dealers in the UK government bond market" by the UK DMO.
[11] For further information about the gilt market structure see Benos and Zikes (2018).
[12] In the current version of our data we have not accounted for those trades that have been reported on behalf of another counterparty. However, we have estimated that the number of such trades is very small so that should not affect the results of our analysis. In future revisions of the work we might revise the data and account for them.
[13] We define the trading day from 1:00am to 11:00pm, unless otherwise specified.
[14] It should also be noted that the sample period considered in this paper is when the EMIR TR data were first collected.

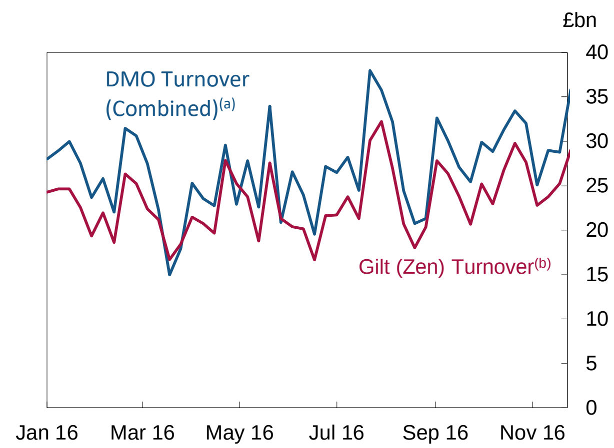
trading volume in our dataset is around £23bn. The differences likely lie in the exclusion of DMO and BoE related activity in the market. Therefore we have a good coverage of the two markets.

Figure 1: Data quality- EMIR trade repository clearing versus Bloomberg



Sources: Bloomberg, EMIR TR and Bank Calculations.

Figure 2: Data quality- FCA Zen versus DMO statistics[(a)(b)]



Source: DMO, FCA ZEN dataset and Bank Calculations.

(a) DMO combined turnover represents the sum of all customer and professional transactions conducted by GEMMs as defined by the DMO.
(b) Zen turnover exceeds DMO turnover on a limited number of occasions due to data quality issues.

An important aspect of the work was to appropriately match the counterparty information in both datasets to determine the unique institutions active in these markets. As the two datasets have different counterparty identifiers, we leveraged on the work done by Czech (2019) on matching similar data on corporate bonds and credit default swaps (CDS) to define Aggregate Standard Names (ASNs) that aggregate multiple firms at parent level but keep different entities separate. More information on this can be found in Annex 2.

As both datasets contain the identity of counterparties, we can classify them into different sectors.[15] As we focus on trading and clearing relationships between dealers and clients, in our analysis we exclude all transactions between clearing members and the CCP in the gilt futures market, and all transactions in the interdealer market (i.e., between GEMMs and interdealer brokers (IDB) and between GEMMs only) in the cash market. Therefore we consider the following sectors for dealers: GEMMs for the gilt cash market and clearing members (CMs) for the gilt futures market; and for clients: asset managers (AMs), insurance companies and

[15] We classify counterparties into sectors using a best-endeavour sectoral classification, and might be subject to uncertainty.

pension funds (ICPF), hedge funds and principal trading firms (PTFs), other banks, and other market participants.

For the analysis of price discovery, we additionally use the Bank's Sterling Money Market Data (SMMD) database[16] for general collateral repo rate data. We also use data on public announcements of UK inflation (CPI/PPI) and unemployment from the ONS and MPC announcements from Bank of England.

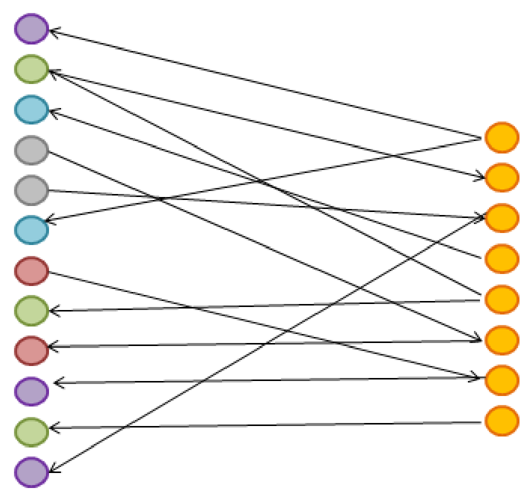
4. Gilt cash and futures market networks

4.1 Methodology of network analysis

In this section, we describe the methodology used to analyse trading relationships between clients and GEMMs in the gilt cash market, and clearing relationships between clients and clearing members in the gilt futures market.

We use bipartite networks where nodes belonging to one set are only connected to those belonging to another, as shown in Figure 3. For instance, GEMMs or clearing members (yellow nodes) are connected to their respective clients (coloured nodes). We use a directed weighted network, where relationships between any two counterparties are modelled as arrows pointing from the seller to the buyer where the volume of the transaction corresponds to the weight attached to the link. For example, if a hedge fund were to buy from a GEMM, a link would be created pointing from the GEMM to the hedge fund with a weight equal to the volume underlying the transaction. In the following, we refer to the bipartite networks associated to both trading relationships between clients and GEMMs in the gilt cash market, and clearing relationships between clients and clearing members in the gilt futures market as dealer to client networks.

Figure 3: Stylised bipartite network. Yellow nodes represents dealers (i.e., GEMMs or clearing members). Coloured nodes clients belonging to different sectors



Formally, for each market and each point in time t we define the network as $T(t) = (U(t), V(t), \boldsymbol{B}(\boldsymbol{t}), \boldsymbol{S}(\boldsymbol{t}))$, where $U(t) = (U_1, \ldots, U_M)$ is the set of vertices corresponding to clients, $V(t) = (V_1, \ldots, V_N)$ is the set of vertices corresponding to dealers (i.e., GEMMs for the cash markets, and clearing members for the gilt futures market), $\boldsymbol{B}(\boldsymbol{t})$ is a $M \times N$ matrix where the generic element $B_{ij}(t)$ denotes the total volume that client i bought from

[16] For more information on the Sterling Monet Market Data see https://www.bankofengland.co.uk/statistics/data-collection/sterling-money-markets.

dealer (i.e., GEMM or clearing member) j , and $\boldsymbol{S}(\boldsymbol{t})$ is a $N \times M$ matrix where the generic element $S_{ij}(t)$ denotes the total volume that client j sold to dealer (i.e., GEMM or clearing member) i.

It is possible to evaluate the matrices $\boldsymbol{B}(\boldsymbol{t})$ and $\boldsymbol{S}(\boldsymbol{t})$ of the bipartite network from the weighted adjacency matrix of the monopartite network $\boldsymbol{W}(\boldsymbol{t})$ corresponding to trading relationships including all counterparties in the gilt cash market and all clearing relationships in the gilt futures market. In order to do that we group market participants active in the two markets in three main categories: (i) dealers, (ii) clients and (iii) residual. Dealers include GEMMs and clearing members. We define clients to be the same in cash and futures markets, and as those that are not GEMMs, clearing members, the CCP (i.e., ICE), interdealer brokers (IDB) or brokers that are not clearing members. Therefore "residual" includes those sectors that we exclude in our analysis- namely, interdealer brokers (IBD) and brokers in the cash market, and the CCP and brokers in the futures market.[17] We can decompose $\boldsymbol{W}(\boldsymbol{t})$ into blocks describing relationships between (i) dealers only, (ii) clients only, (iii) residual only, (iv) clients on the buy side and dealers on the sell side, (v) clients on the sell side and dealers on the buy side, (vi) dealers on the sell side and residual on the buy side, (vii) dealers on the buy side and residual on the sell side, (viii) clients on the sell side and residual on the buy side and (ix) clients on the buy side and residual on the sell side. Our matrices $\boldsymbol{B}(\boldsymbol{t})$ and $\boldsymbol{S}(\boldsymbol{t})$ will correspond to blocks (iv) and (v), respectively.

We investigate the trading behaviour of different clients by looking at the total amount they sold $S_j(t)$ and bought $B_i(t)$ at time t that can be evaluated as the sum of the elements across the columns of $\boldsymbol{S}(\boldsymbol{t})$ and the rows of $\boldsymbol{B}(\boldsymbol{t})$, respectively:

$$S_j(t) = \sum_{i=1}^{N} S_{ij}(t)$$

$$B_i(t) = \sum_{j=1}^{N} B_{ij}(t).$$

Similarly, we evaluate the volume bought and sold by GEMMs and clearing members at time t by summing on the rows of $\boldsymbol{S}(\boldsymbol{t})$ and columns of $\boldsymbol{B}(\boldsymbol{t})$, respectively.

We investigate the structure of the network by looking at how connections are distributed between clients and dealers (i.e., GEMMs or clearing members). For each of our matrices, $\boldsymbol{B}(\boldsymbol{t})$ and $\boldsymbol{S}(\boldsymbol{t})$ we define a matrix that contains information on the presence or absence of links. These are called adjacency matrices and are defined as follows:

$$A_{ij}^{B}(t) = \begin{cases} 1 \; if B_{ij}(t) > 0 \\ 0 \; otherwise \end{cases}$$

$$A_{ij}^{S}(t) = \begin{cases} 1 \; if \; S_{ij}(t) > 0 \\ 0 \; otherwise \end{cases}.$$

[17] Note that under this definition, those firms that are clearing members but not GEMMs will not be included in the dealer to client network corresponding to the cash market. And similarly, those GEMMs that are not clearing members will not be included in the dealer to client network corresponding to the future market. However, their exclusion shouldn't affect our main results as we have estimated that the numbers of GEMMs non-clearing members active in the futures market and clearing members non-GEMMs active in the cash market are small.

