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Evangelos Benos[1] and Filip Zikes[2]

Abstract

We use proprietary transactional data to examine the determinants of liquidity in the UK government bond (gilt) market over a rich sample period that covers both the financial crisis of 2008–09 as well as the onset of the subsequent euro-zone sovereign debt crisis. During this period, gilt-market liquidity fluctuates significantly, with execution costs almost doubling at the peak of the crisis. Consistent with theory, dealer balance sheet constraints and increased funding costs are significant determinants of illiquidity. However, we document that increased funding costs also negatively impact the interdealer segment of the market, which leads to a further reduction in liquidity, consistent with the notion that the interdealer segment enables dealers to share risk and manage their inventories. Additionally, gilt-market illiquidity is also influenced by instances of reduced competition among dealers. Both of these effects were especially pronounced at the peak of the financial crisis and are economically significant: a one standard deviation decrease in the fraction of interdealer trading leads to an increase in trading costs of about £700 thousand to £1.5 million daily for non-dealers, and a one standard deviation increase in dealer activity concentration leads to an incremental cost of about £270 thousand to £1 million daily.

Key words: Gilt market, funding liquidity, market liquidity, interdealer trading, competition.

JEL classification: G10, G12, G14.

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1 Introduction

Liquidity, or lack thereof, was at the heart of the 2008–09 financial crisis. Many large and important financial markets that were previously considered highly liquid exhibited unprecedented deterioration in market liquidity and elevated price volatility, especially after the collapse of Lehman Brothers. Examples include markets where counterparty risk or uncertainty about valuations cannot account for the persistent drops in market liquidity, such as the foreign exchange market (Mancini, Ranaldo and Wrampelmeyer 2013) and the US Treasury market (Engle, Fleming, Ghysels, and Nguyen 2012; Hu, Pan, and Wang, 2013). Dealer funding costs and balance sheet constraints (Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009), along with slow-moving capital (Mitchel, Pedersen, and Pulvino, 2007; Duffie, 2010), have been proposed as likely drivers of the market liquidity dynamics during the crisis, and these dynamics remain an active area of research.

This paper uses primary dealer transactional data to examine the determinants of liquidity in the UK government bond (gilt) market over a sample period that includes the financial crisis of 2008–09, the first round of asset purchases by the Bank of England (commonly known as quantitative easing, or QE), and the onset of the euro-zone sovereign debt crisis of 2011. In particular, we examine whether dealer balance sheet constraints, frictions in the interdealer market and dealer concentration and competition (or lack thereof) have an impact on gilt-market liquidity and how big this impact is.

We use transactional data that cover secondary-market activity for all conventional gilts outstanding at any point during our sample period. The unique feature of our data is that they contain all transactions involving the primary dealers in the gilt market, including the identity of the dealer, transaction price, volume, and buy/sell flag. This allows us to uncover the determinants of gilt liquidity both in the time series and the cross section of gilts and also to condition dealer activity on dealer-specific characteristics.

We start our analysis by describing liquidity conditions in the gilt market over time. We measure aggregate gilt-market liquidity using the yield curve Noise, a measure of mispricing along the yield curve, proposed by Hu et al. (2013). We document that the UK yield curve oise increased almost fivefold during 2008, with the sharpest increase occurring in the wake of Lehman's default between October and December of 2008, similar to the liquidity deterioration experienced by the US Treasury market. We also estimate gilt-specific liquidity by calculating individual gilt quoted spreads as well as a new measure of execution costs that is motivated by Jankowitsch, Nashikkar and

Subrahmanyam (2011) but is not biased by intraday volatility. Using both our new estimator for the effective spread as well as the end-of-day quoted bid-ask spread we show that execution costs in the gilt market almost doubled during the financial crisis and remained elevated for a prolonged period of time.

With this in mind, we next examine more systematically, in time series and panel regressions, the determinants of gilt-market liquidity. We test a number of hypotheses as to the origins of the observed liquidity dry-up. Our first hypothesis is that dealers' balance sheet constraints, perhaps due to increased funding costs, prevented them from providing liquidity at the level and price demanded by their clients, an effect formalized in Brunnermeier and Pedersen (2009).

Our second hypothesis is that liquidity is affected by the functioning of the interdealer market. The microstructure literature (e.g., Ho and Stoll (1983)) suggests that the interdealer segment is used by dealers to share risk in Over-The-Counter (OTC) markets.[1] Consider, for example, a dealer whose client wants to sell him a large quantity of long-term gilts. In the presence of an active interdealer market, the dealer could accommodate the client's order knowing that he can subsequently offload some of these gilts in the interdealer market to reduce his inventory risk. A less active interdealer market might instead force the dealer to charge his client a wider spread as compensation for the increased inventory risk. Therefore, reduced interdealer activity would ceteris paribus imply that dealers end up with riskier inventories because they would be less able to share risk with each other. This, in turn, would lead to wider spreads.

Our last hypothesis is that liquidity is affected by the degree of dealer competition. During the crisis, some dealers were more constrained than the rest while others (such as Lehman Brothers) exited the market altogether. This may have changed market dynamics rendering liquidity provision less competitive and raising execution costs.[2].

We find that dealer balance sheet constraints, interdealer trading and dealer concentration all have explanatory power over liquidity and contributed to the general liquidity dry-up in the gilt market during and after the financial crisis. In particular, using aggregate net dealer volume as a proxy for dealer inventory changes, and thus as a proxy of dealer balance sheet constraints, we find that it is positively and significantly correlated with the Noise measure. This result is consistent with the notion that as dealers expand

[1] See also Lyons (1995) and Reiss and Werner (1998) for empirical evidence in the FX and stock markets respectively.

[2] Effects of dealer market power have been observed in several markets. See for example Christie and Schultz (1994) for evidence of collusion among Nasdaq dealers and Huang and Masulis (1999) for evidence of market power effects in the FX market.

their balance sheets as a result of client order flow, they become increasingly constrained and their ability to warehouse additional risk is diminished, contributing to liquidity dry-ups.

We also document that gilt-market Noise and transaction costs are strongly negatively related with the fraction of interdealer trading, even after controlling for the degree of trading correlation among dealers' clients, gilt characteristics and measures of funding costs and aggregate uncertainty. This suggests that the interdealer market plays a key role in facilitating dealer inventory management and risk sharing, as formalized in Ho and Stoll (1983). The effect is economically significant with a one standard deviation decrease in the fraction of interdealer trading leading to an increase in trading costs for non-dealers, as captured by the effective spread, of about £700 thousand to £1.5 million daily.

Finally, we document that the degree of dealer concentration is positively and significantly associated with illiquidity, suggesting that market power likely also played a role in explaining the elevated execution costs during our sample period. This effect is also economically significant. A one standard deviation increase in the Herfindahl index of dealer activity concentration is associated with an incremental cost of about £270 thousand to £1 million per day for non-dealers.

Given the significant impact of interdealer trading on liquidity we then ask what drives interdealer trading itself. For this, we calculate the fraction of interdealer trading for each individual dealer and condition that on dealer-specific and aggregate market characteristics. We find that dealers resort to trading with each other when they are faced with imbalanced client order flow. Also, when they collectively face funding constraints they tend to trade less with each other, driving down the fraction of interdealer trading. This implies that frictions in the interdealer market constitute an alternative channel through which dealer activity influences gilt-market liquidity above and beyond any direct effects from dealer balance sheet constraints and elevated funding costs.

We conclude our analysis by examining if dealers generally "leaned against the wind" by providing immediacy and by responding to their clients' demand for liquidity during our sample period. We do this by looking at the price impact and reversals associated with client order flow as well as Bank of England purchases. We find that, in general, dealers traded in the opposite direction of price changes, suggesting that they accommodated their clients' demand for liquidity and immediacy throughout the crisis period.

However, Bank of England (QE) purchases had a significant contemporaneous impact on prices which was almost completely reversed on the following day. Additionally, both the initial impact and the subsequent reversal were more pronounced for gilts with longer duration. Given that QE auction dates are preannounced, these reversals are suggestive of limits in the ability or willingness of market participants (including dealers) to deploy capital in order to smoothen the price impact. Breedon (2014) argues that the design of the reverse auctions also contributed to these price dislocations.

The rest of the paper is organized as follows. In Section 2 we briefly discuss the related literature. In Section 3 we describe the structure and recent developments in the UK gilt market and in Section 4 we describe our data. Section 5 presents our analysis on dealer trade direction, in Section 6 we present our time-series regression which utilize the Noise measure of aggregate market liquidity, in Section 7 we show the results of the panel specifications, which utilize gilt-specific execution costs, in Section 8 we examine if dealers provided immediacy by trading in the opposite direction of price changes and in Section 9 we conclude with a short summary and suggestions for future work. The Appendix provides more details on the effective spread measure that we propose in the paper.

2 Related literature

Our paper is most closely related to the literature studying the microstructure and liquidity of sovereign bond markets during periods of significant market stress. As recently highlighted by Engle et al. (2012) and Pelizzon, Subrahmanyam, Tomio and Uno (2013), although there are numerous papers studying the government bond market microstructure, there are only a few studies that cover the recent episodes of market turbulence, such as the 2008–09 financial crisis or the more recent euro-zone crisis, along with the subsequent unconventional monetary policy interventions.

The few exceptions include Engle et al. (2012) who propose a new dynamic order book model and study the joint dynamics of liquidity and volatility in the US Treasury market between 2006 and 2010. They find that liquidity decreased dramatically during the crisis and that liquidity and volatility exhibit negative feedback. Pelizzon et al. (2013) study price and liquidity discovery in the Italian government bond market during the euro-zone crisis of 2011–12 and find that price discovery takes place in the futures market while liquidity discovery takes place in the spot market. Pelizzon, Subrahmanyam, Tomio and Uno (2014) study the microstructure of the Italian government bond market during the same period and document a strong relationship between sovereign risk and market liquidity as well as a positive impact on market liquidity of the European Central Bank interventions.

Our work is also related to the literature on limits to arbitrage and pricing anomalies. Gromb and Vayanos (2010) provide a survey of the theory, while Krishnamurthy (2010) discusses a range of empirical examples from the 2008–09 crisis. In the context of government bond markets, the most relevant paper is that by Hu et al. (2013) who propose to measure marketwide liquidity in the Treasury market by yield curve Noise, i.e., the deviations of bond yields from a smooth fitted curve. They show that in periods of abundant risk capital, arbitrage smooths out the yield curve, while in periods of funding illiquidity and hightened risk aversion, large deviations in prices of similar bonds may persist, consistent with the predictions of Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009) and Duffie (2010), among others. Musto, Nini and Schwarz (2014) find that liquidity characteristics of individual bonds largely explain the cross section of the yield curve pricing errors and that highly levered investors tend to demand more liquid bonds during stressed times thereby exacerbating the pricing discrepancies. Fleckenstein, Longstaff and Lustig (2014) study the large and persistent mispricing between nominal and inflation-linked Treasury securities and, consistent with theory, find that the basis narrows when arbitrage capital flows into the market.[3]

Outside the US Treasury market, Buraschi, Menguturk and Sener (2014) find evidence for significant mispricing between sovereign bonds issued in different currencies and attribute this mispricing to credit and funding frictions. Pelizzon et al. (2014) document that market liquidity in the Italian government bond market was an important determinant of the cash-futures basis, and that this relationship was significantly altered by the interventions of the European Central Bank during the euro-zone crisis. Dick-Nielsen, Gyntelberg and Lund (2013) find sound empirical support for the link between market liquidity and funding liquidity in the Danish government bond market during the crisis.

Because we examine interdealer activity in the gilt market, our paper is also related to a number of studies that aim to understand the role of the interdealer segment in OTC or hybrid markets. The seminal paper is Ho and Stoll (1983), which formally shows how the interdealer market can allow dealers to share inventory risk. On the empirical side, Lyons (1995) documents that an FX dealer systematically uses the interdealer segment to control her inventory, while Reiss and Werner (1998) show that dealers active on the LSE

[3]There are also several related papers that study the pricing effects of liquidity for corporate bonds during the crisis. Examples include Bao, Pan and Wang (2011), Dick-Nielsen, Fedlhütter and Lando (2012) and Choi and Shachar (2013). These papers find that there was a substantial effect of liquidity on corporate bond yields during the financial crisis.

trade with each other more when they have extreme and opposite inventory imbalances. Overall, the empirical literature suggests that the interdealer segment facilitates risk sharing among dealers in various markets.

Our paper is also related to a number of theoretical and empirical studies of dealer competition in OTC markets. On the theoretical side, our paper is closest to Dutta and Madhavan (1997), who model tacit collusion among dealers, and Bondarenko (2001), who formalizes the relationship between the bid-ask spread and the degree of dealer competition as captured by the number of active dealers. On the empirical side, the most relevant paper by Huang and Masulis (1999), who document that bid-ask spreads in the foreign exchange market decrease as competition increases after controlling for volatility. The papers by Christie and Schultz (1994) and Christie, Harris and Schultz (1994) on Nasdaq dealers are also relevant, as they provide strong evidence of the impact of dealer collusion on execution costs in an OTC market.

