The Effects of Quantitative Easing on the cost of issuing UK government debt, on the bid-to-cover ratio at the debt auctions and on the integration of UK capital markets

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Abstract

This thesis examines the impacts of Quantitative Easing (QE) on the UK gilt market, focusing on government debt issuance costs, market demand, and financial market volatility.

Despite a willing buyer of gilts during QE phases, issuance costs were higher, driven by volatility and supply increases during economic turbulence. Costs were particularly sensitive for longer maturity bonds and bonds already held by the Bank of England, indicating diminishing effects of QE over time.

Auction demand, measured by the bid-to-cover ratio, rose significantly during QE phases but fell during periods of financial instability, larger auction sizes, and longer maturities. Liquidity-enhancing mechanisms, such as the Post Auction Option Facility (PAOF), positively influenced demand, while QE improved short-term demand but posed long-term liquidity challenges.

Volatility analysis shows that during QE phases, short-term gilts experienced lower volatility, while long-term gilts showed higher volatility. However, greater intensity of purchases by the Bank of England reduced overall bond market volatility but increased volatility in the equity market. During QT phases, higher volatility was observed across all markets, though QT-active phases mitigated this effect, leading to relatively lower volatility.

This thesis provides a comprehensive understanding of how QE and QT influence sovereign debt management and financial market stability. The findings offer practical insights for policymakers and market participants navigating the complexities of unconventional monetary policy.

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1. Introduction

The global economic landscape has undergone significant shifts in recent years, driven by unprecedented challenges such as the COVID-19 pandemic, and evolving monetary policy frameworks. The economic downturn caused by the pandemic, coupled with subsequent lockdowns, resulted in dramatic policy interventions across the globe. In the United Kingdom, the Quantitative Easing (QE) program became a cornerstone of the Bank of England's response to the crisis. Initially launched during the 2008 financial crisis, QE involves the purchase of government bonds and other financial assets to inject liquidity into the economy and lower borrowing costs. During the COVID-19 pandemic, the scale of QE was unprecedented. The Bank of England's Monetary Policy Committee (MPC) reduced the policy interest rate to a historic low of 0.10% in March 2020 and expanded the Asset Purchase Facility (APF) from £445 billion to £895 billion by November 2020. This massive increase in asset purchases aimed to stabilize financial markets and support economic recovery amid heightened uncertainty. The QE measures, however, also introduced significant challenges for debt management, as the UK Debt Management Office (DMO) had to adjust its issuance strategies to accommodate increased borrowing requirements and market conditions. This thesis explores the far-reaching implications of these policy actions, focusing on their effects on government debt issuance costs, market demand dynamics, and financial market volatility, with a particular emphasis on the UK gilt market.

The first chapter investigates how the dramatic changes in economic policy and debt issuance practices in response to the COVID-19 crisis have influenced the costs of government debt issuance. The Bank of England's Monetary Policy Committee (MPC) implemented significant policy rate cuts and expanded asset purchase facilities to mitigate the economic fallout. The UK Debt Management Office (DMO) also increased the scale and frequency of gilt auctions to meet heightened funding needs. Drawing on studies such as (Beetsma et al., 2016, 2020) and Nyborg et al. (2002), this chapter examines the interplay between auction characteristics, prevailing market conditions, and issuance costs. Specifically, it delves into the influence of variables such as liquidity, volatility, auction size, demand, Asset Purchase Facility (APF) activity, benchmark status, and maturity. By analysing issuance costs during the QE and QT periods, as well as across different maturity segments, this chapter provides a nuanced understanding of the drivers of one aspect of government borrowing costs in a rapidly evolving economic environment. The findings underscore the role of market liquidity, volatility, and institutional factors in shaping the outcomes of sovereign debt auctions, adding to the literature on debt management strategies.

The second chapter delves into the determinants of auction demand, as measured by the bid-to-cover ratio, in the UK gilt market. This metric serves as a key indicator of market confidence and indirectly measures issuance costs. Drawing from theoretical models such as those proposed by Spindt and Stolz (1992) and empirical studies by Beetsma et al. (2020), this chapter investigates how factors influencing issuance costs also affect auction demand. The analysis focuses on the impact of QE and QT, distinguishing between auctions for new and secondary issuances and exploring segmentation premia in these issuance costs across various maturity sectors. By evaluating the bid-to-cover ratio, this chapter connects the supply-side considerations of debt issuance with the demand-side dynamics of investor behavior. Moreover, it introduces a comparative framework to assess whether the determinants of demand align with those influencing issuance costs, thus providing a more integrated perspective. The findings contribute to understanding the conditions for successful auctions, providing actionable insights for policymakers and debt managers aiming to optimize auction outcomes while considering funding objectives and market stability. The results also highlight how investor preferences, influenced by risk and liquidity considerations, interact with auction design features such as benchmark status, Post Auction Option Facility (PAOF), and issuance frequency to shape demand outcomes. These insights are particularly critical during periods of heightened economic uncertainty, as they underscore the strategic role of auction timing and size in mitigating borrowing costs.

The third chapter builds on the findings of the previous chapters to investigate the relationship between monetary policy interventions, market volatility, and their broader implications. While the first chapter examined the effects of bond market volatility on issuance costs and the second chapter explored stock market volatility's impact on auction demand, both revealed a complex and multifaceted relationship. These findings motivate a deeper investigation into volatility using more nuanced definitions and frameworks. This chapter employs a univariate and multivariate GARCH approach to assess how QE and QT influence realized volatility across different asset classes, including short-term bonds (FTSG), long-term bonds (FTLG), and equities (FTSE). By analysing volatility in both bond and stock markets, this chapter provides a comprehensive understanding of its role in shaping issuance costs and auction dynamics. The findings reveal that while QE often stabilizes financial markets by reducing volatility, QT presents more intricate effects, sometimes amplifying volatility due to shifts in liquidity and investor expectations. By exploring the interplay between monetary policy and market volatility, the chapter highlights its critical role in influencing investor behaviour, market stability, and overall economic resilience. These insights emphasize the importance of designing policy interventions that consider the dual effects of volatility on market demand and issuance costs, ensuring more predictable outcomes in sovereign debt management.

Together, these chapters form a cohesive narrative that links monetary policy actions to their tangible effects on government debt markets and broader financial systems. The first chapter sets the stage by identifying the cost implications of issuance practices, providing a foundation for understanding market demand dynamics explored in the second chapter. By examining the bid-to-cover ratio, the second chapter bridges the cost and demand perspectives, offering a comprehensive view of the factors influencing auction outcomes. The third chapter broadens the analysis to include the volatility of financial markets, tying together the effects of QE and QT on both primary and secondary market behaviours. This interconnected approach highlights the complex feedback mechanisms between monetary policy, market demand, and financial stability. Additionally, it emphasizes the importance of distinguishing between short-term and long-term impacts of monetary policies, as well as their asymmetric effects during periods of expansionary and contractionary interventions. The chapters collectively underscore how QE and QT not only influence immediate auction outcomes but also leave lasting imprints on market liquidity, risk dynamics, and investor sentiment.

This thesis contributes to the literature by addressing critical gaps in our understanding of sovereign debt markets during periods of unprecedented monetary interventions. The findings have significant implications for policymakers, debt managers, and market participants. By integrating insights from multiple disciplines, including finance, economics, and public policy, this research provides a holistic framework for analysing the multifaceted impacts of QE and QT. The results underscore the need for coordinated policy approaches that balance short-term stabilization goals with long-term financial sustainability. Ultimately, the thesis offers practical guidance for navigating the complexities of contemporary financial markets, ensuring more informed decision-making in the face of evolving economic challenges and uncertainties. By building on the insights from each chapter, this work highlights the interconnected nature of monetary policy, sovereign debt management, and market behavior, offering a comprehensive perspective on their dynamic interplay.

2. Literature

This study contributes to and supplements academic literature in several major areas: the impact of quantitative easing on the UK government bond market, the empirical analysis of debt issuance via auction, the optimal structure of the government debt portfolio and debt market segmentation, the determinants of demand in the gilt market, asset market correlations, and the impact of QE and QT on stock and bond market volatility.

This literature review is organized into six sections, each addressing a key aspect of the research focus. The first section examines the impact of quantitative easing on the gilt market, exploring its effects on yields, liquidity, and overall market behaviour. The second section delves into government debt issuance, focusing on auction outcomes and their determinants. The third section analyzes optimal government debt portfolio management and segmentation, highlighting strategies for managing debt effectively. The fourth section reviews studies on the correlation between asset markets, emphasizing interdependencies and spillover effects. The fifth section discusses the influence of monetary policy announcements on financial markets, with a particular focus on market reactions. Finally, the last section investigates the impact of quantitative easing on financial market volatility, examining how QE shapes risk and uncertainty in these markets.

2.1. Quantitative Easing and the Gilts Market

The term "quantitative easing" (QE) is used to describe the Bank of England's programme of expansionary monetary policy through asset purchases funded by electronic money creation. The financial crisis that, in the UK, entered public consciousness following the collapse of the Northern Rock bank in September 2007, was accompanied by a succession of policy interest rate cuts from 5 percent to 0.5 percent between October 2008 and March 2009. In January 2009, the Bank of England had announced its attention to establish an asset purchase facility, and the asset purchases began on March 11, 2009, two days after the halving of the policy rate to 0.50%.

Empirical studies of the effects of QE on the gilt market have focussed on the impact of yields around announcements and purchases. Using an event study method, Meier (2009) finds that the first round of QE purchases reduced the 10-year yield on gilts by at least 35 to 60 basis points. Joyce et al. (2011) highlight that QE might have reduced the yields of medium to long-term bonds by roughly 100 Basis Points (BPs), mostly due to the portfolio rebalancing. According to Mamaysky (2018), portfolio rebalancing as well as signalling transmission processes can help to clarify why medium- to long-term bonds react to QE announcements in the US, the Euro area, and the UK more quickly than equities markets and its ensuing volatility. Furthermore, Gagnon et al. (2011) state that portfolio rebalancing caused long-term drops in US longer-term interest rates on a variety of securities, even those not included in the QE programme. Rebalancing appears to have had the greatest impact on term premiums, which fell by 30 to 100 bp. However, studies by both Glick and Leduc (2012) and Meaning and Zhu (2011) find considerably smaller effects closer to 50 basis points. This difference may reflect the different choices of event windows between the studies. Glick and Leduc (2012) and Meaning and Zhu (2011) use a single day event window, whereas Joyce et al. (2011) use a two-day window. Doubling the event window appears to double the reduction in yields.

Joyce and Tong (2012) use high-frequency data to examine the effects of announcements of QE activity, such as decisions to raise the threshold, and also the purchase auctions on the yields of individual gilts. Their evidence suggests that the key QE announcements also reduced yields by around 100 basis points on these days. They also identify local supply effects of gilt purchase auctions, whereby the yields of gilts fall temporarily in response to the quantity of gilts issued and also to those of near maturity substitutes. The yields also responded after the auction to the amount of information that the auction itself conveyed about the supply of gilts. Breedon et al. (2012) examine the impact of QE1 on the UK bond market by using a macro-finance model to construct a counter-factual yield curve. By comparing the difference between the observed yield curve and their estimate of what the yield curve would have been in the absence of QE, they too find a reduction in yields resulting from QE of around 50 basis points at the 10-year maturity.[1]

Joyce et al. (2012) find that yields actually rose slightly during QE2, but only by amounts well within the margins of international yield movements around the same period. Meaning and Zhu (2011) and Goodhart and Ashworth (2012) also indicate limited bond yield impacts of QE2. However, a study Banerjee et al. (2012) that used changes in auction maturity sectors to assist in the identification of supply surprises indicates that the effects of QE2 were of similar sign and magnitude to those of QE1, while Churm et al. (2021) find that the yield reductions were up to 55 basis points across QE2 events. Some event study analysis in Martin and Milas (2012a) undertaken while QE3 was still in progress indicated that yields fell at most by 12 basis points over that short time frame.[2]

There are a small number of studies of the effects of the resumption of QE associated with Brexit uncertainty following the referendum in June 2016. D'Amico and Kaminska (2019) examine the reaction of corporate bond prices and credit spreads to government bond purchases associated during the first four rounds of UK QE, and compare this to the reaction to corporate bond purchases that were a prominent feature of QE4. They find that corporate bond prices react more to their own purchases

1. However, Sinclair and Ellis (2012) note the difficulties in establishing robust counter-factual scenarios in the face of the global decline in yields.
2. Similar results have been observed for other countries. Studies of US bond yields, which encompass a range of movements of between 30 and 100 basis points, include Gagnon et al. (2011), D'Amico and D'Amico amd King (2013), Krishnamurthy and Vissing-Jorgensen (2011), Glick and Leduc (2012), Neely (2012), Liu et al. (2018) and Eren et al. (2023). Studies by, inter alia, Eser and Schwaab (2016), Krishnamurthy et al. (2017), Koijen et al. (2021) and De Santis (2020) show that the yield effects of the ECB's programme of QE beginning in 2015 are similar to those reported in the UK and the US, while Schlepper et al. (2020) use high frequency data to identify the immediate local supply based price reaction to the actual purchases, finding significantly smaller reactions. Studies of asset price responses to Japanese QE include Barbon and Gianinazzi (2017). Mamaysky (2018) shows that the price reactions for equity are much longer than those for bonds, and could be as much as several weeks.