We can obtain the number of dealers (i.e., GEMMs or clearing members) with whom a given client has a relationship by summing across the rows of $A_{ij}^{B}(t)$ and columns of A_{ij}^{S}(t). This is called the client degree for buying and selling relationships and can be formally written as:

$$degree_{client\ i}^{B}(t) = \sum_{j=1}^{N} A_{ij}^{B}(t)$$

$$degree_{client\ j}^{S}(t) = \sum_{i=1}^{N} A_{ij}^{S}(t).$$

Similarly, we can evaluate the dealer degree for buying and selling relationships as follows:

$$degree_{dealer\ j}^{B}(t) = \sum_{i=1}^{M} A_{ij}^{B}(t)$$

$$degree_{dealer\ i}^{S}(t) = \sum_{j=1}^{M} A_{ij}^{S}(t).$$

We then analyse the density of the network that is defined as the number of existing links in the network out of all possible links as follows:

$$d(t) = \frac{\sum_{ij} A_{ij}^{B}(t) + \sum_{ij} A_{ij}^{S}(t)}{2MN}.$$

We also analyse the concentration of volume traded and cleared in the dealer to client networks by looking at the share of volume corresponding to top 3 dealers and clients.

We finally study the persistency of relationships between dealers and clients in the dealer to client networks in to two different ways. First, we evaluate the number of common links between time t and time $t-1$ as follows:

$$P^{u}(t) = \frac{\sum_{i,j=1}^{N} A_{ij}^{u}(t) A_{ij}^{u}(t-1)}{\sum_{ij=1}^{N} A_{ij}^{u}(t)} \qquad u = B, S.$$

Similarly, we also assess the number of common active market participants. Then we evaluate the Jaccard index as:

$$J^{u}(t) = \frac{\sum_{ij=1}^{N} A_{ij}^{u}(t) \cap A_{ij}^{u}(t-1)}{\sum_{ij=1}^{N} A_{ij}^{u}(t) \cup A_{ij}^{u}(t-1)}.$$

4.2 The structure of each market

In this section we apply the methodology described in section 4.1 to analyse the structure of the dealer to client networks associated to both the gilt cash and futures markets over time, highlighting the implication of our results for the resilience of the UK gilt markets. We start with providing an overview of the two networks by looking at the number of active participants and their volumes. We then study the concentration of volume across dealers and clients. Finally, we analyse the density and the degree of the bipartite dealer to client networks, and the persistency of relationships in the networks.

We summarise some descriptive statistics of the daily number of active participants in Tables 1 and 2 for each market. The gilt cash market has on average around 19 dealers (i.e., GEMMs) and 168 clients active on a given day. There were officially 20 GEMMs active at the start of 2016, with 17 of these GEMMs defined as ‘wholesale’ market-makers, and 3 designated as ‘retail’ market makers.[18] Societe Generale resigned as a GEMM in February 2016.[19] Similarly, in the gilt futures market there are on average 15 dealers (i.e., clearing members) and 175 clients active on a given day. The majority of clearing members are banks. Apart from banks, some brokers are also clearing members.[20] This is different to what the market looks like today, where some PTFs also self-clear. In the cash market there are on average around 58 asset managers, 15 hedge funds and PTFs, 22 insurance companies and pension funds and 39 other banks active on a given day. Whereas, on a daily basis in the futures market there are on average 63 asset managers, 45 hedge funds and PTFs, 23 insurance companies and pension funds and 14 other banks. As we would expect in a ‘fast market’, we find that on average there are more ‘fast’ participants like hedge funds and PTFs active in the futures market than in the cash market.

Table 1: Summary statistics of daily active dealers and clients for each market.

	Gilt cash		*Gilt futures*	
	Dealers	*Clients*	*Dealers*	*Clients*
Mean	19	168	15	175
St. dev.	1	19	1	50

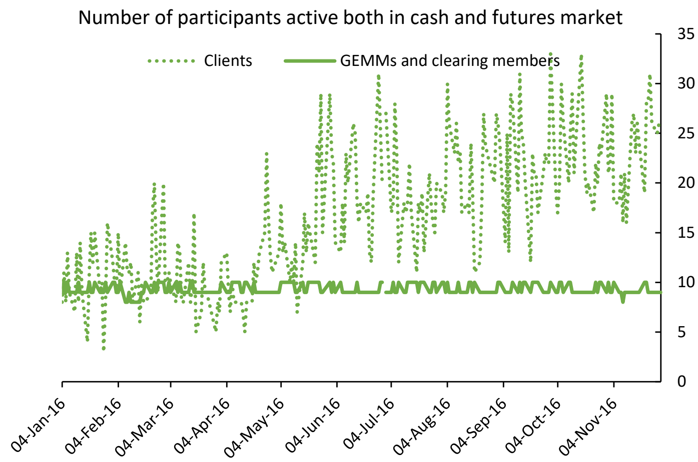
Table 2: Summary statistics of daily active clients by sector for each market.

	Asset Managers	*Hedge funds and PTFs*	*ICPFs*	*Other*	*Other Banks*
Gilt cash					
Mean	58	15	22	35	39
St. dev.	7	3	4	6	7
Gilt futures					
Mean	63	45	23	30	14
St. dev.	22	8	10	10	5

Figure 4: Number of market participants active both in the cash and futures market in any given day.

[18] A list of GEMMs can be found on the DMO website. More details on wholesale and retail GEMMs can be found in “A guide to the roles of the DMO and Primary Dealers in the UK government bond market” by the UK DMO.
[19] See DMO announcement on 29 January 2016. Societe Generale last day as GEMM was 5 February 2016.
[20] The full list of all clearing members can be found on ICE website.

We also analyse market participants that are active both in the gilt cash and futures dealer to client networks in any given day. As shown in Figure 4, we find that between 9 and 10 firms that are both clearing members and GEMMs[21] are active on a daily basis across the two markets throughout the year. This is in line with the key role played by these firms in each market, as designated market makers and clearing members, respectively. We also find that the number of clients active in both markets in any given day increases throughout the year and is on average 17 in any given day (Figure 4).



Most of these firms appear to be long term investors like asset managers, insurance companies and pension funds, who are likely using the futures market for hedging their cash positions.

We find that the average total daily volume traded in the cash market between dealers and clients is around £5bn, while in the futures market is around the double on average (Table 3).

Table 3: Summary statistics of the total daily volume in both bipartite networks.

	Gilt cash (£bn)	*Gilt futures (£bn)*
Mean	5.02	9.97
St. dev.	1.42	7.59
Median	4.73	8.29
25th percentile	4.04	6.80
75th percentile	5.94	10.12

Tables 4 and 5 show the total daily volume bought and sold by clients split by sector for the cash and futures bipartite networks, respectively. We find that in the cash market the total volume sold and bought by asset managers and insurance companies and pension funds on average in any given day is larger than that sold and bought by other clients. While in the futures market total volume sold and bought by hedge funds and PTFs on average in any given day is larger than that sold or bought by other clients.

Table 4: Summary statistics of the total daily volume bought and sold by clients split by sectors in the gilt cash bipartite network.

[21] Given the way we have defined firms that are clients there will be only firms that are both clearing members and GEMMs among dealers that are active in any given day in the two dealer to client networks.

	Clients				
	Asset Managers	*Hedge Funds and PTFs*	*ICPFs*	*Other*	*Other Banks*
	Volume bought (£bn)				
Mean	0.94	0.47	0.58	0.32	0.22
St. dev.	0.34	0.27	0.27	0.21	0.16
Median	0.88	0.41	0.55	0.28	0.19
25th percentile	0.70	0.27	0.39	0.17	0.11
75th percentile	0.11	0.62	0.73	0.43	0.29
	Volume sold (£bn)				
Mean	0.86	0.53	0.57	0.28	0.24
St. dev.	0.36	0.29	0.26	0.18	0.13
Median	0.81	0.46	0.53	0.24	0.23
25th percentile	0.60	0.33	0.40	0.15	0.15
75th percentile	1.07	0.67	0.70	0.37	0.30

Table 5: Summary statistics of the total daily volume bought and sold by clients split by sectors in the gilt futures bipartite network.

	Clients				
	Asset Managers	*Hedge Funds and PTFs*	*ICPFs*	*Other*	*Other Banks*
	Volume bought (£bn)				
Mean	0.72	3.56	0.55	0.08	0.10
St. dev.	1.11	1.53	1.51	0.12	0.12
Median	0.52	3.23	0.14	0.05	0.07
25th percentile	0.29	2.66	0.06	0.03	0.03
75th percentile	0.70	4.00	0.31	0.07	0.13
	Volume sold (£bn)				
Mean	0.72	3.59	0.48	0.08	0.10
St. dev.	1.10	1.54	1.40	0.13	0.12
Median	0.44	3.24	0.14	0.05	0.07
25th percentile	0.26	2.65	0.06	0.03	0.04
75th percentile	0.77	4.02	0.32	0.08	0.12

Also in any given day in the cash market, GEMMs sell and buy much larger notional amounts on average than any client, as shown in Table 6. Among client sectors in a given day in the cash market, hedge funds and PTFs and ICPFs buy and sell the largest notional amounts on average. Similarly in any given day in the futures market, clearing members sell and buy larger notional amounts than any other clients on average; and hedge funds and PTFs buy and sell larger notional amounts than any other client on average, as shown in Table 7.

Table 6: Summary statistics of the average daily volume bought and sold by dealers and clients split by sectors in the gilt cash market.

	Dealers	*Asset Managers*	*Hedge funds and PTFs*	*ICPFs*	*Other*	*Other Banks*
Volume bought (£mn)						
Mean	129.40	16.27	31.50	26.87	8.79	5.70
St. dev.	39.02	5.39	17.85	11.99	5.34	3.94
Volume sold (£mn)						
Mean	132.49	14.82	35.02	26.36	7.73	6.28
St. dev.	40.51	5.62	18.09	11.73	4.87	3.50

Table 7: Summary statistics of the average daily volume bought and sold by dealers and clients split by sectors in the gilt futures market.