3 Institutional framework and market structure

Conventional gilts are nominal fixed-coupon bonds issued by Her Majesty's Treasury (HMT) on behalf of the UK government. Even though the gilts are listed on the London Stock Exchange (LSE), the vast majority of trading takes place over the counter. This involves bilateral transactions between market participants either over the phone or via an electronic trading platform (not operated by the LSE). Central to the functioning of the gilt market are the so-called Gilt-Edged Market Makers (or GEMMs). These are financial institutions that have been designated as primary dealers in the gilt market by the UK Debt Management Office (DMO), an executive agency of HMT responsible for managing the debt of the UK government.

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"[4]. Practically, this means that GEMMs stand ready to make markets and respond to a request for quotes by their customers at all times during normal business hours. The spread between the bid and ask prices that the GEMMs are required to quote should be "reasonable", although the DMO does not provide a strict definition of what a "reasonable" spread is, given that the spread varies depending on market conditions. Overall, the rationale is that by

[4] United Kingdom Debt Management Office (2013). This obligation covers trades between the GEMM and its customers only. The GEMM is not obliged to provide quotes to other recognized GEMMs, interdealer brokers, or agency brokers although the GEMM is not prohibited from doing so. Additionally, this obligation does not cover rump gilts, which are bond issues considered too small to be liquid.

providing liquidity at all times, the GEMMs should ultimately help reduce the borrowing costs for the UK government. In practice, the GEMMs are the primary source of liquidity in the gilt market and are a party to the vast majority of transactions in gilts.

In exchange for their market-making obligations, GEMMs enjoy a number of privileges such as the exclusive right to participate in gilt primary auctions run by the DMO and a non-competitive allowance of 10% of the amount of debt issued in each auction. Additionally, GEMMs have a preferred counterparty status, which means that the DMO will only deal with GEMMs when operating in the secondary market. Although designated as such by the DMO, GEMMs are supervised and monitored by the UK Financial Conduct Authority (FCA) and are required to report all their secondary-market trades in gilts to the FCA.

Apart from the GEMMs, an important element of the gilt-market structure are the interdealer brokers (or IDBs). These are firms that operate exclusively as intermediaries between GEMMs, allowing them to complete transactions anonymously. Should a GEMM wish to trade with another GEMM, a direct communication between the two parties would reveal the parties' intentions to trade and this might compromise dealers' ability to effectively manage inventory, which may in turn adversely affect market liquidity. IDBs themselves are not allowed to take a proprietary positions, and they deal on a matched principle basis. In addition to the IDBs, there are also agency brokers operating in the gilt market who may broker trades between dealers and end investors.

The GEMMs play a key role in the primary market for gilts as well. The DMO typically sells gilts either via outright auctions in which only the GEMMs have the right to participate, or via syndications. In a syndication, the DMO selects a group of GEMMs to manage the sale of a gilt on its behalf. When issuing debt, the DMO may either issue a new gilt or "tap" an existing gilt, i.e., it may sell an additional amount of a previously issued gilt. This typically happens multiple times over a number of years.

In response to the financial crisis of 2008–09, the Bank of England introduced a program of asset purchases financed by central bank reserves, commonly known as quantitative easing (QE). During the first round of QE from March 2009 to January 2010, which overlaps with our sample period, the Bank purchased £200 billion worth of gilts in the secondary market via reverse auctions. These purchases represented a significant fraction of issuance and seemed to have lowered gilt yields (Joyce and Tong, 2012). At the same time, new issuance of gilts by HMT continued at a relatively fast pace amid the recession following the financial crisis. Figure 1 shows the cumulative amount of debt issued by HMT, the cumulative amount of QE purchases, and the difference of the two, i.e., the free float. One can see that the free float remained relatively stable during the QE period, as QE purchases reduced stocks by almost as much as HMT increased them.

4 Data and summary statistics

The main source of our data is the ZEN database maintained by the UK Financial Conduct Authority (FCA). ZEN contains reports for all secondary-market trades in gilts where at least one party is an FCA-regulated entity. Given that all GEMMs are UK domiciled and hence FCA-regulated institutions, our data fully cover the trading activity of these institutions.

Each transaction report contains information on the transaction date and time, gilt International Identification Securities Number (ISIN), execution price, size of the transaction, buyer/seller flag, and an agency/principle capacity flag. The most important feature of the reports is that they contain the identity of the party submitting the report and frequently, but not always, the identity of their counterparty. However, because all FCA-regulated firms have to report their transactions, a trade between FCA-regulated firms would be reported separately by each firm and hence we can match these reports based on transaction characteristics. This way, we can match all reports pertaining to (1) direct interdealer trades, (2) all legs of interdealer trades brokered by interdealer brokers, and (3) dealer–client trades involving FCA-regulated end investors. Dealer–client trades involving non-FCA-regulated end investors would only be reported once, by the GEMM, and we would not always know the GEMM's counterparty.

We match our transactional data with publicly available information on total issuance, maturity, and coupons, obtained from the DMO, as well as end-of-day closing prices, closing bid-ask quotes, and bond durations, obtained from Bloomberg. We use the Bank of England's data on QE auctions to adjust the total amount outstanding of each gilt by the Bank's purchases and construct the total privately held amount of each gilt (free float). We also use daily time series for a number of other variables: we obtain the five-year UK sovereign Credit Default Swap (CDS) spread from Markit, the three-month sterling London Interbank Offered Rate (LIBOR) from Datastream, daily values of the three-month sterling general collateral repo rate from the Bank of England and finally daily values of the FTSE 100 implied volatility index (VFTSE) from Bloomberg.

Our sample covers the period from January 2008 to June 2011 and consists of 883 business days. There were 43 different conventional gilts traded at some point during this period, including gilts issued both prior to the beginning of the sample period and during the sample period. The number of primary dealers over 2008 to 2011 varies as some firms lose their GEMM status (e.g. Lehman Brothers due to bankruptcy in 2008 and Commerzbank AG due to resignation in 2009) while new firms acquire it (e.g. Nomura in March 2009 and Toronto Dominion in April 2010). In total, there were 24 different GEMMs during the sample period.

Table 1 reports summary statistics for the gilts in our sample. For every six-month period, starting in June and December, we group the outstanding gilts into four residual-maturity buckets and calculate for each bucket the number of gilts outstanding together with cross sectional statistics for coupon, issuance and percentage of issuance held by the Bank of England through its QE program. The table shows that the number of gilts outstanding as well as the average issuance increased over time across all maturities. The average coupon decreased during the sample period, mainly for shorter maturity gilts, reflecting the cuts in the Bank rate (i.e., the Bank of England's main policy rate) and the fact that the DMO issues new gilts with market value close to par. The asset purchases by the Bank removed on average between 25% and 45% of the issuance depending on the residual maturity bucket and particular point in time, though the cross sectional maxima show that, at times, as much as 57% of the amount outstanding of a gilt was held by the Bank. Note that the cross sectional statistics vary over time not only because of the Bank's purchases, which were spread over 10 months, or because the gilts transition between the maturity buckets, but also because the DMO tapped some of the outstanding gilts and thus increased the issuance of these gilts.

We next report summary statistics for market activity during our sample period. We measure all activity variables in par value terms throughout. Figure 2 shows that the monthly traded volume fluctuated between £200 billion and £400 billion. These numbers are large – they equal around 3 to 6 times the monthly traded volume of the shares listed on the LSE during the same period. The traded volume is increasing over time, partly reflecting the increasing stock of gilts in issue, as shown in Figure 1. However, the traded volume did not fully keep up with the rising issuance. As the bottom panel of Figure 2 shows, the monthly turnover actually decreased from 0.8 in January 2008 to 0.4 in June 2011. This implies that while in January 2008 the entire stock of gilts outstanding changed hands at a rate of around 10 times per year, in June 2011 it was only around 5 times per year. Similar drops in turnover were also observed in the US Treasury market during this period[5].

Table 2 shows summary statistics of market activity in the cross section of gilts. We

[5] SIFMA, `www.sifma.org/research/statistics.aspx`.

group gilts into the four residual maturity buckets used before and report, separately for each half-year and bucket, statistics for the monthly trading volume, the percentage of interdealer volume, the aggregate net secondary-market dealer volume, and the degree of dealer activity concentration as captured by the Herfindahl index. The statistics are calculated using all gilt-month observations within each half-year and bucket. The reported numbers suggest that there is considerable variation in the trading activity across the gilts in our sample. There are gilts whose monthly turnover equals a multiple of their amount outstanding, while others trade fairly thinly.

The proportion of interdealer trading, reported in the middle set of columns of the table, also varies significantly in the cross section and over time having values anywhere from 0% to almost 75%. Interestingly, the proportion of interdealer trading is substantially lower across all maturity buckets around the peak of the crisis between 2008-H1 and 2009-H2. In the next set of columns we report statistics on net dealer volume, which is the total amount of gilts bought less the total amount sold collectively by all dealers. These statistics show that the dealers as a group tend to maintain relatively flat positions in gilts, as the average net position changes are relatively small compared to the traded volumes and amounts outstanding. However, it is important to reiterate that the net dealer volume reported here only includes secondary-market trading activity, thereby leaving out primary-market transactions.

Finally, in the last set of columns we report statistics on the degree of dealer activity concentration, as captured by the Herfindahl index. The index is calculated using the total volume traded by each dealer and by assigning a 50% share to each dealer in any interdealer trade. The reported averages suggest that dealer activity is generally moderately concentrated, with the shortest and longest maturities being slightly more concentrated than the rest. The reported maxima, however, also suggest that during the peak of the crisis, especially in 2009-H1, there were months and gilts on which trading was highly concentrated, with the Herfindahl Index reaching levels higher than 0.5. A key question, therefore, which we attempt to answer in our analysis, is whether this had any impact on gilt-market liquidity.

5 Gilt-market liquidity

We start our analysis by measuring liquidity in the gilt market during our sample period. For this, we use a variety of different liquidity metrics exploiting both end-of-day quote information as well as our unique transactional data. In total, we construct three liquidity measures, one describing aggregate liquidity and two calculated on a gilt-specific basis.

5.1 Aggregate liquidity

Following Hu et al. (2013), we use the yield curve Noise to measure aggregate liquidity. The idea underlying the Noise measure is that in normal times, when arbitrage capital is abundant, arbitrage forces will smooth out the yield curve and keep pricing errors (Noise) small. When funding conditions tighten and risk aversion rises, however, the ability and willingness of market participants to keep bond prices aligned declines, and consequently the yield curve Noise increases. The existence of arbitrage opportunities due to funding illiquidity is not the only source of variation in the Noise measure. Widening bid-ask spreads can also contribute to the widening of the Noise measure even if the law of one price holds when accounting for transactions costs. The Noise measure therefore captures funding and market liquidity in a bond market and serves as a good metric for gauging overall liquidity conditions.

Constructing the Noise measure requires a smooth model of the yield curve. Following Hu et al. (2013) and Malkhozov, Mueller, Vedolin and Venter (2014), we employ the well-known Svensson model for the instantaneous forward curve (Svensson, 1994):

$$f(m,\boldsymbol{b}) = \beta_0 + \beta_1 \exp\left(\frac{-m}{\tau_1}\right) + \beta_2 \frac{-m}{\tau_1} \exp\left(\frac{-m}{\tau_1}\right) + \beta_3 \frac{-m}{\tau_2} \exp\left(\frac{-m}{\tau_2}\right) \tag{1}$$

where $\boldsymbol{b} = (\beta_0, \beta_1, \beta_2, \beta_3, \tau_1, \tau_2)$.[6] As in Hu et al. (2013), we use conventional gilts with residual maturity between 1 and 10 years to fit the Svensson model. However, we do not use Sterling treasury bills in the estimation because they are known to be illiquid.[7] While the Bank of England uses repo rates to anchor the short end of the yield curve (Anderson and Sleath, 2001), we avoid that so as not to plague our Noise measure with microstructure effects in the repo market. Letting N_t denote the number of gilts with residual maturity between 1 and 10 years at time t, we estimate the parameters of the Svensson model by minimizing the duration-weighted sum of squared pricing errors:

$$\boldsymbol{b}_t = \arg\min \sum_{i=1}^{N_t} \left[(P^i(\boldsymbol{b}) - P_t^i) \times \frac{1}{D_t^i} \right]^2, \tag{2}$$

[6] For robustness, we also experimented with cubic splines with and without a smoothness penalty (Fisher, Nychka and Zervos 1995). The results reported later in this section are qualitatively similar across the different yield curve models and are available upon request.