rather than those of comparable gilts. B De Rezende and Ristiniemi (2020) study UK QE announcements through QE4 in their computation of a shadow rate to capture monetary policy stance and subsequent application to identifying the different effects of conventional and unconventional monetary policy of exchange rates and inflation. Kyriazis and Economou (2017) assess the consequences for the Eurozone of a delayed winding down of UK QE due to Brexit uncertainty. They identify a trade-off between the benefits from liquidity spillovers and the costs of imported inflation. Studies by Breinlich et al. (2018) and Davies and Studnicka (2018) attribute the drop-in equity prices immediately following the Brexit vote result to a fear of a cyclical downturn, revised profit expectations and sterling depreciation. Opatrny (2020) conducts a counterfactual exercise using synthetic control methods and the benefit of a longer span of data to conclude that over the longer term the effects on equity were insignificant, but the effect on the 10 year gilt yield was a sustained 120 basis drop, which is larger than the changes seen in earlier phases of QE.[3]

Recently the literature on QE and the gilt market has turned its attention to the secondary market liquidity effects of the financial crisis and also QE, despite the ambiguity of the relationship identified by Ferdinandusse et al. (2017). This is important for bond issuance, because a deterioration in secondary market liquidity may feed through to a deterioration in primary market liquidity and hence an increase in issuance costs. However, for the gilts market both Steeley (2015) and Benos and Zikes (2016) document a substantial improvement in liquidity following the introduction of asset purchases, although liquidity had deteriorated during the financial crisis prior to the commencement of QE. Liquidity is measured both directly from market spreads and also indirectly from an effective spread calculated from transactions prices and a measure of noise, as in Hu et al. (2013). However, the possibility that purchase decisions themselves depend on liquidity conditions, which is evident in results of Song and Zhu (2018) and Schlepper et al. (2020), leads Boneva, Kastl, et al. (2020) to use purchases auction offer-level data to construct demand and supply proxies that can control the potential reverse causality. They find an improvement in liquidity due to QE, however their domain is the corporate bond rather than the gilts market. Blix Grimaldi et al. (2021) studying Swedish government bonds purchased by the Riksbank find that the boost to liquidity from this additional demand can be offset by a reduction in liquidity as the stock of bonds held by the Riksbank increases, particularly when the holdings exceed 40 percent of the size of an issue. Roh Hee Su (2023) observes that the latter scarcity effect can be offset by central bank lending bonds back into the market but, if that activity is limited, the effectiveness of QE as a means to lower long rates is enhanced. Pelizzon et al. (2024) observe that the scarcity effect can also create arbitrage opportunities between sovereign bonds and their Futures contracts. Christensen and Gillan (2022) demonstrate how quantitative easing (QE) can lower trading costs through a liquidity

3. Opatrny (2020) also provides a brief review of those studies that have considered the impact of the post-2016 Brexit vote induced uncertainty on various economic aggregates. Surveys of the wider economic impacts of earlier episodes of QE across various countries can be found in Haldane et al. (2016) and Papadamou et al. (2020).

channel that works by temporarily boosting sellers' bargaining power in the market for the securities being targeted.[4]

2.2. Government Debt Issuance Auction Outcomes

The use of auctions as a method to sell UK government bonds began, on an experimental basis, in May1987, with the offer of £1bn of Treasury 8% 1992 stock. Two further "experimental" auctions were held, in September 1987 and January 1988, followed by the first regular auction in August 1988. Thereafter, a period of government financial surplus saw a suspension of new issues. The government recommenced new issues in 1991, and auctions have become the main method of public offer. Auctions were undertaken on a roughly bi-monthly basis until March 1993, when a regular monthly calendar was introduced. The Debt Management Review, see Bank of England and H.M. Treasury (1995), formalised this process further with a pre-announced annual auction calendar becoming a component of the Treasury's annual funding remit.

Under the auction procedure, competitive (price and quantity) bids for bonds are submitted to the DMO, which then allots bonds at the bid price. Small non-competitive (quantity only) bids are allotted at a bid-size weighted average of accepted bid prices. Although, some details of the auctions for a forthcoming quarter are published at the end of the previous quarter, the full details are published around 7 working days before the auction date. Most auctions closed at 10.30 am on the morning of the auction day, although since April 2020, some auctions have closed at 10 am and some at 11.30am. Originally, the DMO committed to release the results within 40 minutes of the auction close, but that time span has reduced considerably since the introduction of electronic bidding in 2007. For the 2006/07 financial year, auctions increased in frequency and the maturity selections were regularized (Debt Management Office, 2006). Further changes to issuance procedures were made in time for the 2016/17 financial year, including a reduction in the size of auctions, a more responsive auction calendar, an increase in the post auction option facility from 10% to 15% of the bidder's competitive allocation, and an increase in the non-competitive bid allowance for Gilt-edged Market Makers (GEMMs) from 10% to 15% (Debt Management Office, 2017). This percentage was increased further to 25% on March 31st, 2020 and, from April 7th 2020 the Treasury would sometimes issue two different gilts on the same day. The quarterly issuance of gilts by auction since 1987 is shown in Figure 1, where the consequences of the Covid-19 government policy responses are clear. This dramatic increase in issuance has led to further calls for support for the GEMMs.5 During 2022, the first two auctions of "Green Gilts" were

4. Improvements in corporate bond market liquidity are also observed by Todorov (2020) arising from the ECB's purchase programme. Studies of the sever disruption to liquidity in bond markets in 2020 and in 2022 include He et al. (2022) and Duffie and Keane (2023).

5. W. Allen (2020), for example, recommends that the Treasury underwrite gilt issuance and becomes, as it had been in the past, a buyer of last resort. However, Bicu-Lieb et al. (2020) suggest that the market participants' view that liquidity in the gilt market since the crisis has been constrained by regulatory leverage requirements is not supported by the data without conditioning on funding costs and inventory risk, and that a consideration of dealer heterogeneity further weakens the causal link. However, the number of market makers has decreased in recent years and, as can be seen in Figure 3, average auction sizes have decreased in recent years, both responses to a more challenging liquidity environment.

held, with the funding designed to “help fund projects to tackle climate change, finance much-needed infrastructure investment, and create jobs across the country" (HM Treasury, 2020). Aside from the intention to hypothecate the proceeds and having a different name, the gilts are conventional gilts in all other regards. While the first auction, in May 2022, generated a premium on issuance, it was significantly below the average premium for the period following the ending of QE in December 2021 ($p < 0.01$). The second green gilt issuance premium in November 2022 was also below the average but not significantly so.

Breedon and Ganley (2000) provides the first empirical study of gilt auctions. Drawing on auction theory, they document and explain the under-pricing in the auctions that took place before 1996. Auction theory predicts that under-pricing arises from asymmetrically informed bidders shaving their bids to avoid the winner’s curse of probable over-payment. They found an under-pricing in bonds that were, initially, non-fungible with the parent issue, and that this was mostly associated with whether or not the bond had benchmark (on-the-run) status. For later auctions, when the bonds were fully fungible, the price differential between parent stock and auction tranche reduced to almost zero on the day of the auction.

Nyborg et al. (2002) studied Swedish Treasury auction between 1990-94 and their dataset is unique in their having access to the actual demand schedules of the bidders as well as the auction outcomes. They show that the auction discount and the dispersion of bids are both positively related to volatility, a finding consistent with information asymmetries as a cause of under-pricing. Scalia (1998) finds a role for information asymmetries in Italian Treasury bond auctions and also identifies differences between initial auctions of a bond and subsequent re-openings. Boyarchenko et al. (2021) demonstrate that information sharing increases auction revenues by educating bidders. Dealer chat increases auction revenues for issuers, but it can also enhance risk sharing by reducing asymmetry in information. They discover that how information is shared matters. The beliefs of bidders are more closely correlated when dealers share information with other dealers about anticipated demand. On the other hand, dealer information exchange with customers spreads client beliefs about future demand. Further direct evidence of the role of volatility is provided by Goldreich (2007) for US Treasury auctions. Spindt and Stolz (1992) point out that in the presence of an active when-issued or secondary market, as is the case with gilts, the role of information asymmetry is puzzling. However, Cammack (1991) has argued that even an active secondary market might not reveal all of the information relevant for pricing. Bukhchandani and Huang (1989) show that there is an incentive, in theory, for bidders to send out false signals into the when-issued market, while Drudi and Massa (2001) finding corroborating evidence for Italian Treasury bonds. By contrast, Umlauf (1993) finds evidence consistent with bidder collusion in Mexican Treasury Bill auctions.

Nyborg et al., (2002) also find that the size of an auction significantly increases the dispersion of bids but lowers the auction discount, which is consistent with observation of Spindt and Hoffmeister (1988) that bidders seek compensation for inventory risk. As most gilt dealers typically enter an auction with a net short position from the when-issued or secondary market, the liquidity of the bond is also likely to influence auction outcomes. Jegadeesh (1993) provides evidence of an attempt to squeeze the post-auction market in US Treasury securities, which can be exacerbated by the rise in post-auction when-issued market volatility in discriminatory auctions observed by Nyborg and Sundaresan (1996). According to Eisl et al. (2018), there is evidence that the risk and liquidity of the bond being auctioned affect how much the primary dealers' positions must be adjusted. They draw the conclusion that a higher risk and more lucrative issue of the bond forces the dealers to sell off more of their riskier assets, which raises the auction cycle's amplitude. In contrast, greater bond liquidity may make it easier for dealers to transfer inventory risk to the market, reducing the amplitude of auction cycles. Breedon and Ganley (2000) proxy liquidity with the benchmark status of the bond and find this to be an important explanatory variable in gilt auction outcomes. Sundaresan (1994), who examined the repo market in US Treasuries around auctions, also found a difference between on-the-run and off-the run bonds, for the yield spreads to general collateral.

Keloharju et al. (2005) emphasise the role of the Treasury in timing the auction of particular bonds, in that the choice of actual bond is made only in the few days leading up to the auction, and that this reflects the Treasury's opinions on market conditions and bond valuations. Mann and Klachkin (2015) find that the auction high-yield for US Treasury bonds is more strongly negatively correlated with the level of stock returns and stock return volatility, and that the correlation with the Fed Funds rates changes from positive to negative with the onset of QE in the US. Beetsma et al. (2020) analyse the determinants of the bid to cover ratio (measured as the entire amount of bid during an auction divided by the total amount of new debt allocated) in Eurozone government bonds, and find that it is positively related to the level of yields and negatively related to the volatility of the corresponding futures options. They find more mixed results across the different countries, both for sign and significance, regarding the corporate yield spread, the ex-post issued quantity, the number of dealers and their market capitalization, and the bid to cover ratio at the previous auction. Shida (2023), studying the demand for German Treasury bonds, finds a positive relation with offered volume, secondary market yield, the announcement of upcoming syndications, and previous under-pricing, and a negative relation with volatility and a regulatory change affecting banks' balance sheets. The study also finds a positive effect from central bank purchase activity, but only for 2-year maturity bonds. However, the level of yields is potentially endogenous as Fuhrer and Giese (2021) show that the deviations of the bid to cover ratio from its long-term average in UK gilt auctions influences the shape of the yield curve, particularly at the short and long ends, and that this effect is more pronounced in more volatile conditions.6

The possibility of feedback from auctions to yields is also suggested by the research that has identified auction cycles, where secondary market yields increase ahead of auctions and decrease afterwards. De Vassal (1998) documents a significant drift in yields of US Treasury bonds in the days surrounding auctions, again consistent with pre-auction selling pressure, while Sundaresan (1994) found that significant rents would have accrued to owners of on-the-run issues that lent them into the repo market prior to the auction date.[7] Albuquerque et al. (2024) find that pre-auction selling pressure in US Treasuries directly correlates with the extent of under-pricing in auction bids, while for Italian bonds, Cafiso (2019) finds the opposite result. Spronsen and Beetsma (2022) show that the Eurozone asset purchase programmes dampened the auction cycles in Treasury bonds.

2.3. Optimal Government Debt Portfolio Management and Segmentation

The idea that there could be an optimal maturity structure for government debt follows from the idea of an imperfect substitutability among different asset classes Tobin (1969) and Brunner and Meltzer (1973). They argued that central banks, by varying the relative supplies of assets with different maturities and liquidity, could affect the relative yields on those assets due to imperfect substitutability. Thus, following an asset supply shock, relative prices and yields would adjust to restore equilibrium. The preferred habitat and segmentation theories of Culbertson (1957), Modigliani and Sutch (1966), Vayanos and Vila (2021) and Greenwood and Vayanos (2010), where investors have preference for a particular range of maturities along the yield curve, implies that an imperfect substitutability may exist also within the bond market itself. This local supply effect, in bond markets, also gives rise to the portfolio balance transmission mechanism of quantitative easing.

The recent literature on the structure of the government debt portfolio suggests that governments should favour longer term bonds (Angeletos (2002), Barro (2003), Nosbusch (2008) and Lustig et al. (2008)). However, Buera and Nicolini (2004) and Faraglia et al. (2010) show that this can imply extremely large amounts of debt issuance. Andreolli (2021) looks on the impact of public debt maturity as a mediating element in the transmission of monetary policy shocks to economic activity. A longer debt maturity significantly reduces the influence of monetary policy. Ellison and Scott (2020) construct a monthly dataset of the price and quantity of each UK government debt instrument from the market's initiation in 1694 until 2017. They show that during the 20th century, the UK government

6. Evidence of a similar feedback effect from US Treasury auctions is provided by Gorodnichenko and Ray (2017) and Beetsma eta al (2018a), while Egginton a Hall (1993) examine the effects on yield curve shape of the resulting change in debt maturity structure arising from the time series of issuance activity.
7 Auction cycles have also been documented by Fleming et al. (2024), Lou et al. (2013), Eisl et al. (2018) for US Treasuries, Beetsma et al (2018b)for the Eurozone, OPREA (2021) for Romanian Treasury bonds, and Ahmad and Steeley (2008) for UK gilts.

would have been significantly better off issuing short term bonds than long term bonds, because of the prevailing upward sloping yield curve and long bonds often being an expensive form of fiscal hedging. However, Coe et al. (2005) suggest that the likely cost savings from plausible changes in the composition of the UK debt portfolio between 1985 and 2000 are very small.8 Plessen-Mátyás et al. (2023) provide the first evidence of an effect on government debt portfolio maturity structures from the QE bond purchase activity identifying a relative increase in the maturities of new debt issuance in the Eurozone. Giese et al. (2021) show that investors in the UK government bond market exhibit preferred habitats and that groups identified as having preferred habitats sold proportionately more of their holdings to the Bank of England during QE4.