	Dealers	*Asset Managers*	*Hedge funds and PTFs*	*ICPFs*	*Other*	*Other Banks*
Volume bought (£mn)						
Mean	336.56	9.88	81.87	15.95	2.15	6.59
St. dev.	255.55	10.11	34.59	28.64	1.90	6.01
Volume sold (£mn)						
Mean	339.08	9.66	82.30	13.75	2.24	6.56
St. dev.	258.39	9.85	34.22	23.36	2.08	5.84

We study the concentration of trading volume in the gilt cash and futures markets by looking at the share of daily volume corresponding to top 3 dealers and clients. Trading volume in the gilt cash market appears to be quite concentrated both on the dealer and client side. The top 3 GEMMs account for around 44% of daily volume bought and 43% of daily volume sold on average, and top 3 clients account on average for around 31% of daily volume bought and sold (Table 8). Similarly, clearing activity in futures market is also concentrated in few clearing members, with the top 3 clearing members accounting for around 81% of daily volumes bought and sold on average. Also in the futures market activity seems to be concentrated in top 3 clients, as they account for 53% of daily volume bought and sold on average (Table 8). Overall, we find that volumes are quite concentrated in few players. Particularly, among GEMMs in the cash market and clearing members in the futures market, again suggesting their importance in the each of these markets.

Table 8: Share of daily volume corresponding to top 3 dealers and clients in the bipartite networks of gilt cash and futures.

	Top 3 buy (%)		*Top 3 sell (%)*	
	Dealers	*Clients*	*Dealers*	*Clients*
		Gilt cash		
Mean	43.58	31.26	43.33	31.20
St. dev.	6.46	7.11	6.15	6.83
		Gilt futures		
Mean	80.86	53.17	80.94	52.62
St. dev.	7.49	9.72	7.21	10.21

We find that the density of the dealer to client network associated to the gilt cash market is fairly low, on average 6%, underlying that only a small fraction of possible trading relationships between dealers and clients exists on a given day (Figure 5 and Table 9). We find that dealers have average daily in-and out-degree of around 11 in the gilt cash market- namely, they sell to and buy from 11 clients on average in a given day (Tables 10 and 11). They can have up to around 16 and 17 clients on the buy and sell side in a given day, respectively. Whereas on a daily basis clients tend buy from and sell to around 1 or 2 dealers, and we observe heterogeneity across sectors. For instance, in a given day insurance companies and pension funds and hedge funds and PTFs can have buy and sell relationships with up to around 3 dealers, while asset managers with up to around 2 dealers. This is consistent with the OTC structure of the gilt cash market because of the existing frictions faced by market participants, such as the search for intermediaries, limited access to multiple market makers and limited bargaining powers**.** This is also in line with the findings of other papers that study the structure of other OTC markets (Duffie et al. (2005), Duffie et al. (2007), Di Maggio et al. (2017), Hugonnier et al. (2020)).

Table 9: Summary statistics of the daily density of the bipartite network of gilt cash and futures markets.

	Futures	*Cash*
Mean (%)	4.96	6.42
St. dev. (%)	0.49	0.51

Figure 5: Daily density of the dealer to client network for the gilt cash and futures markets.

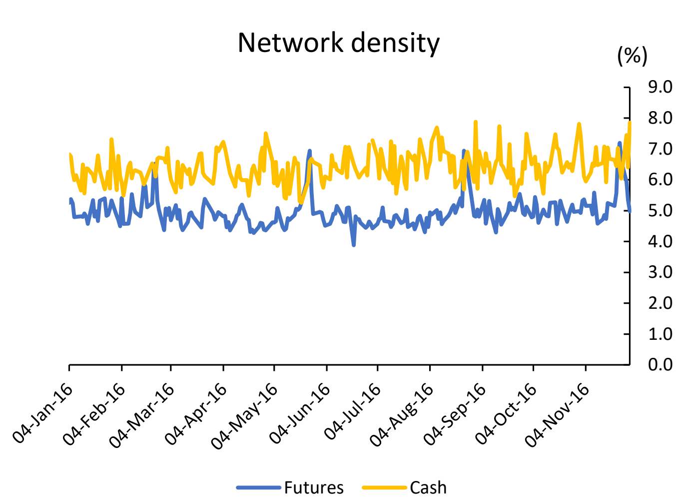


Table 10: Summary statistics of the daily in-degree (number of buyers) of dealers and clients split by sector for the gilt cash and futures bipartite networks.

	Dealers	*Asset Managers*	*Hedge funds and PTFs*	*ICPFs*	*Other*	*Other Banks*
			Gilt cash			
Mean	10.83	1.45	1.54	1.65	0.79	0.96
St. dev.	1.76	0.18	0.40	0.33	0.17	0.17
Max	15.89	1.98	3.22	3.00	1.31	1.61
			Gilt futures			
Mean	8.85	0.73	0.84	0.65	0.65	0.81
St. dev.	3.79	0.13	0.15	0.16	0.15	0.15
Max	24.87	1.05	1.15	1.20	0.98	1.15

Table 11: Summary statistics of the daily out-degree (number of sellers) of dealers and clients split by sector for the gilt cash and futures bipartite networks.

	Dealers	*Asset Managers*	*Hedge funds and PTFs*	*ICPFs*	*Other*	*Other Banks*
			Gilt cash			
Mean	10.83	1.49	1.57	1.70	0.78	0.86
St. dev.	1.81	0.18	0.38	0.32	0.16	0.17
Max	16.83	2.09	2.78	2.70	1.37	1.37
			Gilt futures			
Mean	8.77	0.69	0.85	0.63	0.65	0.81
St. dev.	3.19	0.13	0.15	0.19	0.14	0.15
Max	24.80	1.07	1.18	1.16	1.00	1.22

Similarly, the daily density of the dealer to client network of the gilt futures market is low, on average at around 5% (Figure 5 and Table 9). Clearing members have on average a daily in- and out-degree of around 9, and they can have clearing relationships with up to 25 clients (Tables 10 and 11). While clients typically just access the market through 1 clearing member on a given day (Tables 10 and 11). This is likely related to the high cost of setting up clearing relationships in futures and other derivatives markets, as highlighted in FSB (2018). Overall the density of the dealer to client network of the gilt futures market seems smaller than that of the network of the gilt cash market over time. Few exceptions are related to the roll of futures contracts, when we observe high trading volume and activity. This might suggest that the futures market might be more vulnerable were key dealers (i.e., clearing members) to be unable to perform their role.

We then analyse the number of common dealers and clients between any two consecutive days. We find that in both networks dealers are highly persistent and all of them tend to be active in any two consecutive days (Table 12). The high persistency in activity of dealers in both markets is again related to their key role in gilt cash and futures markets, as designated market makers and clearing members respectively. Also a large fraction of clients tend to be active in any two consecutive days, namely around 66% in the futures market and 57% in the cash market (Table 12).

Table 12: Summary statistics of the number of common dealers and clients between any two consecutive days in the bipartite networks of the gilt cash and futures markets.

	Dealers (%)		*Clients (%)*	
	Futures	*Cash*	*Futures*	*Cash*
Mean	97.62	97.29	66.43	57.40
St. dev.	3.74	7.15	6.84	5.98

Finally we analyse how persistent the relationship between dealers and clients is over time. This informs us on whether clients use the same set of dealers over time or not.

Table 13: Summary statistics of the fraction of common links and the Jaccard index for the bipartite networks of the gilt cash and futures markets.

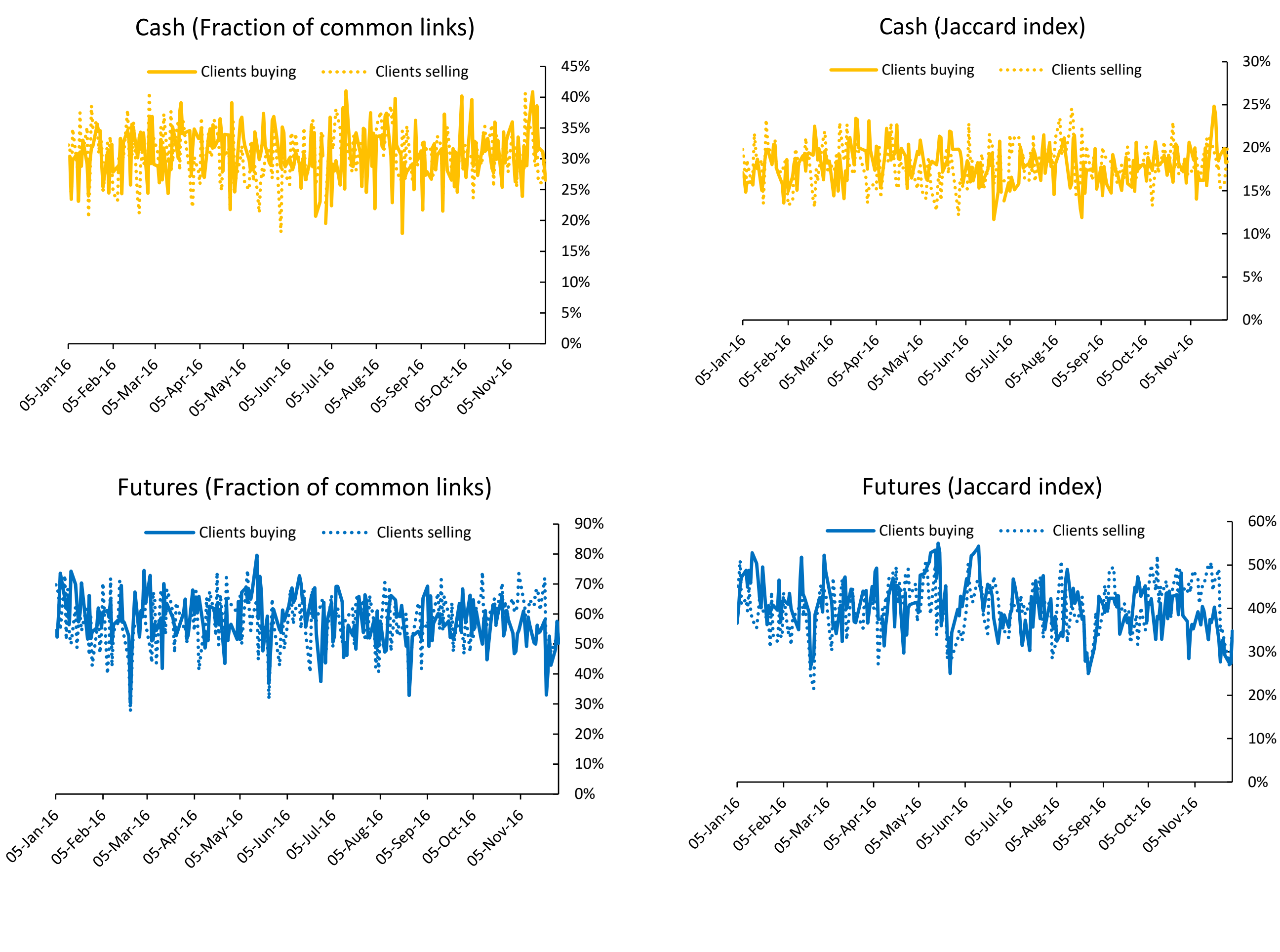
	Fraction of common links (%)				*Jaccard index (%)*			
	Clients buying		*Clients selling*		*Clients buying*		*Clients selling*	
	Futures	*Cash*	*Futures*	*Cash*	*Futures*	*Cash*	*Futures*	Cash
Mean	57.67	30.86	57.75	30.86	40.37	18.10	40.22	18.14
St. dev.	7.80	4.23	8.41	3.98	6.05	2.17	5.87	2.21