[7] `http://www.bankofengland.co.uk/statistics/Pages/iadb/notesiadb/wholesale_tbs_3months.aspx`

where P_t^i denotes the market-observed price of gilt i, $P^i(\boldsymbol{b})$ is the model-implied price of gilt i given parameters $\boldsymbol{b}$, and D_t^i denotes the MacCauley duration of gilt i at time t. Given the fitted yield curve, the Noise measure is defined as

$$Noise_t = \sqrt{\frac{1}{N_t}\sum_{i=1}^{N_t}[y_t^i - y^i(\boldsymbol{b}_t)]^2}, \tag{3}$$

where y_t^i is the market-observed yield of gilt i and $y^i(\boldsymbol{b}_t)$ is the model-implied yield of gilt i obtained from the zero-coupon yield curve corresponding to the instantaneous forward curve $f(m, \boldsymbol{b}_t)$.

Figure 3 shows the evolution of the Noise measure during our sample period. For comparison, we also plot the LIBOR-repo spread and the UK CDS spread. Similarly to the Noise derived from the US Treasury market by Hu et al. (2013), we see that the UK Noise measure tends to be elevated during periods of market turbulence, such as the demise of Bear Stearns in March 2008, the aftermath of Lehman Brothers' default in September 2008 and the euro-zone sovereign crisis of 2011. Additionally, we observe that although the Noise started dropping significantly during the first quarter of 2009, the downward trend was temporarily interrupted during the first few months of the QE purchases by the Bank of England, which were initiated in March 2009.

More importantly though, Figure 3 reveals a high degree of co-movement between the Noise measure, the LIBOR spread and the UK five-year CDS spread. Although not perfectly synchronized, all three variables increase substantially during the financial crisis from the fall of 2008 until the end of 2009. Given that the three variables are, respectively, a measure of liquidity, a proxy for the cost of funding, and a proxy for gilt inventory risk, this degree of co-movement is consistent with the link between market and funding liquidity: Dealers' funding constraints, in combination with increased inventory risk, reduce dealers' ability to either engage in or facilitate arbitrage trades.

5.2 Gilt-specific liquidity

To measure individual gilt liquidity we use two different metrics. The first is the quoted bid-ask spread normalized by the mid-quote. Thus, for gilt j and day t our quoted proportional bid-ask spread metric equals

$$BA_{jt} = \frac{Ask_{jt} - Bid_{jt}}{Mid_{jt}}, \tag{4}$$

where $Mid_{jt} = \frac{Ask_{jt}+Bid_{jt}}{2}$.

The second liquidity metric utilizes our transactional data and measures the proportional effective spread. As our transactions data do not contain reliable time stamps, we cannot construct intraday returns and measure the effective spread by using the first-order serial covariance, as is common in the literature (Roll, 1984). Instead, inspired by the dispersion metric developed by Jankowitsch et al. (2011), we base our measure on the average distance between the transaction price and the end-of-day midquote, which does not require knowledge of the time stamps:

$$\hat{d}_{jt} = \sqrt{\frac{1}{n_{jt}} \sum_{i=1}^{n_{jt}} (p_{ij,t} - m_{jt})^2}, \tag{5}$$

where $p_{ij,t}$ is the logarithmic price associated with transaction i in gilt j on day t, m_{jt} is the logarithmic end-of-day midquote, and n_{jt} is the number of transactions in gilt j on day t. It is easy to see that this metric suffers from an important drawback: centering each transaction price by the end-of-day midquote, rather than the midquote prevailing at the time of the transaction, introduces an upward bias due to intraday volatility of the mid-quote. To obtain an accurate measure of the effective spread, it is therefore necessary to remove the contribution of the intraday volatility to the dispersion metric $\hat{d}_{jt}$. In the Appendix, we show that in the simple model of Roll (1984), where the logarithmic intraday midquote follows random walk and market orders arrive independently over time, the proportional effective spread can be approximated by

$$ES_{jt} = \sqrt{\max\left\{2(3\tilde{d}_{jt}^2 - \hat{d}_{jt}^2), 0\right\}}, \tag{6}$$

where $\tilde{d}_{jt} = \sqrt{\frac{1}{n_{jt}-1} \sum_{i=1}^{n_{jt}} (p_{ij,t} - \bar{p}_{jt})^2}$ and $\bar{p}_{jt} = \frac{1}{n_{jt}} \sum_{i=1}^{n_{jt}} p_{i,j,t}$. The idea underlying this estimator is that $\hat{d}_{jt}$ and $\tilde{d}_{jt}$ both depend on the effective spread and intraday volatility in expectation, but the latter metric is less sensitive to intraday volatility than the former. This gives us two equations with two unknowns and solving these equations for the effective spread in the Roll (1984) model leads to (6). The censoring of the statistic at zero ensures that the estimator remains nonnegative. Our approach is similar in spirit to the metric by Corwin and Schultz (2012), who use daily high and low prices to disentangle the contribution of the bid-ask bounce from the variation due to the mid-quote process, although our measure uses all transaction prices rather than just the daily high and low prices.

To reduce the noise associated with the daily liquidity metrics, we construct calendar-month metrics by averaging the daily observations within each calendar month. Figure 4 plots these two metrics over our sample period. Both metrics are clearly elevated during the crisis, although the effective spread starts from a higher level and drops sooner, by the end of 2009. Both plots suggest that the cost of trading in the gilt market almost doubled during the crisis. Comparing the average bid-ask and effective spreads, we see that the latter is typically about twice as high as the former; this implies that the quoted bid-ask spread significantly underestimates the transaction costs associated with a typical gilt trade.

6 Gilt-market liquidity determinants

Our main goal is to identify the underlying determinants of liquidity in the gilt market. Our transactional data allow us to empirically test a number of hypotheses related to potential liquidity determinants all of which are motivated by theory. Here we list and discuss these hypotheses.

H1. Dealer balance sheet constraints have a negative impact on gilt-market liquidity.

The first hypothesis is that tighter dealer balance sheet constraints that result from elevated funding costs or reduced funding liquidity (or both) translate into a lower liquidity provision by the dealers and thus into reduced gilt-market liquidity.

H2. Less interdealer trading has an incremental negative impact on gilt-market liquidity.

The second hypothesis is that reduced activity in the interdealer segment of the market has a negative effect on liquidity. This can happen if dealers use the interdealer segment to transfer risk and manage their inventories as in Ho and Stoll (1983). Reduced interdealer activity can itself also result from balance sheet constraints.

H3. Less dealer competition has a negative impact on gilt-market liquidity.

Finally, we test whether competition among dealers affects liquidity as in Dutta and Madhavan (1997) and Bondarenko (2001). In an OTC market, such as the one for gilts, there is a limited number of dealers whose ability to warehouse risk varies over time and in the cross section. Thus, it is plausible that liquidity provision can become at times concentrated to only a few dealers who may choose to exercise market power.

In the rest of this section we test these hypotheses by means of time-series and panel regressions using both the Noise liquidity measure as well as the gilt-specific liquidity measures as dependent variables.

Time-series regressions

We first estimate a time-series specification of the aggregate liquidity Noise measure. We use as regressors, variables that capture the various aspects of dealer characteristics and dealer activity related to each of the hypotheses listed above. We also use control variables that capture market conditions and gilt characteristics. Our time-series specification is:

$$\begin{aligned}\Delta Noise_t = \quad & \alpha + \beta_0 Netdealervlm_t + \beta_1 Netdealervlm_{t-1} + \beta_3 \Delta Interdealer_t + \beta_4 \Delta Interdealer_{t-1} \\ & + \beta_5 \Delta Herfindahl_t + \beta_6 \Delta Herfindahl_{t-1} + \boldsymbol{\gamma}_0' \Delta \mathbf{marketvars}_t + \boldsymbol{\gamma}_1' \Delta \mathbf{marketvars}_{t-1} \\ & + \boldsymbol{\delta}_0' \Delta \mathbf{giltvars}_t + \boldsymbol{\delta}_1' \Delta \mathbf{giltvars}_{t-1} + \epsilon_t \end{aligned} \tag{7}$$

where $Netdealervlm$ is the aggregate net dealer volume, $Interdealer$ is the fraction of interdealer trading to total dealer activity and $Herfindahl$ is the standard Herfindahl concentration index which equals the sum of squared dealer market shares. The market share of a dealer is in turn defined as the proportion of trading volume of the dealer over the total trading volume by all dealers.[8]

Aggregate net dealer volume is used as a proxy for changes in dealers' inventories and ultimately their balance sheet capacity to warehouse risk. The hypothesis is that as dealers' inventories increase, dealers become less able to take on additional inventory and their intermediation capacity declines. Thus, in the presence of such balance sheet constraints, we would expect a positive relationship between net dealer volume and marketwide illiquidity (Noise). The fraction of interdealer trading is used as a proxy for dealers' ability to share risk in the interdealer market. If interdealer trading facilitates risk sharing and inventory management, then we would expect a negative relationship with the Noise measure. The last dealer activity variable, Herfindahl, is intended to capture the degree of competition in liquidity provision. If a more competitive market is also a more liquid one, then we would expect a positive coefficient.

In terms of the other variables, **giltvars** is a vector of aggregate gilt-market characteristics and **marketvars** is a vector of market variables capturing funding costs and

[8] For robustness, we also calculate the Herfindahl index using only dealer-to-client volumes.

uncertainty among other things. The gilt characteristics are the aggregate cumulative value of gilt purchases by the Bank of England through quantitative easing and the amount of gilts outstanding net of QE purchases (free float). We include these variables in order to control for supply and demand shocks that might correlate with the aggregate liquidity measure. To proxy for the easiness with which gilts can be obtained to establish short positions outside the repo market, we also include the total amount of gilts available through securities lending.[9]. In terms of the market variables, we include the LIBOR-repo spread as a measure of dealers' and other market participants' funding costs, the UK implied equity volatility (VFTSE index) as a measure of uncertainty, the UK CDS spread as a measure of inventory risk and the three-month sterling general collateral (GC) repo rate as a measure of the cost of secured borrowing. All regressions are estimated using monthly data to reduce the contribution of high-frequency noise but we sample the data weekly to improve estimation efficiency. To account for the overlap in the data, we use Newey-West standard errors throughout.

The estimation results are reported in Table 4. Net dealer volume is generally positively and significantly correlated with Noise (columns 6, 9-10 and 14-19). This would be expected if dealers become more constrained when their inventory increases, rendering them less able to respond to liquidity demands. Interdealer trading is generally significantly negatively correlated with Noise (columns 7, 9-10 and 14-19). This suggests that less interdealer trading is associated with less liquidity (more Noise) consistent with the intuition in Ho and Stoll (1983) that interdealer trading facilitates risk sharing and inventory control. The last dealer activity variable, the Herfindahl index of dealer concentration, is generally positively and significantly related to Noise (columns 8-10 and 13-19). This implies that instances of illiquidity in the gilt market are also associated with a reduced level of competition among dealers. This could have been partly driven in our sample by the exit of some dealers (e.g. Lehman Brothers at the peak of the crisis) which may have further reduced competition for liquidity provision.

In terms of the market variables we find that the LIBOR-repo spread is positively related with Noise and the effect is statistically significant in all specifications. The LIBOR-repo spread alone explains almost 28% of the variation in the Noise (column 1). This is consistent with the idea that the higher the cost of funding, the more difficult it is for dealers to fund their inventories and therefore the less able they are to supply liquidity. The UK CDS spread and the FTSE volatility index are not consistently significant, perhaps because they are highly correlated with the LIBOR spread. The repo rate is

[9] We obtained this data from Markit.

negative and mostly significant. This could be because a higher repo rate could mean that it is easier for a market participant to "borrow" gilts, which can subsequently be used either for liquidity provision, or to eliminate a mispricing across the yield curve. A similar logic applies for the total quantity of available bonds (column 5): the more gilts are available for loan, the lower the search costs and the easier it is for market participants to eliminate any mispricings across the yield curve. However, in most cases, this effect becomes statistically insignificant in the multivariate regressions. Finally, turning to the supply/demand shocks measured by changes in either aggregate free float or cumulative QE activity, we find that free float is negatively related with Noise, as expected, whereas the coefficient on cumulative QE is not consistent across specifications. Overall, the findings of this section suggest that dealer balance sheet constraints along with interdealer activity and competition all have a substantial effect on gilt-market liquidity.