A key feature of the theoretical models is that governments are assumed to repurchase and reinvest the entire debt portfolio each time the structure is needing to be changed. However, Faraglia et al. (2018) show that when the government has an information advantage about the future course of public finances, it will not buyback existing debt before maturity. A similar tilt towards short term debt as a consequence of repurchases costs is predicted by Greenwood et al. (2015). Faraglia et al. (2018) explicitly model and estimate the transactions costs needed to induce low levels of bond repurchases, and they show that transactions costs are the key to explaining observed government debt maturity structures. They identify three types of transaction costs: the resources required to run a debt management office, the bid-ask spread, and price pressure arising from issuance and repurchases activities. A similar conclusion on the key role of transactions costs is reached by Bigio et al. (2023) who both estimate these costs and provide an analytical solution for the optimal maturity distribution. Estimates of the bid-ask spread for UK gilts over different time frames are given in Proudman (1995) for the 1990s and in Steeley (2015) for the period from 2004-2013. The round trip price pressure effects for UK gilts are estimated in Breedon (2018) for the period between March 2009 and May 2012. In this paper, the focus is on these same transactions costs – but in particular the issuance costs – and as a means to estimate debt issuance costs during different market conditions. As this paper will distinguish between different debt maturities, our analysis will also inform the literature on the relative costs of issuing debt of different maturities and how this may depend on concurrent central bank purchases of bonds.

2.4. Asset Market Correlations

Compared to a large amount of research that has been done on examining the international transmission of stock market and bond market volatility, a few studies are indicating the correlation between asset classes. Anderson and Breedon (2000) report considerable volatility spillovers from equities to bonds in the UK, but not in the opposite direction. Similar results have been obtained for Australia by Dean et al. (2010). They show that negative shocks to the equity market have a bigger

8. The UK governments approach to debt management is described in DMO (2004).

impact on bonds and there are spillover effects from the bond market to the equity market. Hassanein and Elgohari (2020) discover the existence of spillover effects between China's stock and bond markets in both directions, but only over the particular time periods, such as bond market volatility, recovery and persistence, and stock market shock. In the European context, Berben and Jansen (2009) utilized time-varying correlation models to study changes in equity market integration during QE interventions. According to Steeley (2006), the present short- and long-term bond volatility as well as the volatility of the FTSE 100 stock market are both significantly influenced by historical long-term bond volatility. Additionally, he discovers that during the post-Millennium stock market collapse, the correlation between the stock market and the bond market changed from positive to negative. Similarly, a Markov switching autoregressive model of the stock-bond return relation is designed by Hobbes et al. (2007) to demonstrate that the stock-bond relation in Australia is responsive to the degree of market uncertainty gauged by the VIX. Moreover, they recognise additional behaviour that alternates between two regimes of positive and negative stock-bond correlations. A positive correlation exists between stock and bond markets over phases of stable economic conditions when investors are enthusiastic about future outlook and are therefore more likely to increase their investment of both stocks and bonds in their portfolios. The correlation between stocks and bonds will be lower (or even negative) when investors become pessimistic about future economic prospects and are more likely to sell their equity holdings in favour of bonds (McMillan, 2019). According to Connolly et al. (2005), the short-term relationship between US stock-bond returns is negative because of the flight to quality phenomenon, which occurs when investors rebalance their portfolios from stocks to bonds during periods of increased market volatility, as measured by the VIX index. Lee et al. (2019) likewise point to evidence in support of the flight to quality, showing that over periods of financial stability, both the Chinese stock and government bond markets move in the same direction. Recently, several phases of flight-to-quality have been detected by Papadamou et al. (2021) during the COVID-19 worldwide pandemic in ten countries, including the regions of Europe, Asia, the US, and Australia by applying a panel data specification and a wavelet analysis.

Recent investigations have discovered different economic variables driving the time-varying stock-bond returns correlation. The research literature provides evidence of employing a variety of linear and non-linear time series methodologies, such as copula methods, multivariate GARCH models, switching regime models, and VAR decomposition techniques, to examine the co-movement between the returns on government bonds and equity indexes (for a relevant review, see Boucher and Tokpavi, 2019; Selmi et al., 2019; Skintzi 2019). The impact of QE on global financial variables was quantified by Pastpipatkul et al. (2016) and Bhattarai et al. (2021) using Markov-switching VAR and Bayesian panel VAR models, respectively. This highlights the significance of methodological diversity in capturing the complex effects of QE. In addition, in order to identify abnormal changes in domestic variables during QE periods, Barroso et al. (2016) created a novel channel identification technique.

Park et al. (2019) demonstrate that the correlation between stock and bond returns depends on the source of the risk that resulted in the crisis. Employing nonlinear quantile regressions in assessing the nature of dynamic comovement between stocks and treasury bonds in Europe, Lee (2021) provide evidence of nonlinear effects of financial volatility and traders' expectations for the future status of the economy on the comovment of the EU asset markets. likewise, a pricing model for stocks and bonds is provided by Bekaert et al. (2010) that includes the possibility of counter-cyclical preference shocks producing time-variation in risk premiums. Their approach simultaneously includes the mean and volatility of the risk premia for long-term bonds and equities as well as the key characteristics of the nominal short rate, dividend yield, and term spread. They demonstrate that the correlation between US stock and bond returns predicted by their model is a little bit stronger than what they found through their empirical research. Analysing the dynamic correlations and spillover impacts between returns on contingent convertible (CoCo) bonds, bank stocks and bank bonds by DCC-GARCH method, Fangfang and Ping (2021) discover that the macroeconomic conditions change the correlations between the returns on CoCo bonds, equities, and bonds. Additionally, considerable effects of spillover from bank stocks and bonds to CoCo bonds have been observed. However, spillover impacts in the opposite direction are significant when the economy deteriorates.

The impact of the European Monetary Union (EMU) on time variations in inter-stock-bond market integration/segmentation dynamics is systematically examined by Kim et al. (2006) utilising a two-step process. First, they note the declining changes in the conditional time-varying correlations between stock and bond market returns in the US, Japan, and Europe. They find evidence that the integration of monetary policy may have contributed to investor concern about the economic outlook of the European Monetary Union and resulted in a flight to quality phenomena.

2.5. Monetary Policy Announcements and Asset Markets

There is a long history of research on the impact of monetary policy on equities markets. The early US research articles, including Sprinkel (1964), Palmer (1970), Homa and Jaffee (1971) and Hamburger and Kochin (1972), discover that variations in the money supply were not instantly transferred to stock market prices. Employing a daily event window, Bernanke and Kuttner (2005) discover that a reduction of 25 basis point in interest rates causes a rise of almost 1 percentage point in broad stock indexes. Ammer et al. (2016) investigate the relationship between non-conventional monetary policy and exchange rate and stock prices in developed countries, finding that the more financial markets are integrated, the more future changes in monetary policy influence stock prices and exchange rate. The information flow from the Fed to the equity market and its effect on the FOMC announcement premium are studied by Morse and Annette Vissing-Jorgensen (2020). Neuhierl and Weber (2018) also state that the return movement around FOMC announcements relies on whether the monetary policy is expansionary or contradictory. Farinha and Vidrago (2021) show that when surprises are expansionary, equity returns are greater, and when surprises are contractionary, equity returns are lower. According to Savor and Wilson (2013), macroeconomic news announcements like FOMC meetings account for 60–80% of the observed stock premium. Additionally, there is evidence that modifications to monetary policy rules have an impact on risk premia. For instance, Bianchi et al. (2022) discover a significant positive correlation between the interest rate component which is affected by monetary policy regime alteration and the conditional equity return premium calculated from statistical data. Furthermore, a mechanism is designed by Kekre and Lenel (2022) to clarify the stock market reactions to monetary policy and magnify its actual impacts. Applying the expected option-implied variance reduction, Ai et al. (2022) evaluate the impacts of monetary policy announcement surprises on stock market. They demonstrate that monetary policy announcements demand considerable risk compensation in the cross section of stock returns. Balcilar et al. (2020) develop a brilliant regime-dependent spillover index based on a smooth transition vector autoregressive (STVAR) model to evaluate the impacts of the Fed's unconventional monetary policy (UMP) on the US financial markets and determine volatility spillover dynamics among the SandP 500 index, the US 10-year treasury yield, the US dollar index futures, and the commodity price index. According to, Ferreira and Serra (2022)unconventional monetary policies had a positive impact on European equities but a mixed impact on government securities. Despite prevailing belief, Hsiao et al. (2022) reveal that monetary policy volatility negatively forecasts equity return uncertainty, defying the notion that greater uncertainty results in greater volatility.

The research on the cross-market correlations through different UMP implementation phases is limited, despite the expanding body of literature on the national and world impact of UMPs. Steeley (2015) documents the limited influence of the quantitative easing (QE) programme of the Bank of England on equity, short-term, and long-term bond volatility in the UK as well as short-term fluctuation in market correlations over the economic downturn and QE phases. According to Kryzanowski et al. (2017), the correlations between bond markets, equity markets, and currency forwards change among the three quantitative easing (QE) programmes implemented by the US Federal Reserve from September 2003 to November 2014. Employing a dynamic conditional correlation analysis, Kenourgios et al. (2019) look into potential variations in the correlation dynamics over four UMP episodes, as well as across a number of developed and emerging market economies. They explain that there is a spillover effect on both markets, and the latest UMP phase, which began in 2014, has a greater influence.

2.6. QE and Volatility of Financial Markets

A crucial unconventional monetary policy tool, QE is particularly useful during economic downturns when conventional interest rate policy becomes ineffective. While several studies have examined how QE affects the prices and yields of different asset classes in the UK, such as Meier (2009), Joyce et al. (2011), Glick and Leduc (2012) and, Meaning and Zhu (2011), Joyce and Tong

(2012), Breedon et al. (2012), and Martin and Milas (2012), these studies, like those on the effects of US quantitative easing, have primarily examined the effects on prices and returns. This section explores how QE affects stock and bond market volatility. According to Tobin (1969) and Vayanos and Vila (2009), the portfolio balance and signalling channels provide the theoretical underpinnings for QE's impact on financial markets. By decreasing the supply of safe assets, QE lowers yields and incentivises investors to shift their portfolios towards riskier products. Long-term market stabilisation is anticipated as a result of this reallocation, but its impact on immediate volatility is more complicated. Empirical research shows that the timing, character, and market perception of QE announcements can have both stabilising and destabilising effects.

The behaviour of stock market volatility has been significantly impacted by QE, with a complex interaction between short-term increases during the announcement and implementation stages and long-term stabilising impacts. A huge amount of research demonstrates how announcement effects, investor behaviour, and local economic variables all influence how sensitive stock markets are to quantitative easing. Mamaysky (2018) found that implied volatility and equity prices both respond strongly to QE announcements, with volatility frequently peaking the day before and staying high for several weeks. This implies that market players predict policy moves, which generates speculation before announcements. With their high-frequency examination of US stock markets, Corbet et al. (2019) supported this, demonstrating that surprise QE announcements cause significant increases in volatility, especially in the hours immediately after the announcements. Their results highlight how surprise might increase short-term fluctuations in the market. The literature frequently discusses how central bank transparency affects volatility. Papadamou et al. (2017a) showed that central bank independence and stock market stability are positively correlated, highlighting the idea that uncertainty can be decreased by clear and consistent communication. In the UK, where operations were expected, Joyce et al. (2011) found that volatility reactions to BoE QE announcements were modest. On the other hand, as markets react to new information, unexpected policy actions—like those outlined by Corbet et al. (2019) —tend to cause sharp increases in volatility. Understanding of volatility dynamics has been significantly enhanced by high-frequency and intraday analyses. Stock markets frequently see a significant reaction in the pre-announcement phase, according to Evans and Speight (2010) analysis of the intraday effects of macroeconomic announcements, including QE. This is consistent with research by Hudepohl et al. (2021), who found that stock prices in Eurozone markets saw euphoric spikes in response to QE announcements, with volatility highest in the lead-up to and immediately following the announcement. The importance of timing and market expectation in influencing volatility reactions is demonstrated by these researches.

International markets are also impacted by QE's impact on stock market volatility. Albu et al. (2016) noted that Central and Eastern European (CEE) stock markets had notable volatility in response to QE announcements in developed markets, such as the UK and Eurozone. These impacts, which were most noticeable the day after the announcements, demonstrated how intertwined the world's financial institutions are and how QE affects less developed markets. Apostolou and Beirne (2017) found that QE spread volatility spillovers to developing markets in large economies including the US and Europe. According to Shogbuyi and Steeley (2017), BoE QE operations in the UK enhanced the correlation between the US and UK stock markets. This emphasises how intertwined the world's financial markets are, and how stability brought about by QE in one area can lead to instability in another. The situation is made more difficult by regional variations in stock market volatility. Although research from the UK indicates that QE has a stabilising long-term impact on equity markets, data from other areas shows conflicting results. Barbon and Gianinazzi (2017), for example, discovered that QE resulted in long-term decreases in stock market volatility in Japan. Albu et al. (2016), on the other hand, noted notable, although transient, spikes in volatility in CEE markets after ECB QE announcements. These results highlight how local economic factors and market systems mediate the effects of QE.