According to the two measures defined in section 4.1, in the gilt cash market on average between around 18% and 31% of relationships between dealers and clients in a given day are in common with the previous day (Table 13 and Figure 6). Relationships in the gilt futures market seem to be more persistent than in the cash market. According to the two measures on average in the gilt futures market between around 40% and 58% of relationships between dealers and clients in a given day are in common with the previous day (Table 13 and Figure 6). We find that there is some persistency in relationships between dealers and clients in both markets. However, clearing relationships seem to be more persistent than trading relationships. Also trading relationships in the gilt cash market seem to be less persistent than in the UK corporate bond market (Mallaburn, Roberts-Sklar and Silvestri (2019)) and this might be due to either the different time frequency at which we analyse the two markets or to the different frictions in the two markets.

It should be noted that our analysis has been based on *observed* daily trading relationships, therefore we are not able to investigate whether clients might have "dormant" relationships with some dealers that they may be able to draw on when necessary, for instance in stress times.

Overall, we find that on a daily basis clients tend to rely on a few GEMMs in the gilt cash market and a few clearing members in the gilt futures market, and that the relationships between clients and dealers (i.e., GEMMs and clearing members) show some persistency between two consecutive days over time. Also daily trading and clearing volumes seem to be concentrated in a few GEMMs and clearing members, respectively. While these findings seem to be consistent with frictions faced by clients when trading in an OTC market and when establishing clearing relationships, they highlight potential vulnerabilities associated with the inability of some of the key GEMMs and clearing members to perform their role in each of these markets. We also find that firms that are both GEMMs and clearing members are active across the two markets in any given day, and therefore highlight that these firms are key players in both markets. If they happened to be unable to perform their role, there could be spillovers across the two markets. In the next sections, we analyse the resilience of the networks over time and to the hypothetical exits of these key players.

Figure 6: Persistency of trading relationships in the gilt cash (top) and futures (bottom) market. Fraction of common links is shown on the left and the Jaccard index on the right.



5. Changes in network structure

In this section, we analyse the resilience of dealer to client networks associated with the gilt cash and futures markets by studying how their structure changes over time. We aim to spot changes in the structure of the networks that might not be evident when looking at simple network statistics, such as those analysed in section 4. Similar to Squartini, Van Lelyveld and Garlaschelli (2013) we use null models, that allows us to create "randomised" versions of the real networks that preserve some real properties (e.g., in- and out- degrees or in- and out-strengths), and then we compare them with real networks. We analyse both changes in the distribution of relationships between dealers and clients within the networks by focussing on the adjacency matrices $\boldsymbol{A^B}(\boldsymbol{t})$ and $\boldsymbol{A^S}(\boldsymbol{t})$ defined in section 4.1, and changes in the distribution of volumes traded by focussing on the weighted matrices $\boldsymbol{B}(\boldsymbol{t})$ and $\boldsymbol{S}(\boldsymbol{t})$ defined in section 4.1.

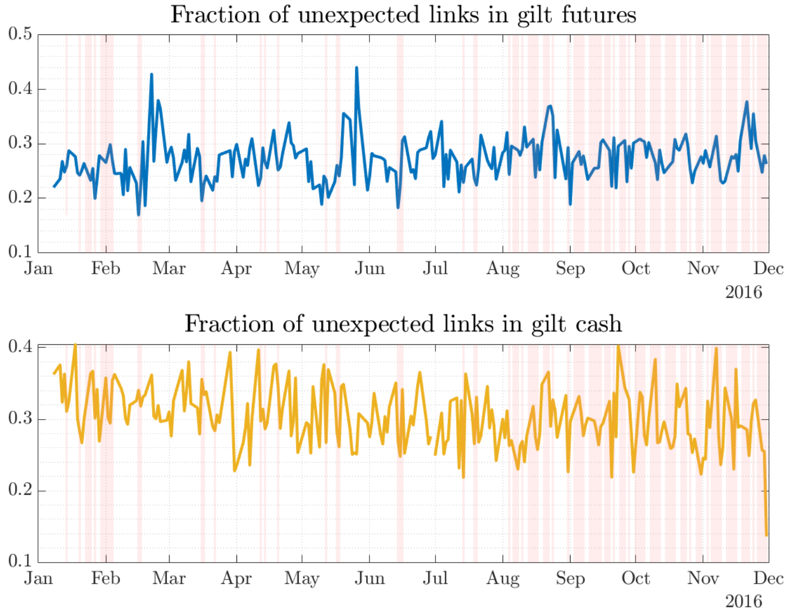
5.1. Changes in the distribution of connections

We use a null model that for each time t generates a distribution of networks, where the distribution of connections between dealers and clients is randomised but the total number of clients and dealers buying and selling in 5 rolling days and the total number of links observed in the real network is preserved. Specifically, the null model generates unweighted networks that have on average the same in- and out-degree for dealers and clients of the real bipartite networks in a 5 day rolling window, and we use the daily network density to adjust for the total number of links in a given day. For each day t the null model creates two distributions of random networks $\widetilde{\boldsymbol{A}}^{\boldsymbol{B}}(\boldsymbol{t})$ and $\widetilde{\boldsymbol{A}}^{\boldsymbol{S}}(\boldsymbol{t})$ sampled using an exponential random graph model.[22] Namely, for each time t the null model assigns a probability of having a link between each pair of dealers and clients for each network in the distribution.

For each link in the real network we tested the hypothesis of its presence being compatible with the null model. We then evaluate the fraction of links for which the null hypothesis is rejected (i.e., with a p-value <0.05 under the null). Our final measure will be the average fraction of unexpected links detected in $\widetilde{\boldsymbol{A}}^{\boldsymbol{B}}(\boldsymbol{t})$ and $\widetilde{\boldsymbol{A}}^{\boldsymbol{s}}(\boldsymbol{t})$. We are not interested in how well our null model fits the real network over time (i.e., the actual value of the fraction of unexpected links) but in detecting deviations in such a measure that could correspond to changes in the structure of the network.

Figure 7: Fraction of unexpected links in the dealer to client network associated to gilt futures (top) and cash (bottom) markets. Red bars correspond to inflation, unemployment and MPC announcements and QE dates.

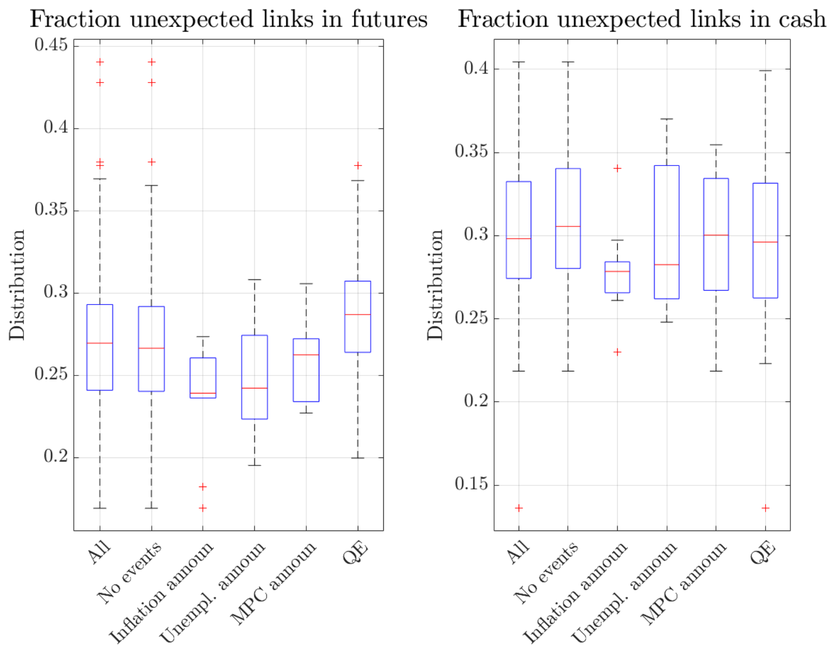
[22] The exponential random graph model we use builds on Holland and Leinhardt (1981), Caldarelli, Capocci, De Los Rios and Munoz (2002) and Chatterjee, Diaconis and Sly (2011). We include some minor changes to account for the bipartite structure.



As shown in Figure 7, we find that the fraction of unexpected links for both gilt cash and futures markets is small and fluctuates over time around a narrow range.[23] The shaded vertical bars correspond to events of interests, such as inflation, unemployment and MPC announcements, and QE dates. In the futures market, some of the peaks correspond to the roll-over of futures contracts that are generally associated to high trading activity. Figures 8 shows the distribution of the fraction of unexpected links in the cash and futures markets for different event types. The distribution of the fraction of unexpected links in the cash and futures markets seem to change around to both macroeconomic announcements and QE. Overall, we don't detect any sharp change in the fraction of unexpected links suggesting that both markets were resilient under this measure during 2016.