Panel regressions

We next exploit the panel structure of our data (i.e., over time and across gilts) and conduct additional tests on the relationship between gilt-market liquidity on one hand and dealer funding constraints, interdealer trading and dealer competition on the other. For this, we employ the gilt-specific liquidity metrics and associate them with gilt-specific dealer activity variables. Specifically, we estimate the following panel specification:

$$\begin{aligned} Illiqmetric_{it} =& \alpha + \beta_1 Interdealer_{it} + \beta_2 Herfindahl_{it} + \beta_3 ClientCorr_t \\ &+ \boldsymbol{\gamma}'\mathbf{giltvars}_{it-1} + \boldsymbol{\delta}'\mathbf{marketvars}_{t-1} + v_i + u_{it} \end{aligned} \quad (8)$$

where i denotes gilts, t denotes months and $Illiqmetric$ is any of the two gilt-specific (il)liquidity metrics defined in equations (4) and (6). These variables are monthly averages of their daily values. $Interdealer$ and $Herfindahl$, the main variables of interest, are defined as previously, albeit at the gilt level. $ClientCorr$ is a measure of the degree to which aggregate client activity is correlated. It is defined as the ratio of absolute client order flow across all ISINs to the amount of dealer-to-client volume: $ClientCorr_t = \frac{|ClientOF_t|}{D2CVlm_t}$. We include this variable so as to capture any order imbalances faced by dealers. Dealers can more easily accommodate clients' demand for liquidity if client order flow is balanced since they simply need to match buyers with sellers. On the contrary, when client order flow is imbalanced, they need to deploy their inventory to accommodate clients' demands. This, however, may be difficult if dealers are faced with balance sheet constraints. All in all, if balance sheet constraints matter, we would expect a positive and significant relation between our illiquidity metrics and the degree to which client activity is correlated.

giltvars is a vector of three gilt-specific characteristics: the duration, the cumulative amount of gilt purchases as part of the Bank of England QE program and the the total amount of gilts outstanding net of the QE purchases (free float). The duration is a proxy for inventory risk since longer duration bonds are more sensitive to interest rate fluctuations, while the cumulative QE and the free float capture demand and supply dynamics.

The next set of controls, **marketvars**, is a vector of market variables. As before, these variables include the three-month LIBOR spread (difference between the three-month LIBOR and the three-month repo rate), the FTSE 100 volatility index, the three-month repo rate and the CDS spread on five-year UK sovereign CDS contracts. For both sets of control variables we use their end-of-month values and they enter the specification with a lag to ensure that they are pre-determined with respect to the dependent variables which are averaged over the entire month.

Table 5 shows summary statistics for the variables used in the regression. These statistics highlight both the temporal and cross sectional variability of our sample. The effective and bid-ask spreads range from 0.02% and 0.01% to 0.55% and 0.27%, respectively, while the fraction of interdealer trading ranges from 0% to 73%. Dealer concentration also varies substantially, ranging from 6.4% to 79%. Duration ranges from a few days (for newly issued gilts) to more than 20 years while the cumulative amount of QE purchases ranges from £0 (for maturities not purchased by the Bank of England) to about £132 million. Finally, the free float ranges anywhere from £2.57 billion to almost £28 billion.

We estimate model (8), allowing for gilt-specific fixed effects. Although our key explanatory variables are unlikely to be endogenous, we also report results of a fixed effects specification where we instrument interdealer trading and dealer concentration using lagged values of these variables.[10]

Table 6 shows the results of these estimations. The coefficients on the share of interdealer trading ($Interdealer$) are negative and significant for both measures of illiquidity,

[10]Wider spreads in the gilt market may negatively affect overall gilt-market activity but there is no obvious reason why they should particularly affect the ratio of interdealer volume to total volume. Similarly, there is no obvious reason why spreads might influence the degree of dealer activity concentration.

across specifications, while the coefficients on dealer concentration ($Herfindahl$) are positive and significant. These results are consistent with the results of the Noise specification (7) and suggest that both reduced activity in the interdealer market as well as a lower degree of competition among dealers are important determinants of the observed gilt-market liquidity deterioration. Furthermore, both effects are economically significant: assuming again an average aggregate (i.e., over all ISINs) daily volume of about £14.5 billion, a one standard deviation decrease in the percentage of interdealer trading is associated with an increase in the cost implied by the effective spread of about £700 thousand to £1.5 million per day for non-dealers, depending on the coefficient magnitudes. Additionally, a one standard deviation increase in the degree of dealer concentration corresponds to an incremental cost of between £270 thousand and £1 million for non-dealers depending on the coefficient magnitude.

The control variables also have the expected signs. The degree of client correlated trading, the LIBOR spread, the volatility index and the CDS spread are all positively (and mostly statistically significantly) related to the illiquidity metrics. This suggests that order imbalances in conjunction with dealer funding costs, risk aversion and inventory risk all matter for gilt-market liquidity. The importance of inventory risk is also evident in the positive and statistically significant coefficient on gilt duration. The coefficient on the repo rate is negative and significant consistent with the results of the Noise specification. Finally, free float is mostly insignificant whereas cumulative QE is mostly negatively associated with the illiquidity metrics.

Overall, the panel regression results confirm our earlier findings (at the aggregate liquidity level) about the importance of dealer balance sheet constraints, interdealer trading and dealer competition in explaining variations in gilt-market liquidity. In particular, the negative relationship between interdealer trading and illiquidity is consistent with the hypothesis that dealers use the interdealer market to share and shift risk and to the extent that they are less able to do so, they will demand a premium in the form of higher spreads for the additional risk that they are forced to bear. In the next section we explore the determinants of interdealer trading in the gilt market.

7 What determines interdealer trading?

Given that interdealer activity has explanatory power over liquidity, we examine next what the determinants of interdealer trading itself are. We exploit the fact that we observe trader identities and calculate the percentage of interdealer trading for each dealer and associate this with dealer-specific and market-wide variables. Our empirical specification is a panel:

$$Interdealer_{it} = a + \beta DealerCorrTrading_{it} + \gamma Dealer\_CDS_{it-1} + \boldsymbol{\delta}'\mathbf{marketvars}_{t-1} + v_i + u_{it}, \quad (9)$$

where i denotes individual dealers and t denotes months. The dependent variable, $Interdealer$, is here the dealer-specific fraction of volume traded with other dealers. $DealerCorrTrading$ is the dealer-specific measure of the degree to which client activity is correlated. This is each dealer's absolute client order flow divided by the dealer's total traded volume with clients. If dealers use the interdealer segment to accommodate any order imbalances, we would expect the coefficient of this variable to be positive and significant. $Dealer\_CDS$ is the dealer-specific five-year CDS spread and is used as an estimate of the credit risk (and therefore of the funding constraints) of each individual dealer. The rest of the controls are the same marketwide variables used earlier.

At this point we should mention that it is not clear a priori what the relation between dealer-specific interdealer trading and dealer balance sheet constraints should be. On the one hand, a dealer who is balance sheet constrained may rely more heavily on the interdealer market to offload risk resulting from clients' trades, given his own limited capacity to bear risk. On the other hand, a constrained dealer may be less capable of accommodating other dealers' requests to transfer some of *their* risk to his balance sheet.[11]

The results of the dealer panel regressions are shown in Table 7. The coefficient on the degree of correlated trading by clients is significantly positive across all specifications suggesting that indeed dealers rely on each other to manage their inventories. The coefficient on the dealer CDS spread is negative throughout, but is barely significant at a 10% level, providing only weak evidence that constrained dealers tend to trade less with other dealers. As explained previously, this could be because of the opposite effect: that constrained dealers also have a stronger incentive to trade with other dealers. However, the fact that the coefficient on the LIBOR spread is negative and significant across all specifications, suggests that when dealers are collectively more constrained, they necessarily become less able to accommodate each others' trades and interdealer trading declines. Given the positive effect of interdealer trading on liquidity, documented in the

[11] Unfortunately our data does not allow us to identify the trade-initiating counterparty in interdealer trades so as to be able to separately test these two hypotheses.

previous sections, this finding further suggests that the impact of funding constraints on market liquidity may be amplified in the presence of a two-tiered market (that features an interdealer segment), as it hampers dealers' ability to share risk with each other.

8 Did dealers "lean against the wind"?

In the final section of the paper we examine the extent to which dealers provided (or consumed) liquidity over our sample period. We do this by looking at whether dealers traded on average in the same or the opposite direction of daily price changes. If dealers respond to their clients' demand for immediacy and assuming that the majority of dealer–client trades are initiated by the latter, then dealers' net (i.e., buy minus sell) volume should be in the opposite direction of the client order flow and thus also in the opposite direction of price changes.[12] To examine this conjecture, we estimate the following panel specification:

$$\begin{aligned}\Delta \log P_{it} = \alpha + &(\alpha_0 + \boldsymbol{\beta}_0'\mathbf{giltvars}_{it})netdealervlm_{it} \\ &+(\alpha_1 + \boldsymbol{\beta}_1'\mathbf{giltvars}_{it-1})netdealervlm_{it-1} \\ &+(\delta_0 + \boldsymbol{\kappa}_0'\mathbf{QEgiltvars}_{i})QEdealervlm_{it} \\ &+(\delta_1 + \boldsymbol{\kappa}_1'\mathbf{QEgiltvars}_{it-1})QEtdealervlm_{it-1} + v_i + u_{it},\end{aligned} \tag{10}$$

where the difference between the end-of-day t and end-of-day $t-1$ (log) price of bond i is regressed on the contemporaneous and lagged daily aggregate net dealer volume and its interactions with bond-specific variables. We do this separately for non-QE and QE volumes in order to capture any differences between these two types of transactions. In regression (10), **giltvars** is the vector of bond-specific variables and includes the bond duration and the amount outstanding of each issue, net of the cumulative QE purchases. **QEgiltvars** contains two additional variables associated with QE auctions: the dispersion of the winning bids and the fraction of accepted bids. The dispersion of the winning bids is calculated as in Song and Zhu (2014) and essentially measures the heterogeneity of private valuations and information of auction participants. The fraction of allocated bids captures the excess supply of gilts by the dealers in an auction. Given that we estimate this model using daily observations, we do not include any marketwide

[12] In order to explain the divergence in the CDS-bond basis during the crisis, Choi and Shachar (2013) do a similar study of dealer activity in the US corporate bond market as well as the corresponding CDS market. They find that in the corporate bond market dealers consistently traded in the opposite direction of price changes.

variables in the specification as they are unlikely to have any material impact on such a high frequency.

Table 8 reports the estimation results. In columns (1) and (2) we run regressions of log price changes on net dealer volumes and QE volumes, respectively, along with their lags. The negative coefficients of the contemporaneous (and lagged) non-QE flows suggest that, in general, dealers traded in the opposite direction of price changes during our sample period, which means that dealers "leaned against the wind" by responding to their clients' demand for liquidity and immediacy. Since net dealer flow equals negative client order flow, the negative coefficient on the lagged flow variable in specification (1) suggests that client flow has a permanent price impact. This finding is consistent with the client order flow being informed and is similar to the results obtained by Dick-Nielsen et al. (2013) who study the Danish government bond market.[13] Turning to the QE purchases, we find that they had a significant contemporaneous price impact that was almost completely reversed the following day. The strong reversals imply that QE purchases made the gilt market temporarily onesided, which created price pressure despite the fact that the QE auctions were preannounced. Similar findings were obtained by D'Amico and King (2013) for the first round of QE purchases by the Federal Reserve, although in their regression they do not control for the secondary market activity on QE auction days. We do so in column (3) and find that the results do not change when we include in the model both the non-QE and QE net dealer volumes.

In columns (4) and (5) we interact the non-QE and QE dealer net volume with gilt-specific variables respectively and in column (6) we include all variables in the regression. The results show that bond characteristics matter, with bonds of higher duration experiencing a larger price impact and subsequent reversals associated with QE purchases. The price impact of QE is also higher for bonds with a higher fraction of allocated bids. This is perhaps not surprising, as a higher allocation is indicative of lower supply during QE auctions, which ceteris paribus implies a larger price impact. The coefficients associated with the offer dispersion interaction term have the expected sign, but they are only marginally significant.

Overall, these results show that throughout our sample period dealers generally

[13] Although it has been established that order flow imbalances account for a significant proportion of the daily variation in bond prices (Brandt and Kovajecz, 2004), it is still unclear whether this is primarily due to client or to dealer order flow. For instance, Valseth (2012) finds that interdealer order flow is more informative than dealer-to-client order flow in the Norwegian market, whereas Dick-Nielsen et al. (2013) find the opposite in the Danish market. Because our transaction reports do not identify the party initiating the trade, we cannot shed more light on this issue here.

traded in the opposite direction of price changes, meaning that, in principle, they fulfilled their role as primary liquidity providers in the gilt market. However, given our previous findings and the fact that liquidity in the gilt market did deteriorate during the crisis, dealers appear to have been restricted in their ability to make markets by balance sheet constraints and by frictions in the interdealer segment. On top of this, instances of concentrated dealer activity appear to have contributed further to illiquidity.

9 Summary and concluding remarks

This paper studies the liquidity of the UK government bond market during and after the financial crisis and relates it to the activity of primary dealers. To this end, it utilizes transactional data from the secondary gilt market that explicitly identify the dealer-executed trades.

We first document a substantial deterioration of liquidity during the peak of the financial crisis. We measure gilt-market liquidity both by the degree of gilt mispricing along the yield curve – the Noise measure of Hu et al. (2013) – as well as gilt-specific trading costs. In calculating the latter, we use a new measure of effective spread that is not biased by intra-day volatility and can be calculated from transactions prices that are not time stamped.