In order to analyse the effect of QE on stock market volatility, sophisticated modelling approaches have been essential. Asymmetrical volatility effects were discovered by Corbet et al. (2019) using EGARCH models, wherein negative surprises caused larger volatility spikes than positive surprises. In a similar vein, Kenourgios et al. (2015) used high-frequency data to show that markets with credible monetary policy frameworks had more muted volatility responses, indicating that the effect of QE depends on how well policy implementation is regarded.

There is also evidence of an inverted V-shaped influence on long-term patterns of stock market volatility under QE. Although volatility rises just following QE announcements, it progressively falls over several months as markets adapt to the new policy, according to Balatti et al. (2016). The theoretical notion that QE lowers risk premia and promotes long-term stability after initial uncertainties are eliminated is supported by this pattern. Shogbuyi and Steeley (2017) discovered that BoE QE programs successfully decreased equities market volatility over the long run in the UK. The study did, however, also point out particular days throughout QE operations when volatility temporarily increased, primarily due to uncertainty around the timing and volume of asset purchases. This demonstrates the double effect of QE, as stabilising liquidity injections offset transient volatility brought on by operational uncertainty. QE's effect on volatility is further amplified by its wider effects on investor behaviour and risk appetite. According to Hudepohl et al. (2021), QE announcements frequently set off speculative bubbles, which boost long-term confidence and price stability while causing short-term volatility surges. These results support those of Mamaysky (2018) and Corbet et al. (2019), which highlight how QE shapes both short-term and long-term market dynamics.

One of the most obvious and extensively researched effects of QE is a decrease in bond yields. When D’Amico and Seida (2024) examined how Treasury yields were affected by QE and QT surprises, they discovered asymmetrical reactions, with QT having a greater impact on rates. Their analysis also showed that, in contrast to predictions of diminishing returns, QE announcements maintained a significant influence on yields over time. Volatility is exacerbated by these impacts when there is increased uncertainty surrounding interest rate decisions. Joyce et al. (2012) examined the Bank of England's (BoE) quantitative easing program and shown that asset purchases, mostly through the portfolio balance channel, lowered medium- to long-term gilt rates by as much as 100 basis points. Similarly, Krishnamurthy and Vissing-Jorgensen (2011) showed that US QE programs lowered Treasury yields through inflation, signalling, and demand for long-duration safe assets. The ways via which QE reduces yields and improves market stability are highlighted in these publications. This research was extended by Lucca and Wright (2024) to Australian Treasuries with a yield curve control (YCC) strategy. Their results demonstrated that although QE is effective in reducing targeted yields, there is little effect it has on other financial instruments. They explained this to the dominance of liquidity effects on channels of signalling and portfolio balance.

The volatility of the bond market is known to be reduced by QE. Eser and Schwaab (2016) showed that the ECB's Security Market Programme (SMP) considerably decreased yield volatility across a range of maturities using high-frequency intraday data. According to their GARCH (1,1) models, volatility significantly decreased during active QE periods, particularly in markets for stressed government bonds. Further investigating the implications of asymmetric volatility under QE, Eric Ghysels (2017) discovered that ECB interventions had stabilising effects on sovereign bond markets that were statistically significant. Similar outcomes were noted in De Santis (2020), where price fluctuations in government debt markets declined and volatility was reduced by unconventional monetary policy. QE counteracted the sixfold increase in bond volatility that occurred during the financial crisis, according to Steeley and Matyushkin (2015) analysis of the UK gilt market. Intriguingly, they observed that shorter-term bonds were more susceptible to QE operations, whereas longer-term bonds had a faster decline in volatility than short- to medium-term bonds. In their analysis of US QE spillovers to overseas bond markets, and Yang and Zhou (2016) found that there were notable transmissions of volatility to foreign markets, especially in the early stages of QE. Their analysis highlighted the systemic consequences of US QE by showing that 40–55% of the increased global bond volatility was directly caused by it.

There are several ways that QE affects bond market volatility. In order to compress yields and stabilise prices, central bank purchases lower the supply of long-duration assets, as explained by the portfolio balance channel (Tobin, 1969; Vayanos and Vila, 2009). According to Joyce et al. (2012) and Eser and Schwaab (2016), this channel is a major factor in suppressing volatility, especially in times of crisis. Additionally, signalling effects are essential for stabilising markets by establishing expectations about future interest rates. According to Krishnamurthy and Vissing-Jorgensen (2012), channels of signalling had a crucial role in lowering yield volatility by lowering uncertainty. By demonstrating that liquidity effects predominate in segmented markets and reduce price volatility more effectively than other routes, Lucca and Wright (2024) expand on this notion. Liquidity and scarcity effects also influence how QE affects bond market volatility. In their analysis of the Japanese government bond market, Han and Seneviratne (2018) discover that because of scarcity effects, large-scale central bank purchases decreased liquidity in targeted assets. Similarly, Grimaldi et al. (2021) pointed out that the stabilising effects of QE are countered by scarcity effects, which increase volatility as central bank holdings beyond specific thresholds. When Nozawa and Qiu (2021) study corporate bond markets during the COVID-19 epidemic, they discovered that while QE had a mixed impact on volatility driven by liquidity, it decreased default risk. These results demonstrate the fine line that must be drawn between maintaining market stability and introducing inefficiencies through asset scarcity

3. Quantitative Easing and the Cost of Issuing UK Government Debt[9]

3.1. Introduction

The economic downturn and fluctuation in the last three years with the beginning of subsequent enforced lock down of social and economic activity in countries around the world, in the face of the global spread of the SARS-CoV-2 virus, was met with economic policy responses unprecedented in both scale and nature. On March 19th 2020, the Bank of England's Monetary Policy Committee agreed to cut the policy interest rate to 0.10%, having already reduced it from 0.75% to 0.25% some 8 days earlier. With the agreement of H.M. Treasury, the committee also increased the limit of asset purchases through the creation of new central bank reserves, the process known as Quantitative Easing (QE), from £445 billion to £745 billion. On March 31st 2020, the UK Debt Management Office (DMO) announced a change to the funding remit for 2020/21, including a three-fold increase in the total planned issuance for April 2020 (DMO, 20th March 2020) through a doubling of the number of auctions per week and an increase in the average size of auctions. In response to the scale of the Covid-19 crisis, the Committee voted unanimously for the Bank of England to increase the APF by an additional £150 billion under QE5 to £895 billion on November 5, 2020. In December 2021, prices had risen by 5.4% compared to a year ago. As result of inflation growth, MPC announced a decision to increase the Bank rate by 0.15 percentage points, to 0.25%, and maintain the total target stock of asset purchases at £895 billion on December 16, 2021. In order to control inflation, The Committee voted in February 2022 for the Bank of England to reduce the stock of UK government bond purchases by ceasing to reinvest maturing assets. As a result, the phase of Quantitative Tightening (QT) started on February 3, 2022, and the Bank rate was increased to 0.5% on this date. The bank rate increased from 0.5% in February 2022 to 3.5% in December 2022. Our research seeks to address the question of what impact this rise in activity, precipitated by the dramatic policy and remit changes, has had on the costs of issuing government debt.

This research question is important because the debt management objective, as set out in the 'Charter for Budget Responsibility' (HM Treasury, November 2022), is:

““to minimise, over the long term, the costs of meeting the government's financing needs, taking into account risk, while ensuring that debt management policy is consistent with the aims of monetary policy.”

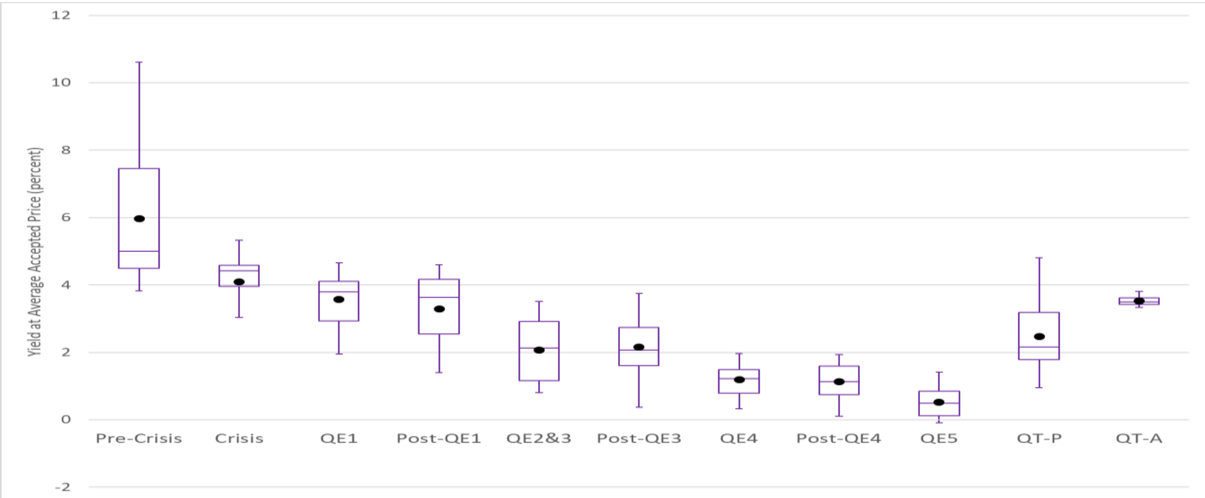
The main cost elements are the payments of coupon and repayments of principal, where coupon rates on new issues are set at or around the prevailing level of interest rates. Here is the distribution of yields

9 A paper co-authored with James Steeley, and based upon some of the work in this chapter, has been presented in early draft at the Annual Brunel Banking conference and at the Annual Financial Market Liquidity conference in Budapest, both in 2023, and that the most recent version is under review at the JMCB

at issue on gilts since 1987. Yields have been low in recent times, but have recently increased dramatically

Figure 1: Auction Yields

The box plots show the distribution of the auction yield (in percent) at the average accepted auction price for all conventional gilt auctions from May 1987 to December 2022 during each of the sub-periods indicated. Y-axis unit is % (percentage points). The boxes measure the median and inter-quartile range (IQR) of the distribution, while the whiskers measure the furthest data points within 1.5 IQR of the outer quartiles. The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive. (Data source: UK DMO). (https://www.dmo.gov.uk/data/gilt-market/)



our analysis seeks to explain auction concession by reference to various bond and prevailing market characteristics, such as liquidity, volatility, auction size, demand, APF activity, benchmark status and maturity.

This work has connections to multiple sovereign debt study fields. Understanding why investors purchase government bonds is one topic of study. The mean-variance model states that investors in foreign bonds want to minimise risk for a given return or maximise portfolio return for a given level of risk. As a result, when bond risk rises in comparison to other investments, a higher interest rate is generally expected. Real-world bond markets are complex, though. According to research by Vayanos et al. (2009), some investors, irrespective of risk, seem to prefer particular bond maturities. These investors affect the demand for government bonds and the interest rates they carry, together with other investors who seek to maximise profits for a particular level of risk.

Our research adds to the body of knowledge already available on sovereign debt auction pricing. Bidder competition and auction results have been linked in the past by studies like Spindt and Stolz (1992), which show that more participants can result in higher stop-out prices and lower under-pricing. While Cammack et al. (1991) examine the effects of bid-to-cover ratios and bidder competition on auction prices and secondary market performance, the degree of under-pricing in discriminatory and uniform price auctions for US government bonds is compared by Goldreich (2007). In addition, research on the complexity of sovereign debt auctions under varied market circumstances, such as repurchase plans and quantitative easing, has been conducted by Nyborg et al. (2002) , Mann and Klachkin (2015), and Song and Zhu (2018). These studies emphasise how investor behaviour and macroeconomic conditions affect auction results, and they frequently use multi-item, multi-unit auction structure.

Our findings also have implications for research on the interaction between the primary and secondary sovereign bond markets. A number of research studies, including Han et al. (2007), have documented yield fluctuation patterns in secondary markets around primary bond auction dates, commonly known as "auction cycles", whereby yields (prices) are bid up (down) prior to auctions and then reverse afterwards. Fleming and Rosenberg (2007), Lou et al. (2013), Beetsma et al. (2016, 2018b), and Sigaux (2024) are among the authors of the research included in this study. Beetsma, Giuliodori, Hanson, and de Jong (2018) discover that, particularly in times of severe market volatility, greater competitiveness in eurozone bond auctions—shown by higher bid-to-cover ratios—can result in lesser yield changes in secondary markets. Klingler and Sundaresan (2023) examine how primary dealers affect Treasury bill yields, emphasising the significance of dealer participation costs and secondary market demand. While the effects of Quantitative Easing (QE) on secondary market outcomes—particularly reductions in yields and improvements in liquidity—have been extensively documented in the existing literature, as seen in the review of the literature in Chapter 2 section 2.1, less attention has been given to its potential impact on primary market conditions. This chapter addresses this gap by investigating whether QE also resulted in improvements in the primary market, such as enhanced demand during government bond auctions, reflected in metrics like the bid-to-cover ratio and auction concession.

The remainder of the chapter proceeds as follows. In the next section, the variables applied in the model are described with a short explanation of our motivation to explain the reason of using it in the model. This is followed by the presentation of our model in Section 3. The next section presents the results of the estimated baseline regression framework and a brief discussion to interpret the results. In section 5, we apply the baseline model to auctions that were secondary issuance and compare the results with the previous section. Section 6 presents the QE period results for baseline estimation and introduces further variables only available in this period. This section also presents the results of the baseline regression model estimated separately for secondary issuance. Section 7 provides an analysis of maturity segmentation in which we apply the model across the different maturity segments to find whether there are segmentation premia in different sectors of the conventional gilt market in regard to the issuance cost. Furthermore, we repeat the analysis for secondary issuance within different maturity segments, and the findings are interpreted in comparison with the results of all issuance. Section 8 concludes the main body of the chapter. An appendix section provides some interesting robustness checks which confirm the results reported in the body of the chapter. We examine whether the results are sensitive to defining the explanatory variables on a maturity segmented basis. Next, we re-examine the QE period when the explanatory variables are also defined on a maturity segmented basis. The appendix also contains an analysis of the auctions that are considered to have outlier values of issuance concessions, and an explanation of how the financial conditions index used as an explanatory variable was created.