Figure 8: Distribution of the fraction of unexpected links in the dealer to client network associated to gilt cash and futures for different types of events.

[23] Given the fact that we estimate the null model in a 5 day rolling window it is not straightforward to account for Societe Generale's exit as GEMM. Therefore, for simplicity, we assume that Societe Generale is not a GEMM but only a clearing member for the whole time frame considered for the results shown in Figures 7 and 8. However, we obtain similar results under the assumption that Societe Generale is also a GEMM for the whole time period.



5.2 Changes in the distribution of volume traded

Next we use a null model that generates networks where the distribution of volumes traded between active pairs of dealers and clients is randomised, while preserving the total volumes sold and bought by dealers and clients and the distribution of connections between dealers and clients associated to the real networks. Specifically, for each day t we "reconstruct" the network subject to the constraints that the total volumes sold and bought by each active dealer and client and the adjacency matrix in a 5 day rolling window correspond to those of the real network. We do so using a Maximum Entropy approach for both matrices $\boldsymbol{B}(\boldsymbol{t})$ and $\boldsymbol{S}(\boldsymbol{t})$ defined in section 4.1.[24] For a given day t we use the RAS model[25] to associate volumes $B_{ij}(t)$ to a given pair of client i and dealer j subject to the constraints that (i) the sum of volumes sold by each dealer and bought by each client are equal to those sold and bought in the real network in a 5 day rolling window, and (ii) the adjacency matrix is equal to the union of the adjacency matrices of the real network in a 5 day rolling window. We do the same to estimate $S_{ij}(t)$.

The RAS model distributes total volume homogeneously across all possible links. But again our purpose is not to develop a null model to fit our real networks, but to use the comparison between real and randomised networks to detect changes in the structure of real networks over time. For each day t we compute the net volume traded between any pair of dealers and clients ij for both real and randomised networks as

[24] The Maximum Entropy is the first methodology that has been proposed to reconstruct networks of bilateral exposures from partial information on the network (see Upper and Worms (2004)). Generally, the knowledge of the in- and out-strengths in the network is assumed. It consists in minimising the relative entropy between the reconstructed network and a priori network where connections are homogeneously distributed subject to the known constraints. The problem is typically solved using the RAS algorithm.
[25] The RAS model is here applied to a rectangular matrix as we are reconstructing bipartite networks.

$$N_{ij}^{\alpha}(t) = B_{ij}^{\alpha}(t) - S_{ji}^{\alpha}(t) \quad \alpha = \{real, random\}$$

where $\boldsymbol{B}^{\alpha}(\boldsymbol{t})$ and $\boldsymbol{S}^{\alpha}(\boldsymbol{t})$ are the weighted adjacency matrices associated to the real network and the random network generated by the null model. For each day t we compare the real and randomised networks by evaluating the distance between the real and random net traded volume matrices as the Euclidean distance between the two matrices as follows:

$$D(N^{real}(t), N^{random}(t)) = \sqrt{\sum_{ij}(N_{ij}^{real}(t) - N_{ij}^{random}(t))^2} \ .$$

Figure 9: Distance between net trading volumes in the real and randomised trading networks for gilt futures (top) and gilt cash (bottom). Red bars correspond to inflation, unemployment and MPC announcements and QE dates.

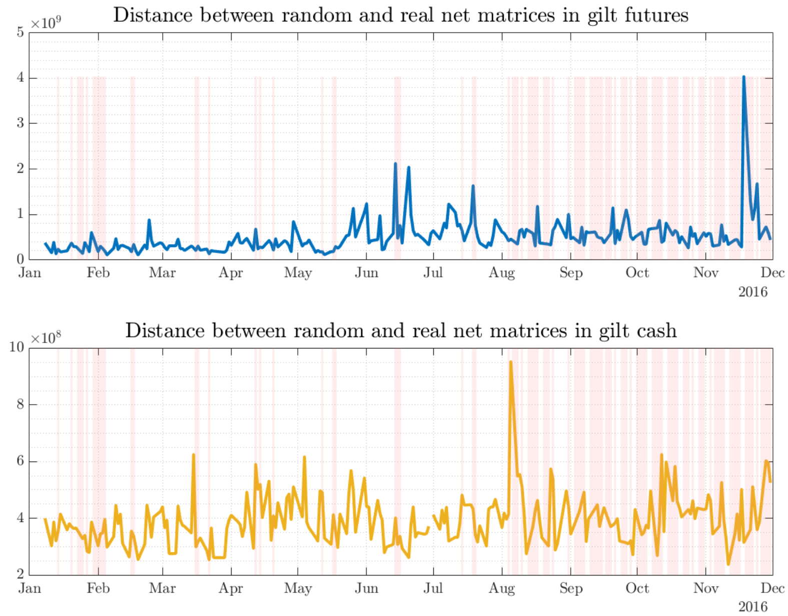
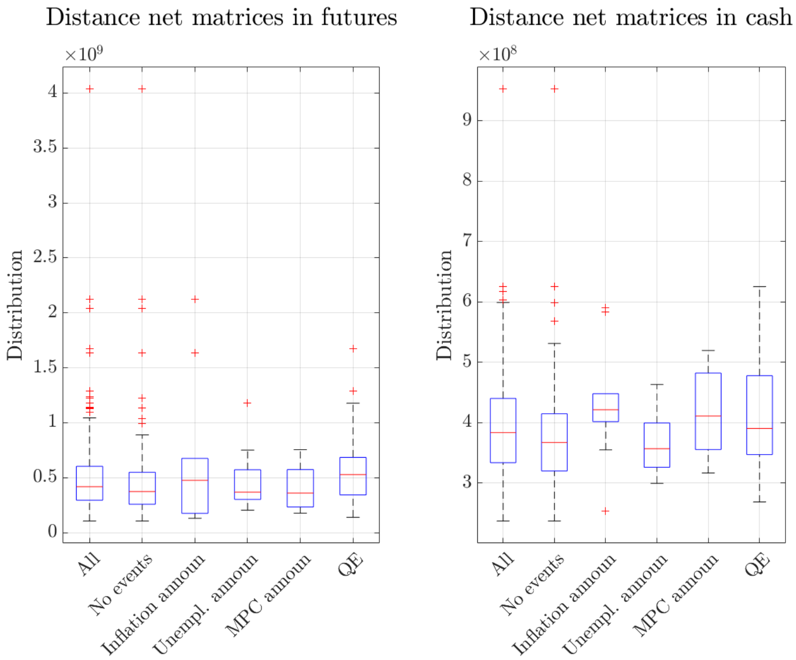


Figure 9 shows the distance between the random and real net traded volume matrices for gilt futures and cash, evaluated using the null model.[26] We find that the distance fluctuates over time, and a number of peaks are present in both markets. In futures, the volumes traded not only reflect roll periods, but also other events of interest (red bars). In cash, the largest peak is observed on 5 August 2016 the day after the MPC announced a set of measures, including QE. Figure 10 shows the distribution of the distance between the random and real net traded volume matrices for gilt futures and cash for different event types. We find that in both markets the distribution of the distance between the random and real net matrices responds to both macroeconomic announcements and QE.

Figure 10: Distribution of the distance between net trading volumes in the real and randomised trading networks for gilt futures for different event types.

[26] As before, given that the model is estimated using a 5 day rolling window we assume for simplicity that Societe Generale is not a GEMM for the whole time frame considered in Figures 9 and 10. Similar results are obtained when assuming that Societe Generale is a GEMM for the whole time frame considered.



6. Network Resilience

The previous section established the significance of clearing members who are also GEMMs in facilitating market-making across the cash and futures markets. In this section, we assess the resilience of trading and clearing networks in these markets to the hypothetical removal (failure) of individual GEMM clearing members. This enables us to assess the implications for the resilience of the gilt market ecosystem across both markets.

We employ a similar methodology to that used in Mallaburn, Roberts-Sklar and Silvestri (2019) by removing key nodes from respective markets and analysing the impact on market volumes and market access for clients. One difference is that our methodology is applied to test network resilience in a bipartite network (that we use to model cash market trading relationships and futures market clearing relationships between dealers and clients as explained in Section 4), rather than a monopartite network which was considered in the aforementioned paper for corporate bond markets.

In order to test the resilience of the cash and futures market, we employ a 'worst-case scenario' approach, which assesses the impact of the removal of the top three GEMM-Clearing member nodes with the highest daily gross volume in the network (illustrated in Figure 11). While this test simulates the impact on the trading and clearing networks of the failure of these systemically important nodes, it does not explain how the networks would respond to the removal of a node or other second round effects.

Figure 11: Hypothetical removal of key GEMM-Clearing Members from bipartite networks.