We next show that variables that proxy for dealers' balance sheet constraints help explain the liquidity dry-up in the gilt market during the crisis and in the period after it. This suggests that dealers' balance sheet constraints hindered their ability to warehouse risk and to fully respond to their clients' demand for liquidity an effect formalized by Brunnermeier and Pedersen (2009). We also find that frictions in the interdealer segment of the market also explain the liquidity dry-up. This finding is consistent with the idea that the interdealer market plays a key role in enabling dealers to share risk which ex-ante allows them to be responsive to clients' requests for immediacy and liquidity. We also document a strong relationship between illiquidity and concentration in dealer activity. Given that some dealers were more constrained than others during the crisis and some withdrew from the market altogether (e.g. Lehman Brothers), market dynamics changed during our sample period in a way that could have allowed the healthier dealers to exercise market power. These effects are economically significant with a one standard deviation decrease in the fraction of interdealer trading leading to an increase in daily trading costs of about £700 thousand to £1.5 million for non-dealers, and a one standard deviation increase in dealer activity concentration leading to a daily incremental cost of about £270 thousand to £1 million.

We then explore the determinants of interdealer trading and find that dealers trade with each other more when they are faced with imbalanced client order flow. This means that interdealer trading helps them share risk and manage their inventories. Additionally, their ability to do so appears to be hampered by constraints on their balance sheets. The conclusion is that elevated dealer funding costs can affect market liquidity, in two-tiered OTC markets, through frictions in the interdealer segment. This is beyond any direct effects on individual dealers' risk-bearing capacity.

In the last part of our paper, we ask whether dealers generally provided immediacy and responded to their clients' demand for liquidity by trading in the opposite direction of price changes. We find that they "leaned against the wind" throughout our sample period and fulfilled their role as primary liquidity providers in the gilt market. However, while the dealers also accommodated the demand for gilts by the Bank of England in its QE operations, instances of QE activity were associated with substantial price reversals suggesting that dealers and other market participants were constrained in their ability to deploy capital to the extent required to eliminate mispricings.

More generally, our paper sheds light on the complex relationship between dealer balance sheet constraints, competition and liquidity in a two-tiered OTC market. It would be interesting to examine in future work how current and future bank capital and liquidity regulation might affect dealers' market-making ability in OTC markets, including gilts. Given that several of the market-making institutions have been systemically important banks, it would also be interesting to examine to what extent these dealers' market-making ability is (or has been) influenced by any implicit (too-big-to-fail) guarantees and whether this is changing in light of the new regulatory initiatives.

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Appendix

In this appendix, we derive the measure of effective spread introduced in Section 4. Suppose that we divide the day into n subintervals of equal length (in tick time) and suppose that a transaction arrives at the beginning of each of these subintervals. We assume that the associated logarithmic transactions prices, p_i, $i = 1, ..., n$, are related to the logarithmic efficient price, m_i, by

$$p_i = m_i + \frac{s}{2} q_i, \quad i = 1, ..., n, \tag{11}$$

where s is the proportional effective spread and q_i is a binary variable indicating whether the i-th transaction is buyer-initiated (+1) or seller-initiated (−1). Since we cannot construct intraday returns, we cannot use the first-order autocovariance to estimate s as is standard in the microstructure literature following Roll (1984). Nor can we use the various realized measures recently developed in the financial econometrics literature (Ait-Sahalia and Jacod, 2014, Ch. 7) to estimate σ in the presence of microstructure noise (induced by q). We can nonetheless construct statistics that use all transactions prices but do not require the knowledge of time stamps.

In many OTC markets, the efficient price may be observable at some point during the trading day. Here we assume for simplicity that m is observed at the end of the day, i.e., at the end of the last subinterval n, and denote it by m_{n+1}. To estimate the effective spread s we follow Jankowitsch et al. (2011) and consider the statistic:

$$\hat{d^2} = \sum_{i=1}^{n} (p_i - m_{n+1})^2 w_i. \tag{12}$$

where w_i, $i = 1, ..., n$ are some weights satisfying $\sum_{i=1}^{n} w_i = 1$. Jankowitsch et al. (2011) take $w_i = V_i / \sum_{i=1}^{n} V_i$, where V_i is the volume associated with transactions i. This measure implicitly assumes that the intraday volatility σ of the efficient price is small, so that substituting m_{n+1} for the unobserved m_i entails only a minor distortion when estimating s. Here we do not make this assumption.

If the efficient price is not observable at all, we can consider instead of $\hat{d^2}$ the statistic

$$\tilde{d^2} = \frac{n}{n-1} \sum_{i=1}^{n} (p_i - \bar{p})^2 w_i, \tag{13}$$

where $\bar{p} = \sum_{t=1}^{n} p_i w_i$ is the mean transaction price. As will become clear shortly, this statistic has similar properties to the one in equation (12) and is superior for estimating s even when m_{n+1} is observable to the econometrician.

To get an idea about the properties of these estimators, we assume that the logarithmic efficient price m follows random walk:

$$m_{i+1} = m_i + \epsilon_{i+1}, \quad i = 0, ..., n, \tag{14}$$

If we further assume that q_i is uncorrelated with m_j for all i, j and take $w_i = 1/n$, it is straightforward to show that

$$\mathrm{E}(\hat{d}^2) = \frac{s^2}{4} + \frac{\sigma^2}{2}\left(\frac{n+1}{n}\right). \tag{15}$$

Similarly, for $\tilde{d}^2$ we get

$$\mathrm{E}(\tilde{d}^2) = \frac{s^2}{4} + \frac{\sigma^2}{6}\left(\frac{n+1}{n}\right). \tag{16}$$

We see that both statistics are affected by the volatility of the intraday price and hence are biased estimators of the squared proportional spread s^2. Clearly, the bias of the latter statistic, $\tilde{d}^2$, is three times smaller than that of the original statistic proposed by Jankowitsch et al. (2011). Moreover, the difference between the two statistics can be used to construct an unbiased estimator of s^2:

$$\hat{s}^2 = \frac{1}{2}(3\tilde{d}^2 - \hat{d}^2). \tag{17}$$

By construction we have $\mathrm{E}(\hat{s}^2) = s^2$. It is easy to see that the estimator is not guaranteed to be nonnegative. To deal with the (occasional) negativity of the estimator, we follow Corwin and Schultz (2012) and censor the estimator at zero. The final estimator of the proportional effective spread is thus:

$$ES = \sqrt{\max\left\{2(3\tilde{d}^2 - \hat{d}^2), 0\right\}}. \tag{18}$$

Our estimator of the proportional spread is based on the key observation that, in expectation, $\hat{d}^2$ is larger than $\tilde{d}^2$ due to intraday volatility. To see if that is the case in our data, we report in Table 3 some descriptive statistics for these metrics. The statistics are pooled over gilts and are calculated for daily metrics as well as for calendar-month metrics, which are obtained by averaging the daily metrics within each calendar month. It is clear from the Table that $\hat{d}^2$ is on average significantly higher than $\tilde{d}^2$: the mean $\hat{d}^2$

is more than twice as high as the mean $\tilde{d}^2$. Moreover, $\hat{d}^2$ exceeds $\tilde{d}^2$ on more than 99.9% gilt-days and gilt-months. The uncensored estimator of the squared effective spread, $\hat{s}^2$, does get occasionally negative, in around 16% of the gilt-days in our sample, but as expected, averaging over calendar months significantly reduces the variability of the estimator and consequently the occurrence of negative estimates. We find negative $\hat{s}^2$ in only around 5% of the gilt-months in our sample.

In general, the lack of accurate time stamps is a common feature of many transactional datasets from over-the-counter (OTC) markets and hence our metric may be useful for measuring liquidity beyond the application in this paper[14].

[14] Examples of recently studied OTC transactional datasets that lack accurate time stamps include the interest rate swap data (Chen, Fleming, Jackson, Li and Sarkar, 2011) and the credit default swap data (Chen, Fleming, Jackson, Li and Sarkar, 2012 and Benos, Wetherilt and Zikes, 2013).

Table 1: Summary statistics for the UK gilts in our sample. For every six-month period starting at the end of December and June of each year, we group the gilts into buckets based on their residual maturity. We then calculate for each maturity bucket the number of gilts outstanding, the average coupon, the average amount issued and the percentage of issuance purchased through QE, together with the corresponding minima, maxima and standard deviations. The sample period is January 2, 2008 to June 31, 2011.

		# Bonds				Coupon (%)				Issuance (£bn)				QE (% of issuance)			
		(0,5)	[5,10)	[10,20)	[20,50)	(0,5)	[5,10)	[10,20)	[20,50)	(0,5)	[5,10)	[10,20)	[20,50)	(0,5)	[5,10)	[10,20)	[20,50)
2008-6	mean	9	7	4	8	5.42	6.21	5.50	4.63	11.5	11.2	15.1	14.2	0.0	0.0	0.0	0.0
	min					4.00	4.00	4.25	4.25	5.4	6.7	11.2	9.1	0.0	0.0	0.0	0.0
	max					9.00	8.75	8.00	6.00	17.1	14.2	18.3	18.0	0.0	0.0	0.0	0.0
	stdev					1.43	1.80	1.47	0.56	4.5	3.1	2.7	2.5	0.0	0.0	0.0	0.0
2008-12	mean	11	6	5	9	5.45	5.92	5.30	4.58	14.2	15.7	14.8	16.0	0.0	0.0	0.0	0.0
	min					3.25	4.00	4.25	4.25	6.1	9.1	5.8	7.3	0.0	0.0	0.0	0.0
	max					9.00	8.75	8.00	6.00	24.4	20.4	20.6	20.3	0.0	0.0	0.0	0.0
	stdev					1.65	1.78	1.37	0.54	6.3	4.7	5.3	3.5	0.0	0.0	0.0	0.0
2009-6	mean	11	7	6	10	5.30	5.71	5.33	4.40	16.2	19.9	17.6	16.7	0.0	30.0	32.5	4.8
	min					2.25	4.00	4.00	4.25	6.7	10.0	9.8	4.5	0.0	13.4	14.2	0.0
	max					9.00	8.75	8.00	4.75	26.9	26.3	22.7	22.8	0.0	52.2	49.7	28.3
	stdev					1.85	1.72	1.35	0.20	6.7	6.3	4.3	6.0	0.0	11.8	14.6	9.8
2009-12	mean	11	8	6	11	5.23	5.19	5.33	4.36	19.8	18.9	20.2	17.1	9.5	30.6	44.6	19.8
	min					2.25	2.75	4.00	4.00	6.7	10.0	16.9	7.0	0.0	0.9	29.3	6.1
	max					9.00	8.75	8.00	4.75	29.3	26.3	22.7	24.6	43.3	55.0	57.3	34.3
	stdev					1.85	1.96	1.35	0.22	8.5	6.8	2.1	5.5	13.9	17.5	9.5	9.1
2010-6	mean	11	8	6	12	5.05	5.44	5.17	4.35	21.2	23.3	18.6	17.7	9.6	33.0	34.6	18.3
	min					2.25	3.75	3.75	4.00	6.7	10.0	3.8	8.0	0.0	8.1	0.0	0.0
	max					9.00	8.75	8.00	4.75	33.8	31.4	23.9	25.6	39.2	48.5	51.0	34.8
	stdev					1.98	1.75	1.47	0.22	9.6	7.7	6.9	4.7	13.5	12.0	17.0	10.1
2010-12	mean	11	9	5	12	4.91	4.94	5.45	4.35	24.4	20.6	22.5	19.1	12.8	24.0	39.7	17.3
	min					2.25	2.00	4.00	4.00	7.3	8.2	17.9	11.5	0.0	0.0	31.5	0.0
	max					9.00	8.75	8.00	4.75	36.6	31.4	25.1	25.6	39.1	48.5	49.7	34.8
	stdev					1.94	2.01	1.45	0.22	9.5	8.7	2.5	4.0	14.8	16.7	6.5	9.7
2011-6	mean	12	7	7	11	4.98	4.93	5.11	4.32	23.9	24.8	21.6	20.2	14.9	24.7	31.8	15.3
	min					2.00	3.75	3.75	4.00	7.3	10.5	10.2	16.4	0.0	0.0	0.0	0.0
	max					9.00	8.75	8.00	4.75	36.6	31.4	27.6	25.6	43.0	48.5	49.7	34.8
	stdev					2.22	1.62	1.37	0.19	10.3	6.3	5.4	3.0	16.2	15.0	14.8	9.2

Table 2: Summary statistics for trading activity in UK government gilts in our sample. For each half-year and residual maturity bucket (as of the beginning of each half-year), we calculate summary statistics for the monthly aggregate traded volume, the proportion of interdealer volume, the monthly aggregate net dealer volume as well as the degree of dealer activity concentration as captured by the Herfindahl Index (HI) on a month-gilt basis.