3.2. Data

In this section, we outline the data and the methods applied to construct the dependent and independent variables. Data is collected in relation to all conventional gilt auctions that occurred from the first auction in May 1987 through to 31st December 2022, from the UK Debt Management Office (DMO) website, DataStream, and the Bank of England. Over the sample period, there were 779 conventional gilt auctions comprising 86% by nominal value of conventional gilt gross issuance. The other current methods include syndication (managed book building through dialogue with investors), tender (small scale auctions) and direct issuance to the DMO.[10] Table 1 indicates the details of methods through which gilts were issued over the sample period.

Table 1: Gilt Issuance

This table summarizes all conventional gilt issuance that occurred between May 1987 to December 2022, and the source of the data is the DMO. (https://www.dmo.gov.uk/data/gilt-market/)

Issuance Method	Number of Issuance	Total Amount Issued (£ million)	Percentage
Auction	779	2,244,373	86%
Conversion	37	41,233	2%
Special Switch Facility sell	1	200	0%
Switch Auction sell	6	11,255	0%
Syndication	41	229,000	9%
Tap	32	9,100	0%
Tender	93	87,200	3%
Grand Total	989	2,622,362	100%

3.2.1. Concession Cost

The approach to measuring costs here is to examine the auction price concession, which is the difference between the average accepted price at the auction and the price that the gilts could have otherwise been sold in the secondary (or when-issued) market, multiplied by the size of auction, and so provides a measure of the cost of issuance. From 2002 to 2014, the DMO measured the secondary market price as the closing clean price on the day before the auction. After 2014, the DMO measured the secondary market price by the mid-price at the time of the auction. The data was provided to us by the DMO for time period 2002 to 2022. To obtain the concession cost for the time-period 1987 to 2002,

[10] In the early years of gilt auctions, gilts were also issued through "tap" sales and fixed price offers for sale (also known as a tender). New gilts were also created through the conversion of maturing convertible gilts or through switch auctions whereby holdings of one gilt could be switched into another. Tenders, which commenced in 2008 in their current form, were a response to the Treasury's activities to recapitalize the banking sector during the financial crisis. Syndications, which had first been used in 2005 to launch a long maturity index-linked gilt, were first used for conventional gilts in June 2009.

we multiply the size of auction by the difference between the clean close price on the day before auction obtained from Data-Stream and the average price at auction collected from the DMO website. This is consistent with the pre-2014 DMO method of calculation. Since Data-Stream does not have intra-day price data for gilts, it is not possible to use the post-2014 DMO definition. This means that for primary issuances occurred before 2002, we are not able to measure the concession cost. [11] As a result of this, the number of observations declined from 779 to 756.

Table 2 shows the average concession (if negative, or premium if positive) and average auction size for all 756 conventional gilt auctions, where we sub-divide the sample into the following sub-periods: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022

Table 2: Auction Concession and Auction Size

This table contains the average auction size (£ million), the number of auctions, the average auction concession (£ million) and the issuance cost (-) or premium (+) as a percentage of the average auction size. For the time-period 1987 to 2014, the concession cost is measured by multiplying the size of auction by the difference between the average price at auction and the clean close price on the day before auction. After 2014, the concession cost is measured by the difference between the average price at auction and the mid-price at the time of the auction, multiplied by the auction size. Since the data provided by DMO is only available from 2002 to 2022, we obtained the data from Data-Stream before 2002. The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive.

Statistic	Average Auction Size (£m)	Average Concession (£m)	Percent cost (-) premium (+)	Number of Auctions
Pre-crisis	2438	-3.128	-0.13%	138
Crisis	2867	-5.936	-0.21%	47
QE1	3767	-1.649	-0.04%	40
Post-QE1	3375	-0.195	-0.01%	59
QE2 and 3	3207	-3.920	-0.12%	38
Post-QE3	3068	0.167	0.01%	105
QE4	2574	1.610	0.06%	17
Post-QE4	2708	1.365	0.05%	95
QE5	2821	1.264	0.045%	178
QT-P	2998	1.256	0.04%	29
QT-A	3324	2.122	0.06%	10
Full Sample	2881	-0.635	-0.022%	756

For the gilts considered collectively across the whole sample period, the average concession is £0.635 million, or 0.022% of the average issuance size. However, during the period of the financial crisis, the average concession was more than double that of most of other periods, and since the onset of QE1 has decreased to £0.195 million. During Post-QE4, debt issuance appeared to earn a premium

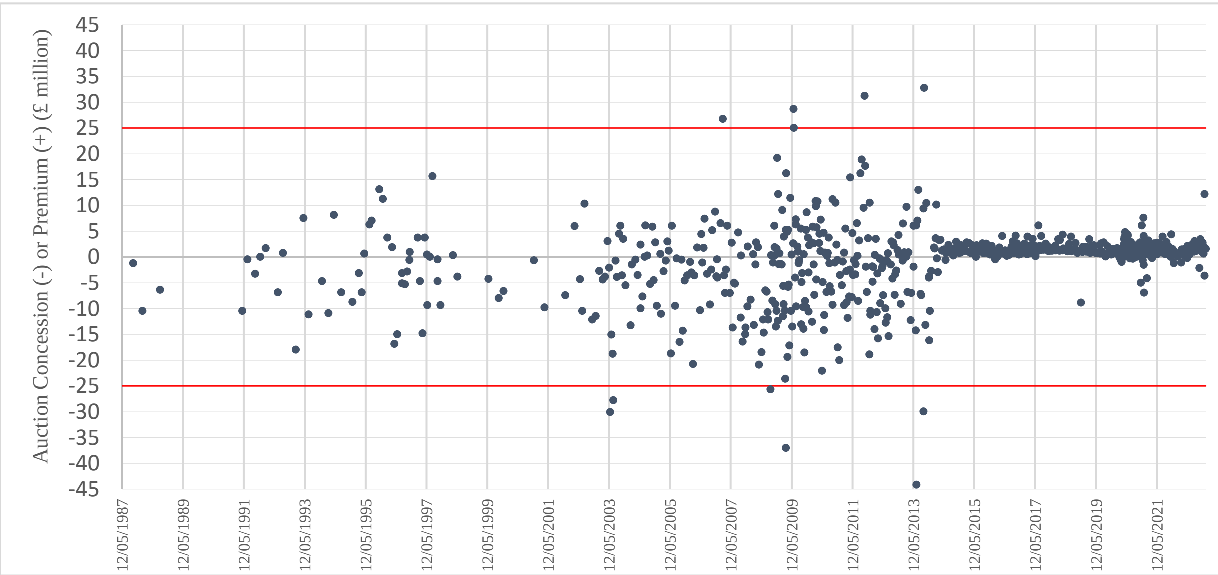
[11] There is no missing data for primary gilt issuance after 2002, since the data was provided by DMO.

and has remained positive until the end of sample. However, this sign change is the result of the modification in DMO's definition of concession costs after 2014. Figure 2 shows the impact of the DMO's definition on concession cost. Auctions with a concession or premium greater than £25 million (11 auctions), which is around 4 standard deviations from the mean, are considered as outliers.

We undertake a between-subjects ANOVA of the difference in average concession across the eleven different time periods in our sample period, and we find that average concession is not constant across the sub-periods ($p < 0.01$, Table 28). We also apply the Tukey Honestly Significant Difference (HSD) tests to make pair-wise comparisons for all gilts. The results show that the average concession during the crisis is significantly greater than all of the sub-periods, however this difference is not significant for QE2and3 (Table 30). We also find that the average concession during the pre-crisis and QE2and3 is significantly more expensive than the sub-periods including post-QE3, post-QE4, QE5, and QT-P. However, this might be due to the modification in DMO's definition of concession costs after 2014. Applying only the pre-2014 definition of the DMO during the entire sample period, the outputs of pair-wise comparisons confirm that the average concession during the crisis is statistically more expensive than some of sub-periods, such as post-QE1, post-QE3, QE4, and QE5 (Table 31). Furthermore, the results of an ANOVA applied to the Concession 2, applying only the pre-2014 definition of the DMO during the entire sample period, are that the sub-sample period variation is a significant determinant of the average auction concession ($p < 0.01$, Table 29).

Figure 2: Auction Concession

Figure 2 presents a scatterplot of the auction concession for all conventional gilt auctions conducted between May 1987 and December 2022. For auctions between 1987 and 2014, the concession cost is calculated by multiplying the auction size by the difference between the average price at auction and the clean closing price from the previous day. From 2014 onwards, it is measured using the difference between the average auction price and the mid-price at the time of the auction, also scaled by the auction size. Data from 2002 to 2022 were obtained from the UK Debt Management Office (DMO), while data prior to 2002 were sourced from DataStream. Observations falling outside the red lines (±£25 million) are classified as outliers. The y-axis indicates the auction concession or premium in millions of pounds (£ million), and the x-axis represents the auction dates in DD/MM/YYYY format.



In order to compare the auction concession under the effect of QE across the twelve different time periods in our sample period, the auction concession is recalculated by applying only the pre-2014 definition of the DMO during the entire sample period. The results of average concession given in Table 3 show that during QE4, debt issuance appeared to earn a premium and QE5 period has seen concessions around 0.023% on average. This reduction in concession during QE4 and QE5 is also seen in Figure 3 that shows the distribution of concessions for each of the eleven sub periods. It can be seen that during QE4 and QE5, more than half of debt issuance has earned a premium.

Table 3: Auction Concession (pre-2014 definition) and Auction Size

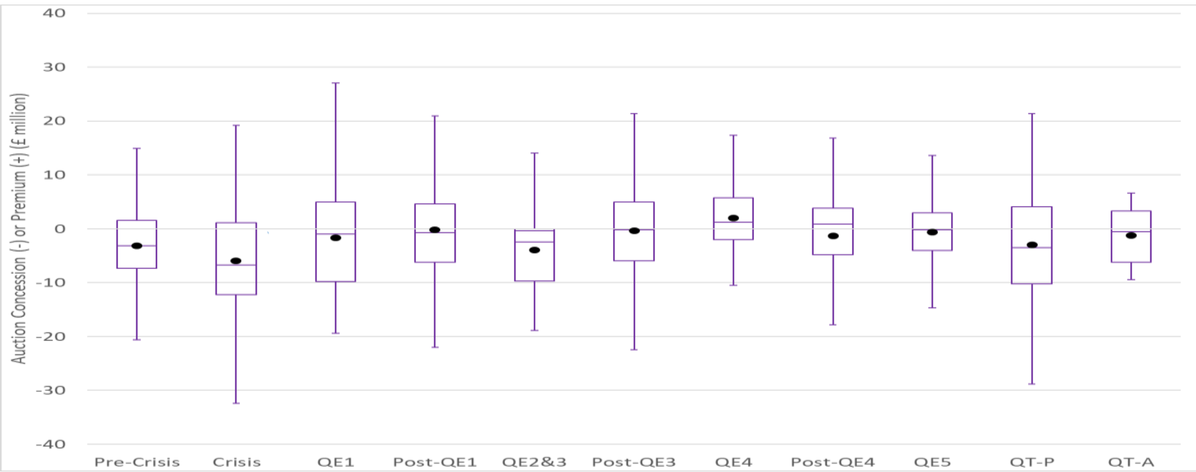
This table contains the average auction size (£ million), the number of auctions, the average auction concession (£ million) and the issuance cost (-) or premium (+) as a percentage of the average auction size. The concession cost is measured by multiplying the size of auction by the difference between the average price at auction and the clean close price on the day before auction. From 2002 to 2022, the data was provided to us by the DMO, and before 2002, the data is obtained from Data-Stream. The sub-periods are defined in and prior to Table 2.

Statistic	Average Auction Size (£m)	Average Concession (£m)	Percent cost (-) premium (+)	Number of Auctions
Pre-crisis	2438	-3.128	-0.13%	138
Crisis	2867	-5.936	-0.21%	47
QE1	3767	-1.649	-0.04%	40
Post-QE1	3375	-0.195	-0.01%	59
QE2 and 3	3207	-3.920	-0.12%	38
Post-QE3	3068	-0.394	-0.01%	105
QE4	2574	1.980	0.08%	17
Post-QE4	2708	-1.330	-0.05%	95
QE5	2821	-0.640	-0.023%	178
QT-P	2998	-2.964	-0.10%	29
QT-A	3324	-1.264	-0.04%	10
Full Sample	2881	-1.698	-0.059%	756

Figure 3 show the distribution of the auction concession which is measured by applying only the pre-2014 definition of the DMO, and so the mean data points correspond to those in table 3.

Figure 3:Auction Concession

This figure displays box plots illustrating the distribution of auction concessions for all conventional gilt auctions from May 1987 to December 2022, segmented by different sub-periods (Pre-Crisis, Crisis, QE1, Post-QE1, QE2and3, Post-QE3, QE4, Post-QE4, QE5, QT-P, and QT-A). The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive. Concession cost is calculated by multiplying the auction size by the difference between the average auction price and the clean closing price from the previous day. Each box represents the interquartile range (IQR), with the horizontal line indicating the median, and whiskers extending to the most extreme data points within 1.5 IQR of the outer quartiles. The black dots denote the mean concession for each sub-period. The y-axis is labelled "Auction Concession (–) or Premium (+) (£ million)," and the x-axis shows the different sub-periods. Data source: UK Debt Management Office (UK DMO).