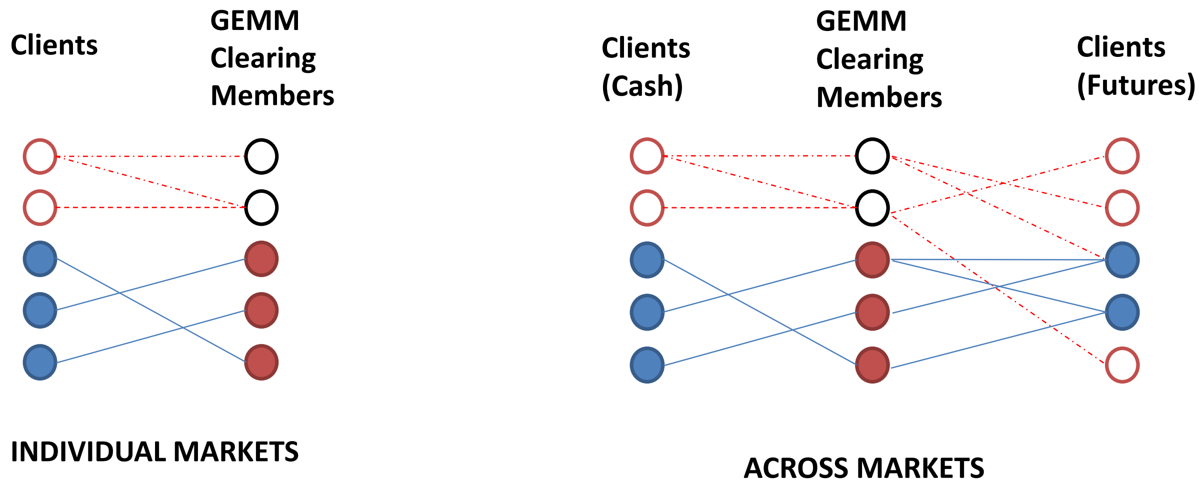


Figure 12 illustrates the first part of our results. The removal of the top 3 GEMM-CM nodes from the cash market trading network reduces daily trading volumes by around 20-45%. In contrast, removing the top nodes in futures markets reduces daily clearing volumes by around 50-95%. The latter result is driven by the concentrated nature of the clearing network in gilt futures markets, with a limited number of key clearing members, as established in Section 4.2.

We can also analyse the impact of the removal of the top nodes in each network on the proportion of total clients who are affected. In order to assess this, we remove clients in the trading (cash) and clearing (futures) network which are only connected to these top nodes on a given day. Figure 13 illustrates these results. In the cash network, removing the top 3 GEMMs affects around 25-45% of client connections on a given day. That said, these clients are likely to have other unused trading connections with other GEMMs, and therefore this may not have adverse implications for market resilience. Indeed, the exit of a specific GEMM-CM from the gilt cash market in early 2016, appears to corroborate this result, although this exit was expected. There was little observable impact from the exit of this clearing member on trading volumes or overall network resilience.

In futures markets, the removal of the top 3 GEMM-CMs results in around 50-80% of client connections being lost. This is another way of illustrating how resilience may be affected by the concentrated nature of the futures, relative to the cash market, given its reliance on a small sub-section of GEMM Clearing members. As clients typically have just 1 clearing relationship on average (Section 4.2), having on average around 67% of the futures clearing network being affected by the failure of key nodes is more significant from a market resilience perspective. That said, a degree of diversification with regards to client-clearing member relationships in the futures market is also likely to be present. In other words, it is likely that clients have relationships with multiple dealers (even if unused), which may mitigate the impact of the failure of even the largest GEMM-CM counterparty on a given day.

Figure 12: Share of daily trading and clearing volumes lost when removing top 3 GEMMs- CMs in gilt cash and futures markets.

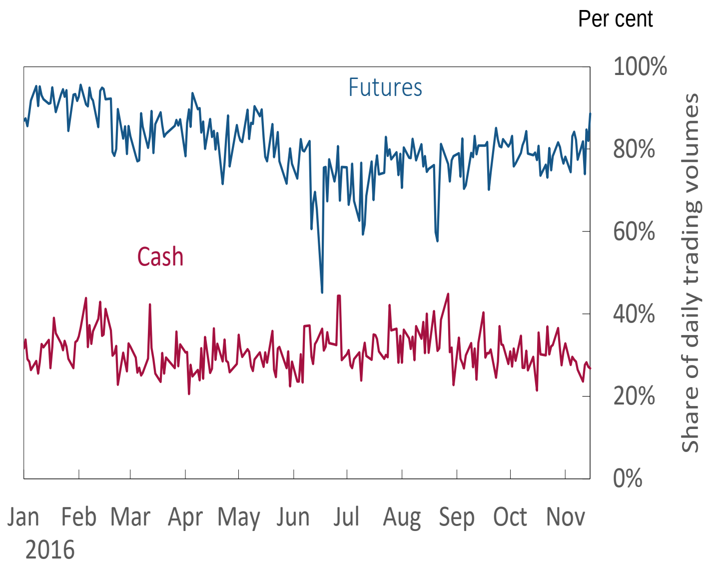
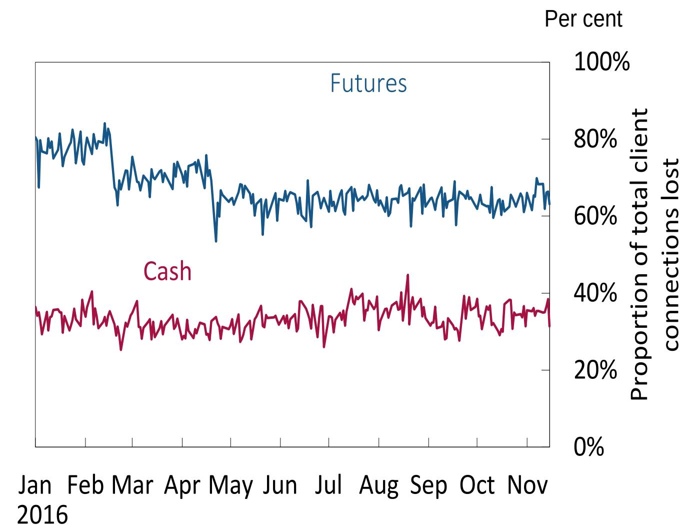


Figure 13: Proportion of daily connections lost when removing top 3 GEMMs-CMs in gilt cash and futures markets.



We can also combine these results to analyse the importance of GEMM-CMs across the two markets, and how market dysfunction due to the failure of key nodes in one market might affect the other. So far, we have established the identities of the top 3 GEMM-CMs based on trading volumes. We can consider a scenario whereby the top 3 GEMM-CMs active in the *cash* market are removed from the *futures* market, and vice versa. The extent of commonality between the top participants in each market may provide a helpful indicator of systemic risks posed by the failure of these key nodes across the gilt market ecosystem. Figures 14 and 15 illustrate these results.

Figure 14: Share of daily trading volume lost in the cash market when removing top 3 GEMM–CMs in the cash market (solid line) and futures market (dashed line).

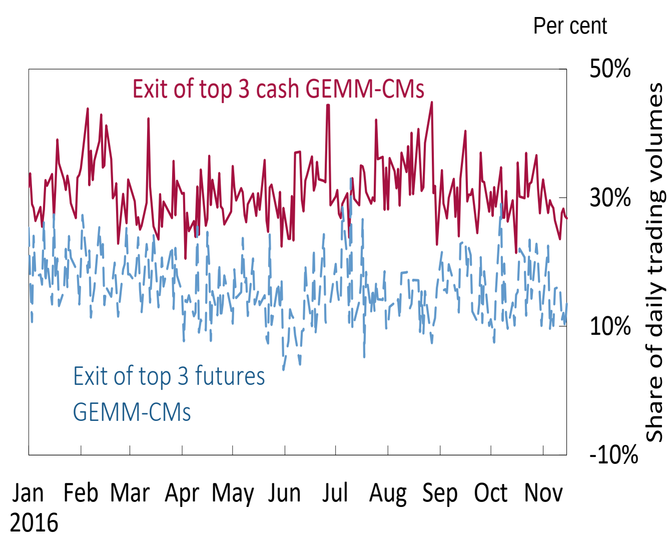
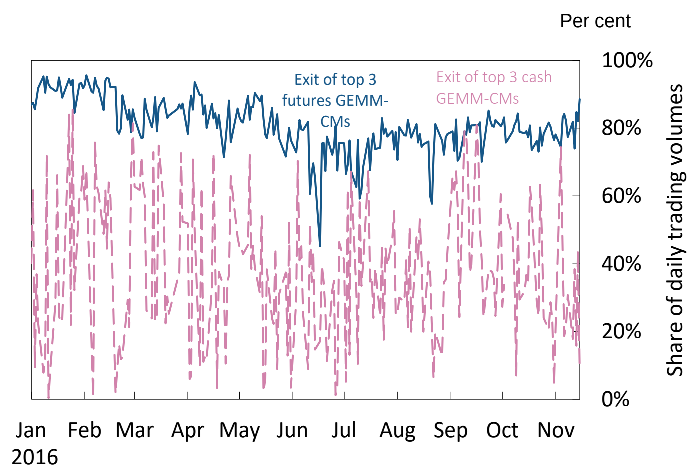


Figure 15: Share of daily clearing volume lost in the futures market when removing top 3 GEMM CMs in the futures market (solid line) and cash market (dashed line).



Intuitively, the frequency of overlap between the plots - i.e., when the top participants are common across the two markets - could provide information about the likelihood of the spill-over from market dysfunction in one market to the other. Overall, we do not find any day when the top three participations overlap across the two markets - any observed overlap between the lines in Figure 14 and 15 is largely due to rounding issues on their respective shares of trading volumes. On average, the top 3 futures nodes account for around 16% of daily trading volumes in cash markets. This suggests that the scope for spillovers of market dysfunction across the two markets is limited, based on this metric.

That said, the share of clearing volumes accounted for by the top GEMMs can be volatile (Figure 15). The top GEMMs on some days can account for up to around 85% of clearing volumes in futures markets and around 40% of clearing volumes on average. This suggests that dysfunction in cash markets due to the failure of key GEMM-CMs could have some spillover effects on the futures clearing network, which in turn, could affect the resilience of the gilt market ecosystem.

7. Price discovery

As shown in section 4, there is some overlap in trading between cash and futures markets, so in this section we explore whether this means that trading in one market can affect prices in the other. We explore the determinants of UK gilt cash market prices and the possible influence of gilt futures on the cash market. Following Brandt et al. (2007) we try to understand whether order flows are the way in which private information is incorporated into prices. Specifically, we want to test whether daily order flows in the UK gilt futures market affect daily prices in the cash market in days without macroeconomic news. We also analyse the role played by the dealer to client network of the cash market, by liquidity in both markets and control for factors that could influence prices in the UK gilt cash market.[27]

7.1 Testable hypotheses and econometric model

We test the following questions and hypotheses:

1. *What is the role of order flows of different client sectors and GEMMs in the gilt cash and futures markets on cash markets prices?*

[27] Due to the fact that intraday timestamps might not always be accurate we are not able to run any intraday analysis of price discovery.