		Volume (£million)				Interdealer volume (%)				Net dealer volume (£million)				Concentration (HI)			
		(0,5)	[5,10)	[10,20)	[20,50)	(0,5)	[5,10)	[10,20)	[20,50)	(0,5)	[5,10)	[10,20)	[20,50)	(0,5)	[5,10)	[10,20)	[20,50)
2008-H1	mean	8837.2	5875.5	12811.2	5877.9	20.4	24.6	24.8	22.6	73.6	-51.7	-193.1	-134.7	0.143	0.143	0.151	0.162
	min	536.4	783.9	2748.6	1755.1	3.2	3.4	12.5	11.1	-1612.2	-1576.2	-2219.9	-1485.6	0.097	0.098	0.112	0.107
	max	23723.9	28227.7	50294.9	16867.0	37.8	56.4	42.8	48.5	1766.7	1607.8	1997.6	1306.0	0.296	0.292	0.229	0.248
	stdev	6249.0	4650.9	14317.1	3449.5	7.7	11.0	8.4	9.4	599.0	515.4	841.0	537.8	0.042	0.043	0.032	0.033
2008-H2	mean	7095.2	8350.0	5643.6	5094.7	23.5	26.0	23.9	23.8	-186.6	332.1	146.4	-60.7	0.145	0.130	0.126	0.139
	min	261.9	464.4	2427.9	1388.5	3.6	7.6	10.4	5.3	-2768.9	-844.1	-977.9	-2498.4	0.102	0.095	0.099	0.096
	max	20369.1	53261.6	10086.2	17041.4	48.7	52.3	58.9	48.9	1212.4	10964.3	2342.2	783.4	0.362	0.203	0.157	0.220
	stdev	5667.1	12299.1	1783.0	3225.6	10.6	11.1	11.3	10.8	753.8	1709.1	707.4	536.3	0.050	0.024	0.017	0.029
2009-H1	mean	6542.0	10060.5	7213.1	5274.6	23.3	29.6	27.6	19.6	-14.3	476.1	263.9	212.9	0.151	0.116	0.120	0.171
	min	175.4	553.6	1456.7	1087.9	0.5	0.1	12.6	1.0	-2752.7	-3439.6	-1972.7	-686.0	0.084	0.087	0.092	0.103
	max	40059.1	37466.7	56939.6	14302.5	49.2	60.1	54.6	46.3	1766.6	3104.8	1631.8	2272.9	0.796	0.155	0.207	0.565
	stdev	6791.4	10011.3	9220.0	3552.2	10.1	13.2	11.4	11.7	743.1	1295.4	703.3	533.4	0.097	0.020	0.027	0.083
2009-H2	mean	5944.3	11461.5	5621.4	3931.1	27.1	28.5	24.3	23.7	-13.1	209.9	43.4	254.1	0.134	0.133	0.122	0.133
	min	353.5	188.6	554.3	1187.0	0.6	2.2	1.1	4.4	-1478.7	-1263.7	-2279.5	-883.0	0.093	0.082	0.083	0.088
	max	22280.3	69243.1	15256.5	16249.2	48.0	56.5	50.6	62.2	1411.6	2574.8	1413.7	1643.3	0.248	0.296	0.283	0.397
	stdev	5120.0	17453.0	4277.0	3179.3	12.0	13.6	10.8	13.6	559.9	660.8	737.7	470.3	0.036	0.053	0.043	0.047
2010-H1	mean	6111.1	11716.9	6536.2	3986.0	30.3	30.3	30.5	27.4	-48.0	-153.4	-114.8	-55.7	0.130	0.120	0.114	0.123
	min	151.7	185.2	1065.5	1065.8	1.0	5.2	11.3	5.4	-1756.7	-2218.7	-5181.4	-1849.7	0.086	0.081	0.088	0.081
	max	16516.3	59343.0	50146.4	19056.3	51.8	61.4	58.8	62.3	2035.6	1875.0	1161.2	1585.6	0.374	0.246	0.233	0.288
	stdev	4468.5	14494.6	9043.1	3830.6	13.1	14.6	9.1	11.8	743.8	748.2	921.4	417.6	0.048	0.041	0.027	0.034
2010-H2	mean	4962.1	11076.1	5745.3	4128.1	36.6	33.4	31.3	30.6	-71.4	-75.9	-38.1	-123.7	0.115	0.116	0.118	0.115
	min	272.9	234.7	1284.7	1348.3	10.8	0.0	19.0	7.4	-2153.3	-1910.9	-1989.7	-4773.4	0.072	0.078	0.087	0.082
	max	17990.5	73284.0	21007.2	18578.3	67.3	66.1	61.7	73.2	1103.6	1423.3	1186.9	1592.7	0.227	0.234	0.198	0.199
	stdev	4043.4	16696.3	4680.0	4068.9	11.8	14.7	7.3	13.1	614.1	561.1	574.1	718.9	0.036	0.038	0.028	0.025
2011-H1	mean	6844.6	15068.9	5927.4	5334.8	29.6	33.2	28.5	36.1	37.7	-253.3	-0.6	-42.5	0.121	0.110	0.105	0.115
	min	91.6	258.3	1258.4	983.4	0.7	8.0	13.4	5.6	-2649.1	-4404.0	-2100.6	-2043.9	0.066	0.072	0.078	0.076
	max	19932.9	70060.6	17093.5	24506.0	59.8	67.8	37.4	70.4	2718.1	1844.2	2059.3	1823.7	0.286	0.302	0.149	0.347
	stdev	5173.6	17311.8	4375.1	4763.8	14.5	14.8	5.7	11.4	832.6	1075.2	798.1	450.6	0.052	0.044	0.016	0.041

Table 3: Descriptive statistics for the dispersion metrics $\hat{d}^2$ and $\tilde{d}^2$. We report results for daily metrics ("daily") and for calendar-month averages of daily metrics ("monthly"), pooled across gilts (i.e., for gilt-days or gilt-months). The bottom rows of the table report the percentage of gilt-days/gilt-months where the statistics $(\hat{d}^2 - \tilde{d}^2)$ and $(3\tilde{d}^2 - \hat{d}^2)$ are negative.

	daily		monthly	
	$\hat{d}^2$	$\tilde{d}^2$	$\hat{d}^2$	$\tilde{d}^2$
no. obs.	24,110	24,110	1,402	1,402
mean	0.985	0.441	0.987	0.445
std. dev.	2.682	0.930	1.282	0.532
skewness	15.28	7.649	3.097	2.555
kurtosis	440.6	95.85	16.91	11.97
negative $(\hat{d}^2 - \tilde{d}^2)$	0.004%		0.071%	
negative $(3\tilde{d}^2 - \hat{d}^2)$	16.28%		4.921%	

Table 4: Time-series OLS regressions of aggregate gilt-market illiquidity (*Noise*). We report estimation results of model (7) of the Noise illiqidity measure on various dealer activity variables as well as aggregate market and gilt variables. *Noise* is defined in equation (3). *Netdealervlm* is the monthly aggregate net dealer volume (in £billions), *Interdealer* is the fraction of dealer-to-dealer volume over total trading volume and *Herfindahl* is the sum of squared market shares of the dealers. The market share of each dealer is her traded volume over the sum of the volumes traded by all dealers. *Liborspread* (in %) is the difference between the three-month LIBOR and the three-month repo rate; *VFTSE* is the FTSE 100 volatility index, *UK_CDS* is the spread (in bps) on the UK sovereign five-year CDS contract and *Reporate* (in %) is the three-month cost of secured lending. *Available* is the total amount of gilts (in £billions) available for borrowing, *CumQE* is the cumulative volume of the Bank of England gilt purchases and *Freefloat* is the total amount of gilts outstanding adjusted for the Bank of England stock of gilt purchases (both in £billions). The sample period is January 2, 2008 to June 31, 2011. All regressions are run in first differences using monthly overlapping data sampled weekly. Newey-West t-statistics are given in parentheses. *, ** and *** denotes significance at 10%, 5% and 1% respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Netdealervlm_t$						0.0489*			0.0694***	0.0850***
						(1.78)			(2.77)	(3.26)
$Netdealervlm_{t-1}$						0.0982**			0.0859*	-0.0000
						(2.03)			(1.97)	(-0.23)
$\Delta Interdealer_t$							-6.6141**		-5.4893**	-5.8258**
							(-2.38)		(-2.41)	(-2.44)
$\Delta Interdealer_{t-1}$							-3.8069		-4.2374*	-4.4185*
							(-1.55)		(-1.87)	(-1.75)
$\Delta Herfindahl_t$								26.7377*	19.3381	23.5844*
								(1.75)	(1.59)	(1.82)
$\Delta Herfindahl_{t-1}$								12.8697	10.2068	10.2289
								(0.85)	(0.79)	(0.73)
$\Delta LIBORspread_t$	0.7029									
	(0.67)									
$\Delta LIBORspread_{t-1}$	2.7680***									
	(7.06)									
$\Delta VFTSE_t$		0.0116								
		(0.31)								
$\Delta VFTSE_{t-1}$		0.0629***								
		(2.75)								
ΔUK_CDS_t			0.0163							
			(1.19)							
ΔUK_CDS_{t-1}			0.0063							
			(0.52)							
$\Delta Reporate_t$				-1.1129*						
				(-1.69)						
$\Delta Reporate_{t-1}$				-0.7717						
				(-1.21)						
$\Delta Available_t$					-0.0266**					
					(-2.52)					
$\Delta Available_{t-1}$					-0.0254***					
					(-2.62)					
$\Delta CumQE_t$						0.0489*	-0.0001	-0.0000	0.0693***	0.0849***
						(1.78)	(-1.49)	(-1.25)	(2.76)	(3.25)
$\Delta cumQE_{t-1}$						0.0982**	0.0000	0.0000	0.0859*	
						(2.03)	(0.78)	(0.34)	(1.97)	
$\Delta Freefloat_t$						0.0025	0.0110	0.0080	0.0064	0.0085
						(0.15)	(0.60)	(0.42)	(0.40)	(0.48)
$\Delta Freefloat_{t-1}$						-0.0119	-0.0095	-0.0065	-0.0102	
						(-0.59)	(-0.51)	(-0.33)	(-0.57)	
cons	0.0059	0.0130	-0.0315	-0.2051	-0.1228	0.5127**	0.0981	0.1433	0.5002**	0.2423
	(0.04)	(0.08)	(-0.20)	(-1.41)	(-0.82)	(2.09)	(0.45)	(0.61)	(2.22)	(1.53)
R^2	0.282	0.104	0.043	0.170	0.186	0.128	0.108	0.071	0.203	0.192
N	175	175	175	175	175	175	174	174	174	174

Table 4 continued.