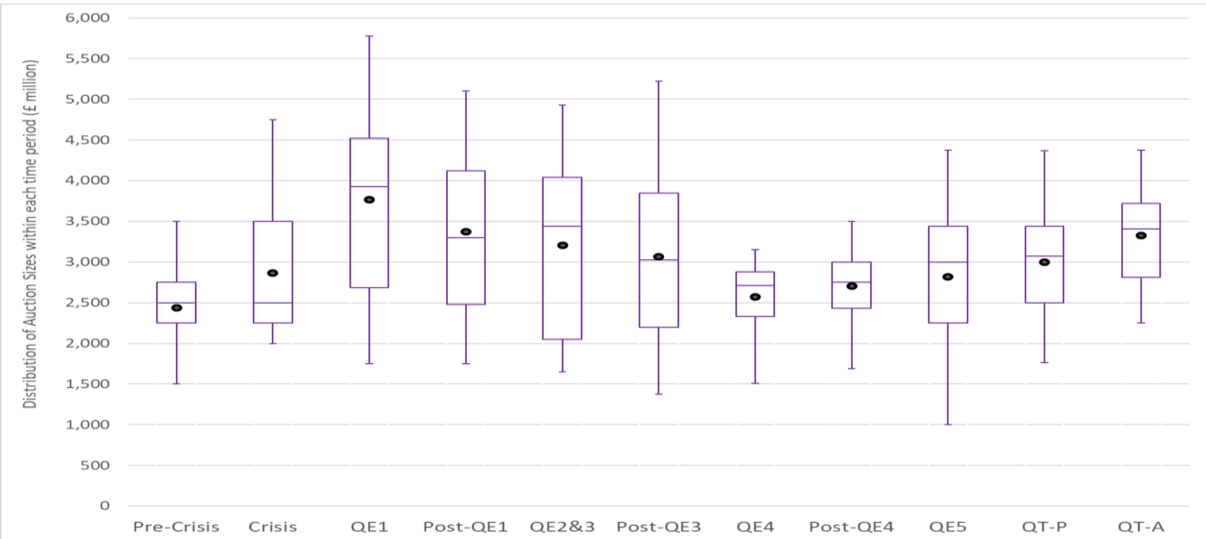
3.2.2. Auction Size

The first of the independent variables that I will examine is auction size, which captures the relative liquidity of the auction, and is measured by the natural log of auction size. This is motivated by the Nyborg et al. (2002) findings that the size of an auction significantly increases the dispersion of bids but lowers the auction discount and Lou et al. (2013) illustrating that the V-shaped pattern is more evident within larger auction sizes. The data is collected from the DMO website.

Table 2 also shows the average auction sizes during the different time periods, where we can see that even though the DMO announced an increase in average auction sizes on March 31st 2020, during QE5, this has not yet fed through to larger average auction sizes than had been experienced during the first phase of QE. The distribution of auction sizes is shown in Figure 4, where it can be seen that during phases of QE, the mean auction size is clearly below the median auction size.[12]

Figure 4: Auction Size

This figure displays box plots illustrating the distribution of auction sizes for all conventional gilt auctions from May 1987 to December 2022, segmented by different sub-periods (Pre-Crisis, Crisis, QE1, Post-QE1, QE2and3, Post-QE3, QE4, Post-QE4, QE5, QT-P, and QT-A). The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive. Each box represents the interquartile range (IQR), with the horizontal line inside the box indicating the median auction size within each sub-period, while the whiskers extend to the furthest data points within 1.5 IQR of the outer quartiles. The black dots indicate the mean auction size. The y-axis is labelled "Distribution of Auction Sizes within each time period (£ million)," and the x-axis shows the corresponding sub-periods. Data source: UK Debt Management Office (UK DMO).



The reduction in the size of auction from the start of QE4 shown in Figure 4 is the result of the changes to issuance procedures were made in time for the 2016/17 financial year as discussed in the literature (section UK Gilt Auctions).[13] While average auction size is significantly lower than it was in

12 Summary statistics for all the independent variables are in section 2.11.

13 Further changes to issuance procedures were made in time for the 2016/17 financial year, including a reduction in the size of auctions, a more responsive auction calendar, an increase in the post auction option facility (where successful bidders can bid for additional stock at the weighted average accepted price) from 10% to 15% of the bidder's competitive allocation, and an increase in the non-competitive bid allowance for Gilt-edged Market Makers (GEMMs) from 10% to 15% (Debt Management Office, 2017).

QE1 ($p<0.01$), it had been trending downward thereafter and is not significantly different from its level in either QE2and3 or QE5 ($p>0.17$). Hence, to fully capture the continuous variation in auction size that reflects on-going changes in issuance practices, no explicit modelling of these changes to auction size in the following regression analysis is undertaken.

3.2.3. Benchmark Status

We consider a variable that takes the value unity if the issuance is of or into a 5,10- or 20-year benchmark issue and zero otherwise, reflecting the liquidity of the stock. This is included as an explanatory variable since Breedon and Ganley (2000) discover that bonds having benchmark maturities typically are traded at a higher price than identical non-benchmark bonds. Due to this effect, an auction may appear to undervalue a security.

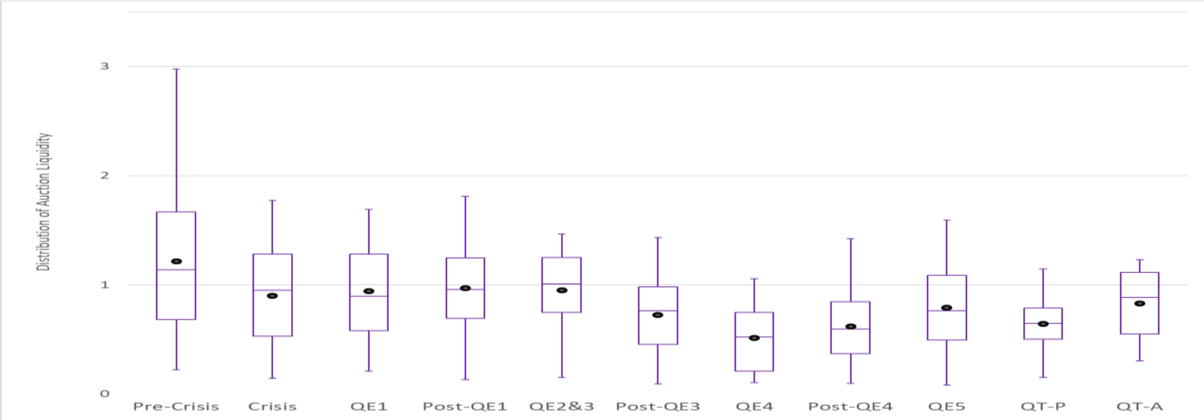
3.2.4. Liquidity of the gilt

This variable captures the liquidity of the outstanding issue by measuring the size of the outstanding gilt that is being auctioned (including the auctioned amount) divided by the average size outstanding of all other (conventional) gilts, on the auction day. This is important to the bond issuance since a decline in secondary market liquidity could lead to a decline in primary market liquidity, which could result in higher issuance costs. Furthermore, Song and Zhu (2018) and Schlepper et al. (2020) find that the condition of liquidity affects purchase decisions of portfolio managers.

The distribution of auction liquidity is shown in Figure 5, where liquidity had deteriorated during the financial crisis prior to the commencement of QE, and improvements in the liquidity of the outstanding issue are observed during time periods QE1 and QE5.

Figure 5: Liquidity of the Gilt

This figure presents box plots showing the distribution of gilt liquidity for all conventional gilt auctions from May 1987 to December 2022, segmented by different sub-periods (Pre-Crisis, Crisis, QE1, Post-QE1, QE2and3, Post-QE3, QE4, Post-QE4, QE5, QT-P, and QT-A). The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive. The liquidity variable captures the liquidity of the outstanding issue and is calculated as a ratio: the size of the gilt being auctioned (including the auctioned amount) divided by the average size outstanding of all other conventional gilts on the day of the auction. A ratio of 1.0 indicates that the size of the gilt being auctioned is equal to the average size of all other conventional gilts, while values above or below 1.0 suggest relatively larger or smaller auctioned gilts compared to the market average. Each box represents the interquartile range (IQR), with the horizontal line indicating the median value, and whiskers extending to the furthest data points within 1.5 IQR of the outer quartiles. The black dots denote the mean liquidity for each sub-period. The y-axis is labelled "Distribution of Auction Liquidity," and the x-axis shows the relevant sub-periods. Data source: UK Debt Management Office (UK DMO).

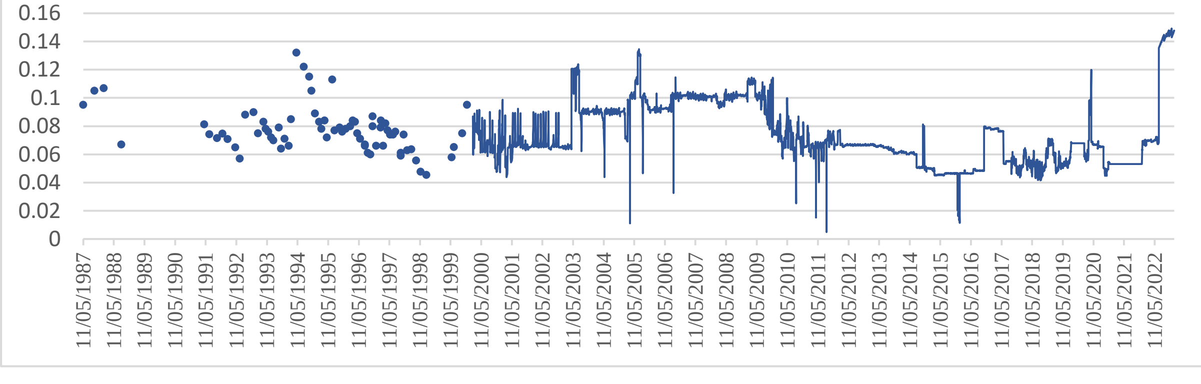


3.2.5. Volatility

We measure volatility by using the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract on a day before the auction. It is designed to measure information dispersion and risk, and has potential effects on the cost of issuance as a result of the research conducted by Beetsma et al. (2020) documenting that the volatility of the corresponding futures options was negatively correlated with the bid to cover ratio measured as the entire amount of bid during an auction divided by the total amount of new debt allocated. The implied volatility data is collected from DataStream. Figure 6 shows gilt market volatility which is fluctuating extremely, and the years 2021 to 2022 get to the highest peaks of market volatility.

Figure 6: Volatility

This figure shows the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract. The data consist of daily observations from 2000 onward, sourced from DataStream, and the data from 1987 to 2000 by auction is based on hand-collected data from Ahmad and Steeley (2008). The implied volatility is expressed as an annualized standard deviation of returns; for example, a value of 0.1 corresponds to an annualized return volatility of 10%.

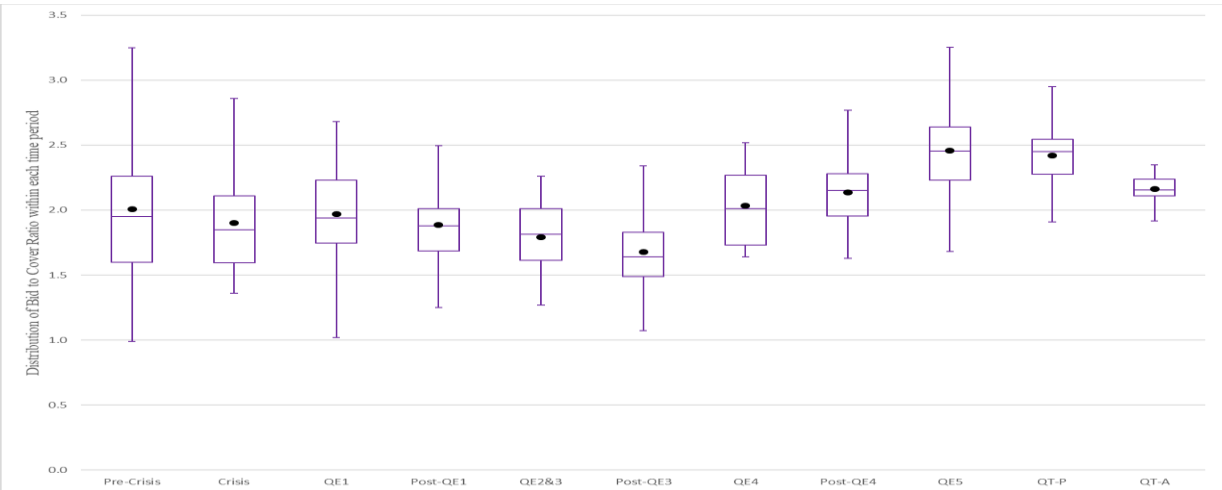


3.2.6. Demand for Gilts

This variable is a measure of market demand is measured by the bid to cover of the last auction, that is, the entire amount of bid during that previous auction divided by the total amount of new debt allocated at that previous auction. Spindt and Stolz (1992) note that the more participant bids at auctions leads to less under-pricing of the asset. Relatedly, Cammack (1991) proves that a higher bid-to-cover ratio reduces the under-pricing in the auction. Demand at an auction is measured by the bid to cover ratio of the previous auction. If two consecutive auction days within the sample period feature two auctions each, we use the bid-to-cover ratio of the previous auction of the gilt with the closest maturity duration. However, if the previous auction day features only one auction, we use the bid-to-cover ratio of that gilt for both gilts auctioned on the subsequent auction day. Figure 7 shows that the average bid to cover ratio dropped during the crisis, and after the first phase of QE decreased slightly. However, it had upward trend from QE4 until the last phase of QE.