We expect the excess order flow (proxied by net demand) of the different sectors on the clients' side in both gilt cash and futures markets to increase cash prices, while that of GEMMs in the cash market to decrease gilt cash prices.[28]

2. *Does the density of the dealer to client network in the gilt cash market affect gilt cash prices?*

We expect to find evidence that an increase in dealer-client interconnectedness would increase competition, and ultimately would contribute to lower prices.

3. *To what extent liquidity in gilt cash and futures markets and their interaction with order flows matter for gilt cash prices?*

We would expect high levels of liquidity in both markets to facilitate trades and lead to lower prices in the cash market. Also we would expect that a more liquid futures market leads to lower cash prices if some clients execute their strategies via the futures market rather than the cash.

We proxy the order flow of different counterparty sectors with their net volume (i.e., difference between buy and sell volume). As in the rest of the paper, the sectors we would refer to as clients are asset managers, hedge funds,[29] insurance companies and pension funds, others, other banks.[30] The counterparty sectors we will refer to as dealers are GEMMs. In our econometric framework we use other market participants and other banks as the reference category.

In order to study how the structure of the dealer to client network of the gilt cash market affects cash market prices, we use the measure of network density defined in Section 4.1. We also use the density of the dealer-IDB network as control as the interdealer market is used by GEMMs for inventory management (Benos and Zikes (2018)). Where values could not be constructed for these variables we have used previous day values for compatibility with the dependent variable data. For liquidity in the gilt cash market, we use the noise measure defined as root-mean-squared difference between end-of-day actual and fitted yields on bonds with maturity between one and ten years with fitted yields as Bank of England's fitted nominal gilt curve based on Anderson and Sleath (2001) 'variable roughness penalty' (VRP) approach. For the gilt futures market liquidity we use the roundtrip Xetra liquidity measure (XLM200) defined in Fullwood and Massacci (2018).[31] We control for alternative financing costs using SMMD's volume-weighted average general collateral repo rate to control for cheapest to deliver rate which may impact gilt cash prices. Where business days are not matching, previous day's values were used.

[28] In this part of the analysis, we do not consider order flows of clearing members in the futures markets. As our data allows to observe the clearing network it is difficult to evaluate their actual order flow as we would need to take into account clearing members' activity with both clients and CCP.
[29] In this part of the analysis, we focus on hedge funds only.
[30] As in the rest of the paper, we exclude trades between GEMMs and interdealer-brokers (IDB) when evaluating GEMMs' order flows.
[31] The Xetra liquidity measure (XLM200) measures the roundtrip cost in basis points of price (and not in basis points of yield) and it moves inversely with liquidity. It is more informative than the instantaneous price impact in that it uses the entire sequences of volumes that sum up to £200, along with the corresponding sequence of prices.

Following Brandt et al. (2007), we have adjusted for rolling period months and macro announcements in the sample. As shown in Fullwood and Massacci (2018), the first notice days[32] of the long gilt futures contract are the most important in determining when positions are rolled over, and so there could be a surge in rebalancing activity on or around these days in the absence of physical delivery of underlying contract. Regarding macroeconomic news, we focused on public announcements of UK inflation (CPI/PPI) and unemployment and MPC announcements. We also accounted for two events of interest that we proxy with dummies: the exit of Societe Generale as GEMM on 6 February 2016 and the EU referendum held on 23 June 2016. These were all events well known to market participants. The exit of Societe Generale as GEMM was announced by the DMO on 29 January 2016 and the date of the EU referendum was announced on 20 February 2016.

Another key hypothesis we test is the inventory costs hypothesis, as tested in Brandt and Kavajecz (2004), namely that the response of yields (and thus prices) to order flow in the absence of public information releases is due to inventory effects. By including order flow imbalances which we show are associated with permanent and not transitory price changes in gilt cash prices, our results contradict this inventory costs interpretation and suggest price discovery as the main underlying mechanism.

Descriptive statistics for the main variables used are in Table 14. Figure 1 in Annex 1 illustrates how gilt cash market prices moved in 2016.

Table 14: Descriptive statistics for the gilt cash and futures markets in 2016.

	Mean	SD	Min	Max	Obs
Average gilt cash market price level (£)	113.63	19.68	105.85	128.36	238
Dealer-client network density	6.4%	0.6%	4.2%	7.9%	238
Dealer-Interdealer/Broker network density	58%	7.4%	19%	77%	238
Gilt futures market liquidity (XLM200)	17.5	17.2	6.7	218	238
Gilt cash market liquidity (noise measure)	3.9%	0.09%	2.5%	5.1%	237
Dealers' net volume (cash market)	7	503	-1300	1360	232
Clients' net volume (cash market)	21	290	-992	960	232
AMs' net volume (futures market)	-11	337	-3370	2480	238
ICPFs' net volume (futures market)	32	645	-1850	6290	238
Hedge funds' net volume (futures market)	34	795	-1010	7590	238
Other's net volume (futures market)	-9.7	80	-572	314	238
Other banks' net volume (futures market)	-3.3	80	-340	240	238
Dealers' net volume (futures market)	-7	1540	-6790	5900	238
General collateral repo rate (cash market)	0.37%	0.14%	-0.38%	0.59%	238

* Volumes in million GBP

[32] Long gilt futures contracts' delivery months are March, June, September, and December and the rule is that the notice days are two business days before the last working day of these delivery months.

In order to explore if and how the gilt futures market could impact the gilt cash market, we posit that changes in futures market order flows would ultimately be reflected in cash market prices. To test the above questions we employ GLS time-series econometric regressions in which we regress gilt cash prices on their previous values, contemporaneous and lagged order flows in the gilt cash and futures markets, liquidity measures and control factors described above. Specifically, the general form of the model we run is:

$$P_t^c = \alpha + \vartheta P_{t-1}^c + \sum_{k=0,j\in\{sectors\}}^{5} \beta_{jk} O_{j,t-k}^c \ + \sum_{k=0,j\in\{sectors\}}^{5} \gamma_{jk} O_{j,t-k}^f + \delta_1 Density_t^c + \delta_2 Density_t^{c,IBD} + \theta_1 L_t^f + \sum_{k=0,j\in\{sectors\}}^{2} \phi_{cjk} O_{j,t-k}^c L_{t-1}^c + \sum_{k=0,j\in\{sectors\}}^{2} \phi_{fjk} O_{j,t-k}^f \, L_t^f + \varphi R_t^c + \rho C_t + \epsilon_t, \qquad (1)$$

where P_t^c are daily average volume-weighted gilt cash market prices as defined below; $O_{j,t-k}^c$ are the gilt cash market order flow of counterparty sector *j* with lag *k;* $O_{j,t-k}^f$ are the gilt futures market order flow of counterparty sector *j* with lag k, $Density_t^c$ is the density of the dealer to client network of gilt cash market; $Density_t^{c,IBD}$ is the density of the network between dealers and interdealer brokers in the cash market; L_t^c and L_t^f are the liquidity measures for the gilt cash and futures markets, respectively; R_t^c is the general collateral repo rate; C_t are the control variables for macro-economic announcements, and ϵ_t is the error term.

We use average daily gilt cash market prices, weighted by maturity but only for those cash market gilts which are eligible futures deliverable maturities- namely, gilt futures with maturity outstanding from 8 years and 9 months to 13 years- for a clean comparison. These prices are weighted by their corresponding nominal volume in pounds sterling.

7.2 Results

As a first step, following Brandt et al. (2007) we compare the R-squared obtained by estimating the model of equation (1) when including only cash market variables and both cash and futures market variables. We find that the R-squared increases from 56% to 61%, supporting our hypothesis that the futures market affects the cash market. The results of the estimation of Equation (1) are shown in Table 15.

Based on our regression estimates, we do not find that any single counterparty in the gilt cash market could reliably and significantly move gilt cash market prices but rather that the effect is at the aggregate level- i.e. the client level and the dealer level. However, we found evidence that hedge funds in the futures market, as well as ICPFs and marginally asset managers could influence gilt market prices in a statistically significant manner. This may mean that hedge fund demand in the futures market can have a procyclical effect, while ICPF demand a countercyclical effect on gilt cash prices, however, there would be little economic impact even if net buy demand is large since coefficients are rather small in absolute value.

Clients' net demand in the cash market increases gilt cash prices which is consistent with what is expected in a competitive market when net demand is met with limited supply. Dealers' net volume on the other hand decreases prices which is consistent with their market-making role. When the gilt cash market is more illiquid these effects are further strengthened – both by about 25%.

Table 15: Regression results from Equation (1) for the whole sample.

Dependent variable: Cash market prices	Coef.	p-value	Units
	Cash market		
Clients' net volume (cash market)	2.27	0.027**	£ 1 bn
Dealers' net volume (cash market)	-1.85	0.002***	£ 1 bn
Clients' net volume (cash market) * Gilt cash market illiquidity	0.586	0.025**	£ bn * bps
Dealers' net volume (cash market) * Gilt cash market illiquidity	-0.507	0.001***	£ bn * bps
Dealer-client network density	-1.68	0.007***	Number of dealer-client connections
Dealer-IDB network density	-0.20	0.000***	Number of dealer – IDB connections
	Futures market		
Gilt futures market illiquidity (XLM200)	-0.098	0.000***	Roundtrip £200
Hedge funds' net volume (futures market)	0.009	0.040**	£ 1 bn
ICPFs' net volume (futures market)	-0.009	0.033**	£ 1 bn
AMs' net volume (futures market)	-0.015	0.081*	£ 1 bn
Repo rate (cash market)	-0.194	0.000***	%
Lagged dependent variable	0.07	0.000***	£100
Macro announcements	-0.576	0.835	Dummy
Rollover periods	1.420	0.335	Dummy
Constant	98.9	0.000***	£
Adj. R^2	65%		
N	231		

*, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

Density in the dealer to client network of the gilt cash market is on average low on a daily basis as explained in section 4. However, gilt cash market prices tend to be lower when dealer to client density is significantly higher. In the gilt cash market, where most clients have one or two counterparties on average as shown in section 4, an increase in clients' access to one more dealer would lead to almost two pounds sterling reduction in prices. Increases in the dealer-IDB network density also reduces prices but to a much lower extent.