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
$Netdealervlm_t$	0.0304			0.0493**	0.0480**	0.0477**	0.0403*	0.0399*	0.0518**
	(1.32)			(2.18)	(2.10)	(2.13)	(1.70)	(1.68)	(2.07)
$Netdealervlm_{t-1}$	0.0088			0.0530	0.0584	0.0717**	0.0068	0.0073	-0.0000
	(0.36)			(1.47)	(1.53)	(2.11)	(0.29)	(0.29)	(-0.92)
$\Delta Interdealer_t$		-1.8430		-4.5306*	-4.3625*	-3.7475*	-1.5581	-1.6062	-2.1547
		(-1.14)		(-1.97)	(-1.96)	(-1.82)	(-1.01)	(-1.02)	(-1.43)
$\Delta Interdealer_{t-1}$		-1.7986		-3.8618*	-4.0448*	-3.9071**	-1.5463	-1.6174	-3.2358**
		(-1.51)		(-1.92)	(-1.87)	(-2.10)	(-1.21)	(-1.26)	(-2.09)
$\Delta Herfindahl_t$			11.9198	20.2034*	19.7431*	15.0386	11.7706	12.0068	18.9592**
			(1.58)	(1.83)	(1.80)	(1.46)	(1.57)	(1.58)	(2.36)
$\Delta Herfindahl_{t-1}$			14.8253*	10.3634	9.2004	7.1556	13.4690*	13.6703*	15.3615*
			(1.90)	(1.04)	(0.91)	(0.84)	(1.71)	(1.71)	(1.68)
$\Delta LIBORspread_t$	1.1863***	1.3017***	1.3806***	0.3199	0.7441	0.3042	1.2521***	1.2231***	1.3011**
	(2.90)	(2.91)	(2.99)	(0.37)	(1.07)	(0.42)	(2.93)	(2.69)	(2.47)
$\Delta LIBORspread_{t-1}$	2.9534***	2.8754***	2.8548***	2.6681***	2.5771***	2.9477***	2.8691***	2.8413***	3.0873***
	(6.05)	(5.79)	(5.92)	(7.71)	(5.26)	(6.89)	(6.03)	(5.84)	(5.66)
$\Delta VFTSE_t$	0.0115	0.0087	0.0109		-0.0235	-0.0326	0.0121	0.0123	0.0147
	(0.74)	(0.54)	(0.64)		(-0.95)	(-1.50)	(0.76)	(0.77)	(0.83)
$\Delta VFTSE_{t-1}$	0.0024	0.0006	-0.0011		0.0000	-0.0011	0.0044	0.0044	0.0032
	(0.17)	(0.04)	(-0.07)		(0.00)	(-0.08)	(0.32)	(0.32)	(0.22)
ΔUK_CDS_t	0.0132	0.0105	0.0096			0.0287***	0.0113	0.0109	0.0001
	(1.21)	(0.97)	(0.91)			(2.86)	(1.10)	(1.03)	(0.01)
ΔUK_CDS_{t-1}	-0.0185*	-0.0203**	-0.0195**			-0.0061	-0.0197**	-0.0202**	-0.0272**
	(-1.87)	(-2.09)	(-2.06)			(-0.57)	(-2.08)	(-2.00)	(-2.59)
$\Delta Reporate_t$	0.3829	0.2550	0.1709				0.3171	0.3639	1.2059***
	(0.72)	(0.49)	(0.32)				(0.60)	(0.69)	(2.70)
$\Delta Reporate_{t-1}$	-2.7935***	-2.6471***	-2.7342***				-2.6861***	-2.6576***	-2.5262***
	(-5.48)	(-5.60)	(-5.56)				(-5.86)	(-5.59)	(-4.42)
$\Delta Available_t$	-0.0006	-0.0021	-0.0014					0.0002	-0.0064
	(-0.09)	(-0.30)	(-0.20)					(0.03)	(-0.84)
$\Delta Available_{t-1}$	-0.0019	-0.0037	-0.0036					-0.0036	-0.0081
	(-0.24)	(-0.50)	(-0.47)					(-0.46)	(-1.09)
$\Delta CumQE_t$	0.0304	-0.0001	-0.0001	0.0492**	0.0479**	0.0477**	0.0402*	0.0398*	0.0518**
	(1.32)	(-1.46)	(-1.47)	(2.18)	(2.09)	(2.13)	(1.70)	(1.68)	(2.06)
$\Delta CumQE_{t-1}$	0.0089	0.0001*	0.0001*	0.0530	0.0584	0.0717**	0.0069	0.0074	
	(0.37)	(1.93)	(1.95)	(1.47)	(1.53)	(2.11)	(0.29)	(0.29)	
$\Delta Freefloat_t$	-0.0256***	-0.0233***	-0.0251***	-0.0024	-0.0014	-0.0117**	-0.0233***	-0.0236***	-0.0125**
	(-4.40)	(-4.27)	(-4.32)	(-0.48)	(-0.26)	(-2.22)	(-4.20)	(-4.14)	(-2.12)
$\Delta Freefloat_{t-1}$	-0.0385***	-0.0366***	-0.0369***	-0.0133	-0.0136	-0.0266**	-0.0347***	-0.0343***	
	(-3.23)	(-3.14)	(-3.20)	(-0.97)	(-0.99)	(-2.12)	(-3.07)	(-2.90)	
$cons$	0.4418**	0.3195*	0.3479**	0.4201**	0.4183**	0.6024***	0.4478***	0.4459***	0.1343
	(2.57)	(1.91)	(2.01)	(2.36)	(2.18)	(2.91)	(2.78)	(2.69)	(1.08)
R^2	0.573	0.573	0.573	0.398	0.405	0.455	0.588	0.588	0.535
N	175	174	174	174	174	174	174	174	174

Table 5: Summary statistics of the variables used in the empirical specification (8). The illiquidity metrics are defined in equations (4) and (6). *Interdealer* is the percent of interdealer trading in each bond-month and *Herfindahl* is the sum of squared market shares of the gilt-market dealers. The market share of each dealer is the ratio of her traded volume over the sum of the volumes traded by all dealers. *ClientCorr* is the absolute aggregate client order flow scaled by the volume of dealer-to-client trading. *CumQE* is the cummulative amount of QE purchases by the Bank of England in each bond (in £billions) and *Freefloat* is total amount of debt outstanding for each bond (in £billions) adjusted for the Bank of England stock of bond purchases; *Duration* is the bond duration in years; *Liborspread* is the difference between the three-month LIBOR and the three-month repo rate (in %); *VFTSE* is the FTSE 100 volatility index; *reporate* is the three-month cost of secured lending; and *UK_CDS* is the spread (in bps) on the UK sovereign five-year CDS contract. The sample period is January 2, 2008 to June 31, 2011.

	N	*Mean*	*Std. Dev.*	*Min*	*Max*
bid-ask spread (%)	1402	0.077	0.048	0.001	0.274
effective spread (%)	1402	0.131	0.075	0.017	0.547
Interdealer	1402	0.278	0.126	0.000	0.730
Herfindahl	1402	0.123	0.045	0.064	0.788
ClientCorr	42	0.016	0.012	0.001	0.049
CumQE (£billion)	1402	0.003	0.004	0.000	0.132
Freefloat (£billion)	1402	15.211	5.749	2.573	27.766
Duration (years)	1402	8.675	6.084	0.020	21.930
LIBORspread (%)	42	0.499	0.514	0.070	2.280
VFTSE	42	25.197	8.473	15.050	54.150
Reporate (%)	42	1.482	1.761	0.430	5.220
UK_CDS (bps)	42	63.939	30.166	8.620	145.300

Table 6: Liquidity, interdealer trading and dealer competition. Panel regressions of the two liquidity metrics on the fraction of interdealer trading, the degree of dealer activity concentration and controls. The panel is over ISINs (bonds) and months. The dependent variables are the bond-specific liquidity metrics defined in equations (4) and (6). *Interdealer* is the percent of interdealer trading in each bond-month and *Herfindahl* is the sum of squared market shares of the gilt-market dealers. The market share of each dealer is the ratio of her traded volume over the sum of the volumes traded by all dealers. *ClientCorr* is the absolute aggregate client order flow scaled by the volume of dealer-to-client trading. *CumQE* is the cummulative amount of QE purchases by the Bank of England in each bond (in £billions) and *Freefloat* is total amount of debt outstanding for each bond (in £billions) adjusted for the Bank of England stock of bond purchases; *Duration* is the bond duration in years; *LIBORspread* is the difference between the three-month LIBOR and the three-month repo rate (in %); *VFTSE* is the FTSE 100 volatility index; *reporate* is the three-month cost of secured lending; and *UK_CDS* is the spread (in bps) on the UK sovereign five-year CDS contract. The sample period is January 2, 2008 to June 31, 2011. Robust t-statistics are in parentheses. *, ** and *** denotes significance at 10%, 5% and 1% respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	bid-ask spread	effective spread	bid-ask spread	effective spread	bid-ask spread	effective spread	bid-ask spread	effective spread
$Interdealer_{it}$	-0.0613***	-0.1154***			-0.0535***	-0.1038***	-0.0391***	-0.0631***
	(-3.41)	(-4.84)			(-3.28)	(-4.67)	(-2.91)	(-2.83)
$Herfindahl_{it}$			0.1395***	0.2187***	0.0671*	0.1007**	0.0534*	0.0576**
			(2.89)	(3.52)	(1.83)	(2.34)	(1.95)	(2.18)
$ClientCorr_t$	0.5578***	0.5380***			0.5401***	0.5113***	0.3987***	0.4768***
	(11.35)	(7.88)			(11.25)	(7.37)	(9.85)	(6.99)
$CumQE_{it-1}$								
$Freefloat_{it-1}$								
$Duration_{it-1}$								
$LIBORspread_{t-1}$							0.0056*	0.0046
							(1.89)	(1.18)
$VFTSE_{t-1}$							0.0011***	0.0019***
							(9.88)	(7.00)
$Reporate_{t-1}$							-0.0009	0.0042**
							(-1.12)	(2.41)
UK_CDS_{t-1}							0.0001***	0.0003***
							(2.87)	(2.73)
$cons$	0.0849***	0.1546***	0.0596***	0.1042***	0.0748***	0.1394***	0.0373***	0.0612***
	(17.31)	(22.74)	(10.07)	(13.64)	(12.20)	(17.73)	(5.51)	(4.39)
R^2	0.1213	0.0992	0.0331	0.0317	0.1281	0.1051	0.3539	0.3217
N	1402	1402	1402	1402	1402	1402	1359	1359
Specification	FE	FE	FE	FE	FE	FE	FE	FE

Table 6 continued

	(9)	(10)	(11)	(12)	(13)	(14)
	bid-ask spread	effective spread	bid-ask spread	effective spread	bid-ask spread	effective spread
$Interdealer_{it}$	-0.0445**	-0.0771***	-0.0274*	-0.0554**	-0.0336	-0.0771**
	(-2.64)	(-3.55)	(-1.85)	(-2.40)	(-1.29)	(-2.23)
$Herfindahl_{it}$	0.0502	0.0721*	0.0461	0.0630**	0.5106***	0.1539
	(1.50)	(1.90)	(1.62)	(2.10)	(4.09)	(0.93)
$ClientCorr_t$	0.4288***	0.3883***	0.3106***	0.2931***	0.0926	0.2019*
	(9.71)	(5.32)	(5.58)	(3.49)	(1.20)	(1.96)
$CumQE_{it-1}$	-2.2634***	-2.0840*	-2.6035***	-1.5273	-1.8571***	-1.3414**
	(-3.85)	(-1.75)	(-4.01)	(-1.39)	(-4.31)	(-2.34)
$Freefloat_{it-1}$	0.0004	0.0012*	-0.0008**	-0.0001	-0.0000	0.0001
	(0.77)	(1.96)	(-2.10)	(-0.24)	(-0.01)	(0.15)
$Duration_{it-1}$	0.0041	0.0268***	0.0024	0.0208***	0.0061***	0.0213***
	(1.59)	(8.67)	(0.83)	(4.94)	(2.66)	(7.02)
$LIBORspread_{t-1}$			0.0044	0.0082*	0.0005	0.0020
			(1.30)	(1.79)	(0.12)	(0.35)
$VFTSE_{t-1}$			0.0009***	0.0011***	0.0009***	0.0014***
			(5.05)	(3.35)	(3.43)	(4.02)
$Reporate_{t-1}$			-0.0048***	-0.0022	-0.0046***	-0.0011
			(-3.14)	(-0.95)	(-3.94)	(-0.74)
UK_CDS_{t-1}			0.0001	0.0002*	0.0001	0.0002***
			(1.46)	(1.83)	(1.10)	(2.61)
$cons$	0.0416	-0.1092***	0.0515**	-0.0815**	-0.0432	-0.0975**
	(1.41)	(-3.29)	(2.40)	(-2.63)	(-1.40)	(-2.38)
R^2	0.2058	0.2534	0.3956	0.3618	0.0324	0.3619
N	1359	1359	1359	1359	1316	1316
Specification	FE	FE	FE	FE	IV	IV
1st stage F-stats						
$Interdealer$					53.87	
$Herfindahl$					15.20	

Table 7: Interdealer trading panel regressions. This table shows the estimation results of model (9). The dependent variable is the individual dealer fraction of interdealer trading, across all ISINs. *DealerClientCorr* is the dealer-specific absolute client order flow divided by the dealer-specific amount of the dealer-to-client volume. *Dealer_CDS* is the dealer-specific five-year CDS spread (in bps), *LIBORspread* is the difference between the three-month LIBOR and the three-month repo rate (in %); *Reporate* is the three-month cost of secured lending; *VFTSE* is the FTSE 100 volatility index and *UK_CDS* is the spread (in bps) on the UK sovereign five-year CDS contract. The sample period is January 2, 2008 to June 31, 2011. Robust t-statistics are in parentheses. *, ** and *** denotes significance at 10%, 5% and 1% respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$DealerClientCorr_{it}$	0.3090***		0.3689***	0.3556***	0.3611***	0.3554***
	(4.05)		(5.04)	(5.24)	(5.18)	(5.21)
$Dealer\_CDS_{it-1}$		-0.0002*	-0.0002*	-0.0002		-0.0002
		(-1.85)	(-1.73)	(-1.58)		(-1.54)
$LIBORspread_{t-1}$					-0.0407**	-0.0387*
					(-2.11)	(-2.02)
$VFTSE_{t-1}$				0.0002	0.0016	0.0019
				(0.19)	(1.49)	(1.63)
$Reporate_{t-1}$				0.0119**	0.0155**	0.0169**
				(2.23)	(2.83)	(2.81)
UK_CDS_{t-1}				0.0004	0.0004	0.0006
				(1.34)	(1.37)	(1.63)
cons	0.0606***	0.1088***	0.0747***	0.0308	-0.0163	-0.0106
	(8.12)	(8.69)	(5.05)	(1.13)	(-0.47)	(-0.35)
R^2	0.153	0.008	0.189	0.203	0.199	0.208
N	776	745	745	745	745	745