Figure 7: Bid to Cover Ratio

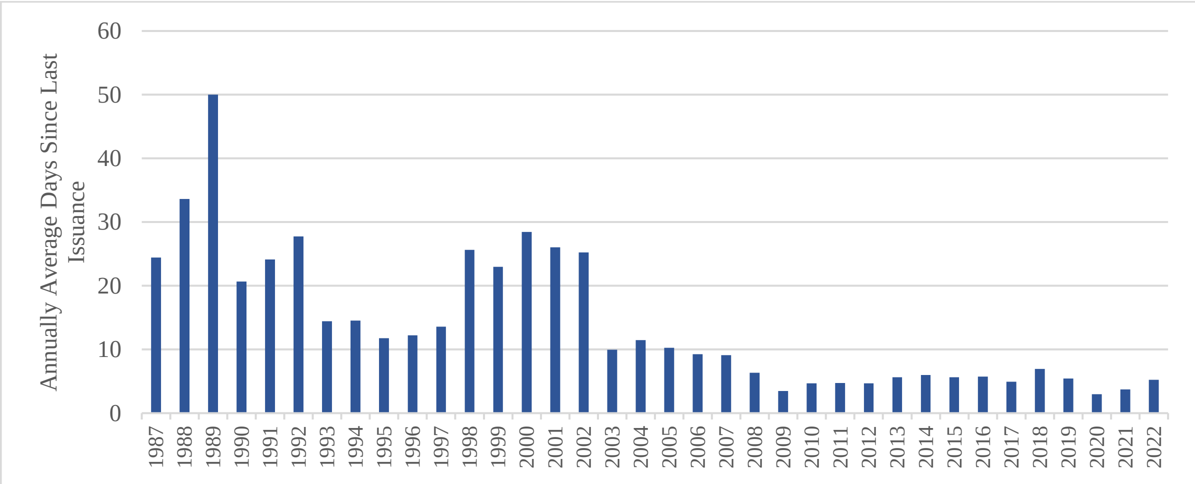
This figure presents box plots showing the distribution of the bid-to-cover ratio for conventional UK gilt auctions from May 1987 to December 2022, segmented by different sub-periods (Pre-Crisis, Crisis, QE1, Post-QE1, QE2and3, Post-QE3, QE4, Post-QE4, QE5, QT-P, and QT-A). The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive. Each box represents the interquartile range (IQR), with the horizontal line indicating the median, whiskers extending to the furthest data points within 1.5 IQR of the outer quartiles, and black dots showing the mean value. The y-axis is labelled "Distribution of Bid-to-Cover Ratio within each time period (the value of 1.0 means the value of bids equals the value of stock being auctioned. A value of 2.0 means that bids were double the auctioned amount)," and the x-axis represents the sub-periods. Data source: UK Debt Management Office (UK DMO).



We also design another variable that measures gilt market activity and demand for the bonds. It is the natural log of the number of days since the last conventional gilt issuance. The average days since the previous issuance since 1987 is shown in Figure 8, where the increase in market activity as a result of the Covid-19 government policy responses is clear. Figure 8 also depicts an additional spike in market activity throughout 2009, which is the consequence of responses to the financial crisis.

Figure 8: Annually Average Days since Last Issuance

This figure presents a bar chart showing the annual average number of days between successive conventional gilt issuances from 1987 to 2022. The variable captures the average waiting period between auctions in each calendar year, serving as a proxy for issuance frequency. A higher value indicates less frequent issuance activity. The y-axis is labelled "Annually Average Days Since Last Issuance (trading days)," and the x-axis shows each year within the sample period. This measure reflects changes in the UK Debt Management Office's issuance strategy over time.



3.2.7. Gilt Market Turnover

The turnover of the Gilt-Edged Market Makers (GEMMs) is used as a measure of market liquidity. The DMO issues gilts to financial organisations entitled to as Gilt-Edged Market Makers (GEMMs), who have been designated as primary dealers for the gilt market. The GEMMs must continuously quote bid and ask prices to their clients in order to provide secondary market liquidity. The DMO is still of the opinion that the presence of GEMMs, who commit to supporting the gilt issuance programme and making effective two-way prices in the gilts, is the best way to maintain liquidity in the gilt-edged market. Preserving liquidity lowers the Government's finance costs by stimulating broad demand and investment in UK Government gilts.[14]

The DMO collects and collates the turnover data provided by the GEMMs on a weekly basis. The DMO determines total aggregate turnover volumes in terms of maturity bonds, types of gilt, and overall based on the data received from GEMMs and distinguishes between counterparties deemed to be "professional" and those deemed to be "customers".

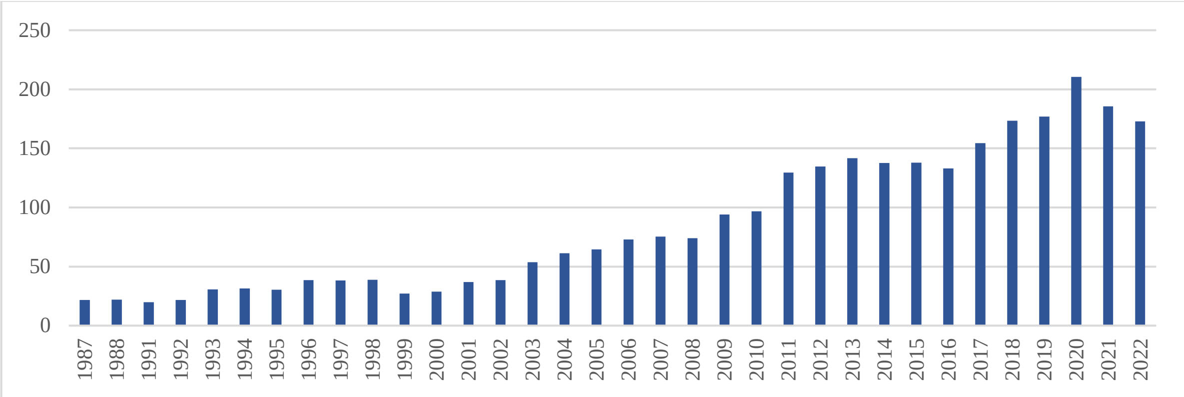
We construct a novel dataset containing gilt market turnover from 1987 to 2022. The data is available in the DMO website from 2001 to 2022. Prior to the year 2001, the data is extracted from reports' Numbers and figures published by DMO and BOE.[15] The average daily turnover is the only data that was available before 1997. However, since 1997, DMO has released aggregate turnover data on a weekly basis.[16] As a result, the observations made prior to 1997 are multiplied by 5, the number of

14 DMO (2011) "A Guide to the Roles of the DMO and Primary Dealers in the UK Government Bond Market" DMO, DMO August 2011.
15 BOE : https://www.bankofengland.co.uk/sitemap/quarterly-bulletin and DMO: https://www.dmo.gov.uk/publications
16 DMO combined turnover is the total of all consumer and business transactions conducted by GEMMs in accordance with the DMO's definition.

weekdays. Figure 9 is the annual average of “weekly aggregate GEMM market Turnover” from 1987 to 2022 and shows significant increases in the gilt market turnover during the years 2009, 2011, 2017, and 2020, continuing to reflect the raise in gilt issuance throughout these years which align with QE program in the gilt market. Overall, we can see a clear upward trend in Turnover of GEMM market.

Figure 9: Yearly Average of “weekly aggregate GEMM Market Turnover (£bn nominal)

This figure presents a bar chart showing the annual average of weekly aggregate market turnover by Gilt-Edged Market Makers (GEMMs) from 1987 to 2022, measured in billions of pounds (£bn nominal). The variable reflects the total nominal trading volume in the gilt market conducted by GEMMs, averaged across weeks within each year. It serves as an indicator of secondary market activity and liquidity conditions over time. The y-axis is labelled “Turnover (£bn nominal),” and the x-axis shows calendar years. This metric captures trends in trading intensity and institutional participation in the gilt market.



3.2.8. Post Auction Option Facility

The Post Auction Option Facility (PAOF) is a facility offered by the DMO since June 1st 2009 to all successful bidders, available during a take-up window following the auction, to buy an additional percentage of the gilt that each participant was allocated at that specific auction. We capture the presence of the PAOF at an auction by using an indicator variable.

3.2.9. Time to Maturity

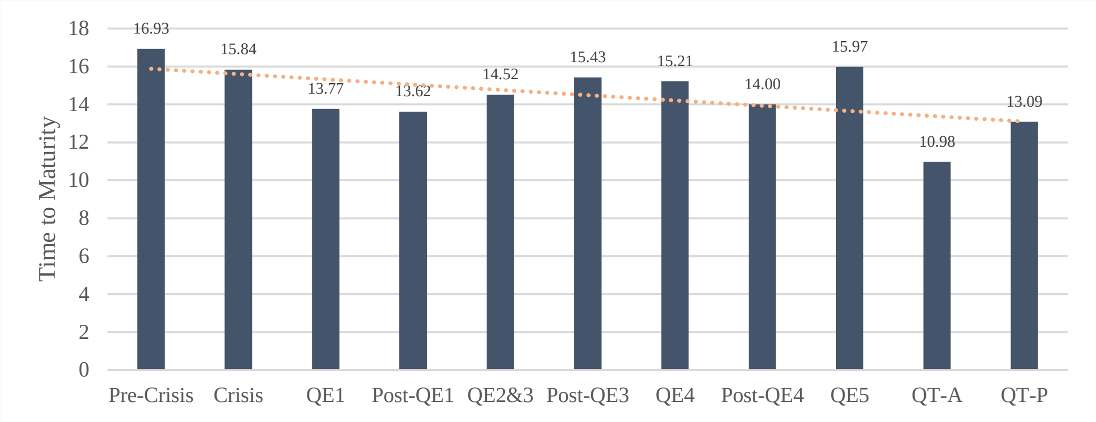
This variable is an indicator of the remaining maturity of a gilt that is being auctioned. Auction valuations may include a "term premium" that could, in part, reward the bidder for enduring this relatively high risk caused by owning long-maturity investments. Therefore, this variable captures the impact of maturity. The average of time to maturity for 779 gilts is 15.3 years. Time to maturity is measured by the following equation:

$$MAT = \frac{\text{Maturity Date} - \text{Auction Date}}{365.25} \tag{1}$$

So that time to maturity is measured in years, calculated as the number of days remaining until the gilt’s maturity date divided by 365.25. This approach ensures consistency across the sample period. In Figure 10, the values are also reported in years to match this definition.

Figure 10: Time to Maturity

This figure presents a bar chart showing the average time to maturity (in years) of newly issued gilts from May 1987 to December 2022, grouped by different sub-periods (Pre-Crisis, Crisis, QE1, Post-QE1, QE2and3, Post-QE3, QE4, Post-QE4, QE5, QT-A, and QT-P). The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive. The average is calculated based on the original maturity of gilts issued within each sub-period. The red dotted line represents the overall trend in average maturity over time. The y-axis labelled "Time to Maturity" is measured in years (365.25 days per year) and the x-axis displays the sub-periods. This measure reflects changes in the UK government's debt issuance strategy, particularly in relation to maturity preferences over different economic and policy phases.



3.2.10. Financial conditions

A financial condition index (FCI) is an index to measure stability in financial system and economy. It takes value unity if the index identifies the episodes of systemic financial distress.

We assemble a set of 20 UK financial indicators to cover a broad spectrum of potential indicators of financial condition distress including default free spread, corporate bonds spread, Asset prices, Lending, and Broad money and debt level. The variables are selected to be included in FCI according to their power to explain the variance of economic activity measured by GDP growth.[17]

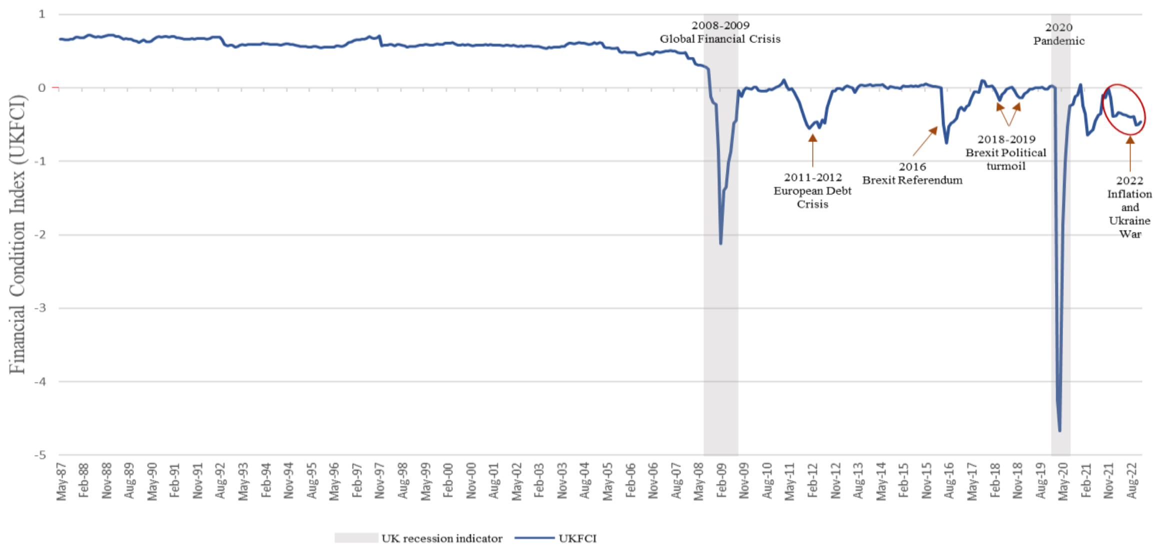
The results of the analysis suggest that the Financial Condition Index (UKFCI) is best constructed by using the following six variables: TED Spread (3-month LIBOR –3-month Tbill), £commercial paper Issuance (Relative to 24-month MA), £real effective exchange rate, Government bonds outstanding value, Investment grade corporate bond index, Stock of M0 (notes and coins and reserves).