An increasingly illiquid futures market drives gilt cash market prices down. This is consistent with our hypothesis that many strategies in the cash market are executed via the gilt futures market. When liquidity in the gilt futures market worsens this would impact the cash market as well. Increases in the general collateral repo rate, which accounts for specificity of bonds reflected in the cheapest to deliver bond, decreases gilt cash market prices as expected.

Brandt et al. (2007) test the inventory cost hypothesis which posits that only contemporaneous changes should have effect on prices, not lagged ones (for everyone apart from the market makers). We test this inventory hypothesis and do not find that any evidence of the net volumes of any counterparty sector separately, or the ones of clients or dealers (jointly), with lags up to 1 week to significantly impact prices (some specifications of (1) and marginally so for clients with one day lag). In this we support the finding of Brandt et al. (2004) that inventory costs hypothesis does not hold true, i.e. market prices are not a reflection of dealer inventory management.[33]

We tested the robustness of our results across maturities of gilts. The results from the model also hold true for maturities 10 years and under, and 10 year and over, as well as for individual gilt submarkets including the most liquid gilts eligible for delivery. Results from specification (1) for cash market gilts with maturities 10 years and under are in Table 16. We also checked the robustness of our results for different measures of market liquidity in the cash market, such as the bid-ask spread. However, we don't find statistically significant results.

Table 16: Regression results from Equation (1) for cash market gilts with maturities 10 years and under.

Dependent variable: Cash market prices	Coef.	p-value	Units
Cash market			
Clients' net volume (cash market)	2.22	0.023**	£ 1 bn
Dealers' net volume (cash market)	-1.84	0.001***	£ 1 bn
Clients' net volume (cash market) * Gilt cash market illiquidity	0.346	0.027**	£ bn * bps
Dealers' net volume (cash market) * Gilt cash market illiquidity	-0.406	0.016**	£ bn * bps
Dealer-client network density	-2.17	0.008***	Number of dealer-client connections
Dealer-IDB network density	-0.21	0.002***	Number of dealer – IDB connections
Futures market			
Gilt futures market illiquidity (XLM200)	-0.102	0.000***	Roundtrip £200
Hedge funds' net volume (futures market)	0.012	0.043**	£ 1 bn
IPFs' net volume (futures market)	-0.011	0.030**	£ 1 bn
AMs' net volume (futures market)	-0.012	0.110	£ 1 bn
Repo rate (cash market)	-0.271	0.000***	%
Lagged dependent variable	0.08	0.000***	£100
Macro announcements	-0.234	0.560	Dummy
Rollover periods	0.533	0.392	Dummy
Cons	96.2	0.000***	£
Adj. R^2	67%		
N	231		

*, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

8. Conclusions

In this paper, we have analysed the resilience of some of the linkages in the UK gilt cash and futures markets. In the first part of this paper, we have used a network approach to study trading and clearing relationships between dealers (i.e., GEMMs and clearing members) and clients belonging to different sectors in the gilt cash and futures markets, respectively. We found that trading and clearing activity appear to be concentrated across

[33] This is true when the most liquid gilts are considered.

a few key players, given that clients trade and clear their trades with a small number of dealers over time. Firms that are both GEMMs and clearing members are important for the two markets as they are active across both of them over time, and given the nature of their role in each market (i.e., market maker and clearing member). Our analysis shows that, if firms that are both GEMMs and clearing members were to become unable to perform their role, a large proportion of clearing and trading activity (both in terms of client access and volumes) would be affected. However, both markets appeared resilient during most of 2016, including the EU referendum and the subsequent policy announcements.

In the second part of the paper, we have studied price discovery between the two markets, focussing on whether order flows (that we proxy with net volume traded) in the UK gilt futures market can affect UK gilt cash prices. We found that price discovery in the UK gilt cash market happens mostly at the aggregate level of dealers (i.e., GEMMs) and clients, and that only a few client sectors appear to play a role in price discovery. We also found that clients' access to more GEMMs in the cash market leads to a reduction in gilt cash markets' prices. Moves in cash markets in 2016 were also influenced by the liquidity of the gilt futures market.

Here, we have analysed the resilience of gilt cash and futures markets to some of the vulnerabilities that could affect financial stability. However, other factors could affect financial stability. For instance, other vulnerabilities are around potential imbalances between demand and supply of liquidity in both markets that negatively affect prices. However, it should be noted that as gilt futures are traded on exchange, using EMIR TR data as done in this paper we are able to observe clearing activity rather than trading activity. While clearing activity should correspond to trading activity for clients or those firms that self-clear, for firms that clear trades on behalf of clients it might be harder to extrapolate their trading activity from EMIR TR data. The level of liquidity of the futures market and imbalances between its supply and demand could be studied using tick-by-tick data on the order book as done by Fullwood and Massacci (2018).

Another source of vulnerabilities can be related to 'flash events' in the 'fast' futures market. These events might be connected to the activity of high-frequency players, however it is still not clear whether these short lived events might have broader implications for financial stability (see Bank of England Financial stability Report July 2019).

In this paper, we focussed on most of 2016 but the methodology proposed here could be used to assess the resilience of the UK gilt cash and futures markets during other time frames, potentially including more recent stress events. For example, the resilience of these markets was tested during the turmoil related to the spread of Covid-19 in 2020, when during the so-called "dash for cash" the UK gilt market experienced high levels of dysfunctionality that required interventions from central banks (Hauser (2020)). The methodology described here could provide insights on how trading and clearing relationship between dealers and clients changed during stress times, and whether they were resilient or not. Similarly, using a similar approach to the one developed in this paper it might be possible to understand how price discovery between the two markets was affected by stress.

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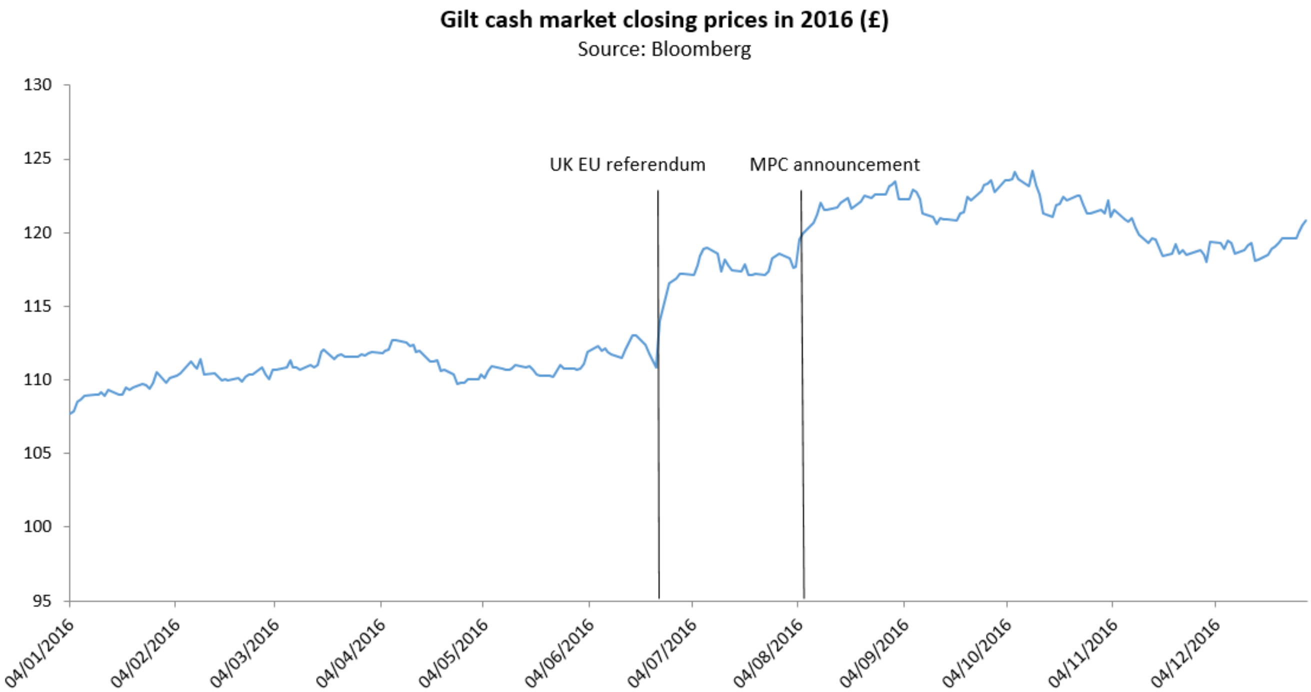
Annex 1 – Additional charts

Figure 1: Gilt cash market closing prices.



Annex 2 – Matching FCA Zen data and EMIR TR data

The FCA Zen data on gilt cash transactions and the EMIR TR data on gilt futures transactions have different conventions on the counterparty identifiers to be reported. In the FCA Zen data counterparty identities can be reported using either BIC codes, FRN codes or internal codes. While in the EMIR TR data counterparty identities are reported using LEIs. In both datasets apart from code identifiers also the names of the counterparties are reported. We therefore face the problem of mapping institutions that are reported using different identifiers.

We follow the approach taken by Czech (2019) when mapping FCA Zen data on corporate bond transactions and EMIR TR data on CDS transactions. Specifically, we map counterparty identifiers in the FCA ZEN data and in EMIR TR data into what we call Aggregate Standard Names (ASNs) that aggregate multiple counterparty identifiers. Aggregate Standard Names do not necessarily coincide with the parent company, as when possible we tried to split out different business lines of a large company (e.g., asset manager branch of a large banking group). We mapped identifiers to ASNs and then ASNs into the sectors defined in Section 3 on a best effort basis.