Table 8: Dealer net volume and trade direction. This table shows the estimation results of model (10). *Netdealvlm* is the aggregate dealer buy volume minus the dealer sell volume, excluding trades associated with QE. *QEdealervlm* is dealer QE (sell) volume. *Duration* is the bond duration in years; *Freefloat* is total amount of debt outstanding for each bond (in £billions) adjusted for the Bank of England stock of bond purchases; *Allocation* is the fraction of dealer bidding offers filled in the QE auctions; *Qdisp* is the dispersion of dealer winning bids in QE auctions; The sample period is January 2, 2008 to June 31, 2011. Robust t-statistics are in parentheses. *, ** and *** denotes significance at 10%, 5% and 1% respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$Netdealervlm_t$	-0.0925		-0.1089	0.9159**		0.9414**
	(-0.94)		(-1.04)	(2.17)		(2.24)
$Netdealervlm_{t-1}$	-0.2787***		-0.2468**	-0.1441		-0.1991
	(-3.00)		(-2.79)	(-0.47)		(-0.65)
$Netdealervlm_t \times Duration_t$				-0.0330		-0.0439
				(-1.08)		(-1.42)
$Netdealervlm_{t-1} \times Duration_{t-1}$				-0.0315		-0.0192
				(-1.02)		(-0.65)
$Netdealervlm_t \times Freefloat_t$				-0.0478**		-0.0472**
				(-2.29)		(-2.27)
$Netdealervlm_{t-1} \times Freefloat_{t-1}$				0.0051		0.0063
				(0.35)		(0.42)
$QEdealervlm_t$		-0.8379**	-0.8726**		2.4133*	2.7000**
		(-2.24)	(-2.27)		(1.86)	(2.09)
$QEdealervlm_{t-1}$		1.3914***	1.3394***		-0.8894	-0.8502
		(5.50)	(5.37)		(-0.63)	(-0.60)
$QEdealervlm_t \times Freefloat_t$					0.0159	0.0053
					(0.44)	(0.15)
$QEdealervlm_{t-1} \times Freefloat_{t-1}$					0.0297	0.0285
					(0.60)	(0.57)
$QEdealervlm_t \times Duration_t$					-0.2123**	-0.2299**
					(-2.29)	(-2.48)
$QEdealervlm_{t-1} \times Duration_{t-1}$					0.2037***	0.1918**
					(2.83)	(2.66)
$QEdealervlm_t \times Allocation_t$					-2.7816***	-2.8270***
					(-2.85)	(-2.92)
$QEdealervlm_{t-1} \times Allocation_{t-1}$					0.0874	0.1195
					(0.08)	(0.10)
$QEdealervlm_t \times Qdisp_t$					-2.6026	-2.5583
					(-1.41)	(-1.35)
$QEdealervlm_{t-1} \times Qdisp_{t-1}$					2.3872**	2.2394**
					(2.37)	(2.25)
N	29,474	29,474	29,474	29,474	29,474	29,474

Figure 1: Total issuance, free float and the stock of QE purchases in face-value terms (£billion) for the gilts in our sample. The sample period is January 2, 2008 to June 31, 2011.

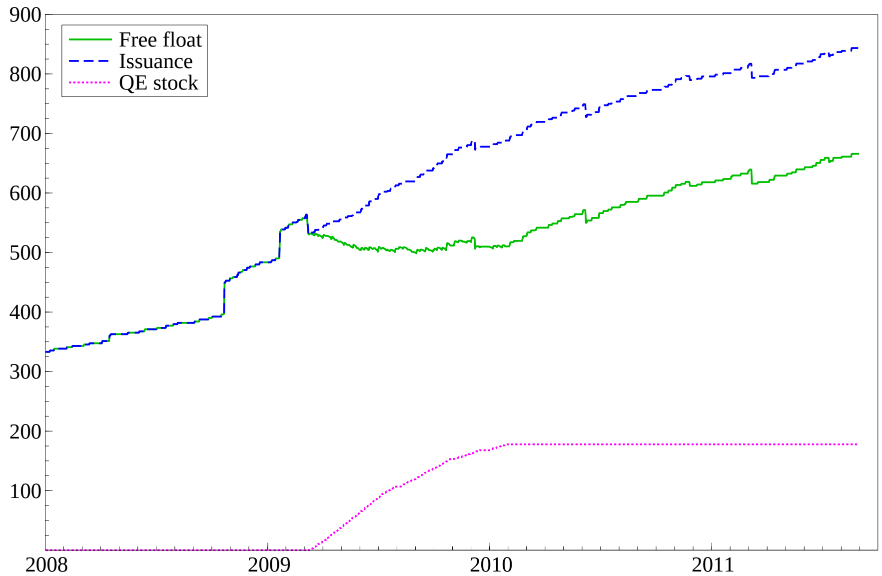

Figure 2: Trading activity. The top panels shows the total monthly volume and monthly interdealer volumes (£billion, face value). The bottom panel shows the total monthly volume divided by the amount of gilts outstanding (monthly turnover). The sample period is January 2, 2008 to June 31, 2011.

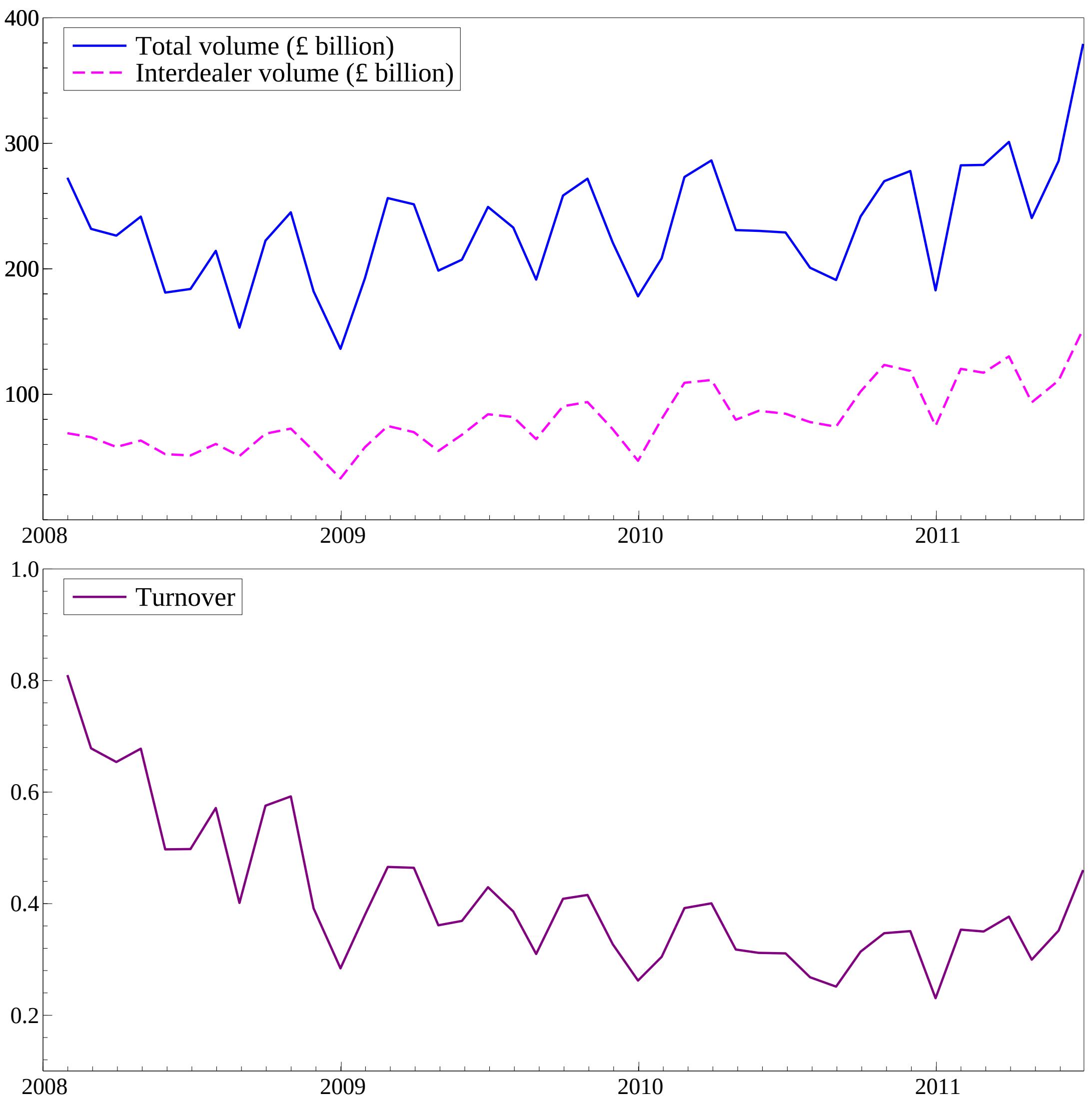

Figure 3: Noise (bps, top panel), LIBOR-Repo spread (%, middle panel) and the UK five-year CDS spread (bps, bottom panel). The Noise measure is defined in equation (3). The sample period is January 2, 2008 to June 31, 2011.

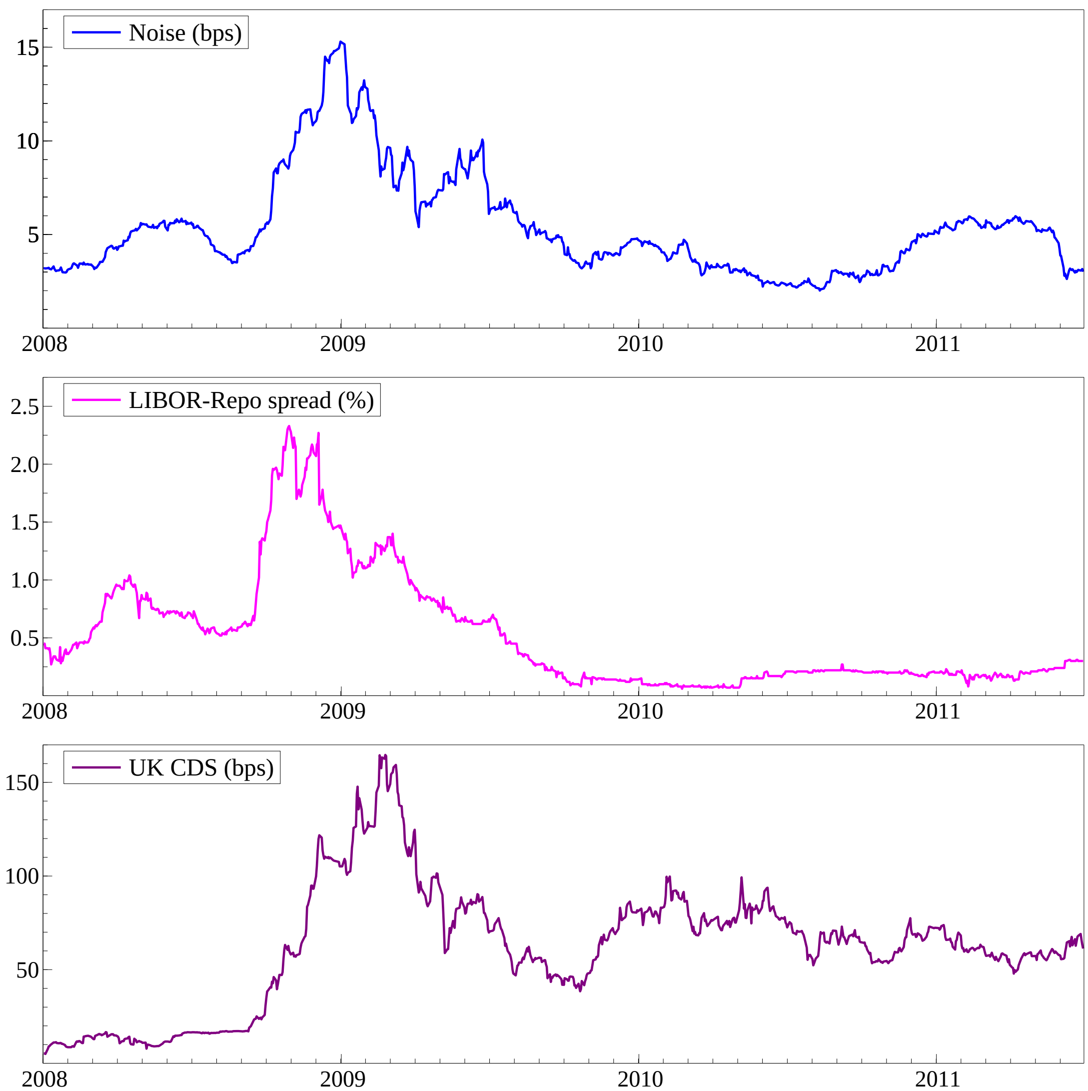

Figure 4: Average bid-ask spread and dispersion for the gilts in our sample. The gilt-specific versions of these variables are defined in equations (4) and (5) respectively. The sample period is January 2, 2008 to June 31, 2011.