UKFCI identifies several episodes of financial crisis, as shown in Figure 11. We discover that the financial condition had a significant downturn in 2008, which can be explained by the Global Financial Crisis, and then steadily improved, but dropped substantially in 2020, which may have been caused by the Covid-19.

[17] The complete set of variables and results are reported in appendix. (3.10.5)

Figure 11: UK Financial Condition Index

This figure shows the UK Financial Condition Index (UKFCI) from May 1987 to December 2022. Notable economic and political events are annotated, including the 2008–2009 Global Financial Crisis, the 2011–2012 European Debt Crisis, the 2016 Brexit Referendum, and the 2020 COVID-19 pandemic. The shaded areas represent official UK recession periods. The y-axis is labelled "Financial Condition Index (UKFCI)", a decline in the FCI signifies a tightening of financial conditions, and the x-axis shows the timeline.



3.2.11. Phases of QE

We design the variable *QEDUM* to be an indicator variable that takes value unity during the sub sample corresponding to the periods of asset purchase facility throughout QE, and captures the impact of QE purchase. There are seven announcements relating to commencement of phases of UK QE, explained in the previous chapter, table1. Following the 2008 financial crisis, the MPC started the program of QE through the Bank's Asset Purchase Facility in 2009, and the last episode of QE started in November 2020 as the BOE responded at pace and scale to the Covid-19 crisis. Since the last three asset purchase programmes were announced in 2020, we count them as one round of QE. The QE phases are: QE1 – March 11th 2009 to 26th January 2010; QE2and3 – 10th October 2011 to 30th October 2012; QE4 – 8th August 2016 to 1st February 2017; QE5 – 19th March 2020 to 15th December 2021; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive period in the model.

3.3. Summary Statistics

The Table 4 reports summary statistics for all the variables across the 779 auctions from 1987 to 2022. The summary statistics for all variables using the data without the observations on dates corresponding to the dates of the concession outliers in Estimation 1 and Estimation 2 are reported in the appendix (Table 22 and Table 23). A table of correlation coefficients between the explanatory variables can be found in Section 9.1 in the appendix.

Table 4: Summary statistics of main variables

This table contains the summary statistics for seven variables across 779 auctions from May 1987 to December 2022. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. VOL is the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract; the implied volatility is expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days. MAT is the time to maturity, calculated as the number of days from the auction to the gilt's maturity date divided by 365.25, and expressed in years. LIQ is the ratio of the size of the gilt being auctioned (including the auctioned amount) to the average outstanding size of all other conventional gilts on the auction day; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover ratio of the previous auction, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). Mean is the sample mean of the variable, SD is the sample standard deviation, Min and Max are the minimum and maximum observations, and p25, p50, and p75 indicate the observation in percentile 25, 50, or 75, respectively. Skewness essentially is a commonly used measure in descriptive statistics that characterizes the asymmetry of a data distribution, while kurtosis determines the heaviness of the distribution tails. Skewness is a descriptive statistics measure that characterises the asymmetry of a data distribution. Kurtosis determines the heaviness of the distribution tails. P(S) shows the P-value for skewness, and P(K) shows the P-value for kurtosis. The last column shows the means are significantly different from zero.

Variable	Observation	Mean	SD	Min	P25	P50	P75	Max	Skewness	Kurtosis	Pr(S)	Pr(K)	Ha: mean=0 Pr (|T| > |t|)
SIZE	779	7.92	0.31	6.62	7.72	7.92	8.14	8.66	-0.44	3.63	0	0	0.00
LIQ	779	0.87	0.49	0.08	0.51	0.82	1.16	2.98	0.86	4.05	0	0	0.00
ACT	779	1.77	0.96	0	1.10	1.61	2.48	4.37	0.01	2.77	0.911	0.18	0.00
VOL	779	0.07	0.02	0.02	0.05	0.07	0.09	0.15	1.17	4.17	0	0	0.00
DEM	779	2.08	0.49	0	1.72	2.06	2.38	4.81	0.57	5.05	0	0	0.00
TGEMMs	779	4.78	0.57	2.74	4.45	4.94	5.19	5.72	-1.06	3.66	0	0	0.00
MAT	779	15.3	11.9	2.12	5.5	10.16	23.21	53.3	1.05	3.13	0	0.4	0.00

3.4. Methodology

From both the theoretical and empirical literature on auction under-pricing and bid to cover ratio, we construct the following regression to identify possible determinants of auction concession. The following regression is the baseline model of our study.

$$\begin{aligned} Y_i = c + b_1 QEDUM_i + b_2 SIZE_i + b_3 LIQ_i + b_4 BENCH_i + b_5 VOL_i + b_6 ACT_i + b_7 MAT_i \\ + b_8 DEM_i + b_9 TGMMs_i + b_{10} PAOF_i + b_{11} UKFCI_i + \varepsilon_i \end{aligned} \quad (2)$$

The variable Y, representing the concession cost, is calculated as follows: for the period from 1987 to 2014, it is measured by multiplying the auction size by the difference between the average auction price and the clean close price on the day prior to the auction. From 2014 onwards, the concession cost is computed as the difference between the average auction price and the mid-price at the time of the auction, again multiplied by the auction size. $QEDUM$ is an indicator that takes value unity during the sub sample corresponding to the periods of asset purchase facility throughout QE and reflects the impact of QE activity. The variable *SIZE* is the natural log of auction size and captures the relative liquidity of the auction. *TGEMMs* is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers and measures the liquidity of market. *VOL* is the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract and designed to measure information dispersion and risk. *BENCH* is an indicator that takes the value unity if the issuance is of or into a 5,10 or 20-year benchmark issue, and also reflects the liquidity of the stock. *PAOF* is another variable designed to measure the liquidity and takes the value unity if the issuance has the Post Auction Option Facility (PAOF). *ACT* is the natural log of the number of days since the last conventional gilt issuance and captures market activity and demand. *MAT* is the difference between maturity date and auction date divided by 365.25 and reflects the impact of maturity. *LIQ* is the size of the outstanding gilt that is being auctioned (including the auctioned amount) divided by the average size outstanding of all other (conventional) gilts, on the auction day and represents the liquidity of the outstanding issue. *DEM* is the bid-to-cover of the previous auction and supposed to indicate the effect of demand. *FCI* is an indicator that takes value unity if the *FCI* identifies the episodes of systemic financial distress.

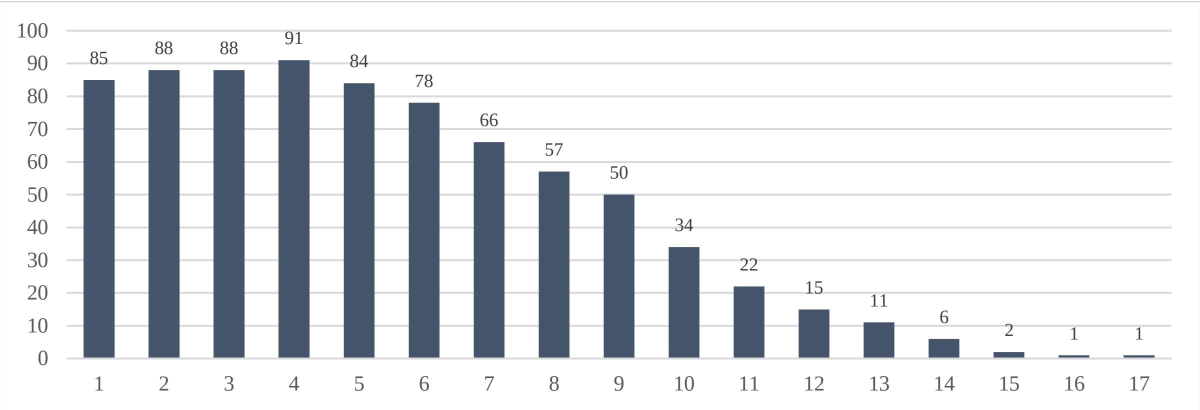
In line with the literature, several explanatory variables are expected to exhibit a negative relationship with concession cost—meaning that increases in these variables raise the government's cost of issuance. For auction size (*SIZE*), studies such as Nyborg et al. (2002) and Lou et al. (2013) suggest that larger issuance volumes may increase bid dispersion and under-pricing due to heightened inventory and pricing risks for dealers. Volatility (*VOL*) is similarly expected to increase concession costs, as heightened market uncertainty leads investors to demand higher risk premiums. This is consistent with Scalia (1998) and Goldreich (2007), who show that bond market volatility contributes to under-pricing and reduced auction efficiency. For *ACT*—the number of days since the last issuance—a longer interval can disrupt investor familiarity and weaken participation as stated by Fleming et al. (2024), who argue that infrequent issuance strains dealer inventories and impairs liquidity provision. Maturity (*MAT*) is predicted to increase concession costs due to their greater sensitivity to interest rate risk. This aligns with studies by Albuquerque et al. (2024), who show that longer-maturity bonds are less attractive in uncertain environments and require a yield premium. Lastly, although *QEDUM* (a dummy for QE periods) might intuitively lower issuance costs by boosting demand, studies such as Joyce et al. (2011) and Martin and Milas (2012a) suggest that repeated QE interventions may raise investor expectations and reduce bidding competitiveness, thereby increasing concessions.

Conversely, variables such as *LIQ*, *BENCH*, *PAOF*, *TGEMMs*, *DEM*, and *FCI* are expected to have a positive relationship with concession cost, meaning that increases in these variables reduce the cost of issuance for the government. For *LIQ*, the measure is designed to capture the relative size of the gilt being auctioned compared to the average outstanding size of other gilts. A larger outstanding size is typically associated with higher liquidity, as it reduces inventory holding costs and shortens holding periods due to increased trading activity. Klingler and Sundaresan (2023) show that dealers often resell auctioned bonds in the secondary market rather than holding them, making liquidity a key factor in pricing. Benchmark status (*BENCH*) is associated with lower concession costs as shown by Breedon and Ganley (2000) that bonds having benchmark maturities typically are traded at a higher price than identical non-benchmark bonds. *PAOF* (Post Auction Option Facility) allows bidders to purchase additional stock post-auction, encouraging greater initial participation and lowering the required risk premium—an effect highlighted by the Debt Management Office (2017). *TGEMMs*, which capture turnover by Gilt-Edged Market Makers, reflect active dealer participation and market depth. A higher GEMM turnover improves auction outcomes, consistent with Beetsma et al. (2020) and Fleming et al. (2024). Demand (*DEM*), proxied by previous bid-to-cover ratios, signals strong market appetite, which reduces the need for the issuer to offer price concessions. This is consistent with the findings of Spindt and Stolz (1992) and Beetsma et al. (2020). A positive relationship is also expected for the Financial Conditions Index (*FCI*). During periods of financial stress or heightened uncertainty, investors often seek safe-haven assets such as government bonds, leading to increased demand at gilt auctions. This phenomenon, known as flight-to-safety, can reduce the required concession as investors are more willing to accept lower yields in exchange for security. Connolly et al. (2005) provide evidence of this effect, showing that in times of elevated market volatility, investors tend to shift capital from equities to government securities, thereby strengthening demand and potentially lowering issuance costs.

Because many of the gilts are subject to multiple auctions over time, there is the possibility of both cross-sectional and serial dependencies that have not been captured by the explanatory variables. So, we apply standard error adjustments as a means to control for different forms of error dependencies. We apply clustered standard errors, clustering on the frequency of issuance. For the clustering variable, we use the number of times a gilt has been issued at the time of and including that auction. Figure 12 shows the number of clusters, and the maximum of times a gilt being auctioned is seventeen, and cluster 4 having the highest number of observations, meaning that the modal auction number is the fourth auction for a gilt. The number of observations per cluster decreases as the number of auctions per gilt increases.

Figure 12: Number of times a gilt being auctioned

This figure presents the distribution of gilts based on how many times each one was auctioned from May 1987 to December 2022. The x-axis shows the number of times a gilt has been auctioned (ranging from 1 to 17), and the y-axis shows the number of gilt issues that fall into each category. The highest number of observations corresponds to gilts that were auctioned four times, indicating that the modal auction number is four. As the number of auctions per gilt increases, the frequency of such cases declines. This distribution is used to define clusters for adjusting standard errors based on the frequency of issuance. The y-axis is labelled "Number of Gilts," and the x-axis is "Number of Times Auctioned.



3.5. Empirical Results

The concession cost is the difference between the average accepted price at the auction and the price that the gilts could have otherwise been sold in the secondary (or when-issued) market, multiplied by the size of auction. From 2002 to 2014, the DMO measured the secondary market price as the closing clean price on the day before the auction. After 2014, the DMO measured the secondary market price by the mid-price at the time of the auction. Due to the change in concession cost definition by the DMO in 2014, two sets of estimation results are presented. Estimation 1 reflects the DMO's use of two definitions of the secondary market price at the time of an auction. In Estimation 2, the concession cost is measured by using the pre-2014 definition of concession used by the DMO to calculate the concession cost throughout the entire sample period.

Prior to the estimation of the coefficient of the regression model, equation (2), the sample is trimmed to remove outliers. Specifically, all auctions with a concession or premium greater than £25 million which is around 4 standard deviations from the mean in estimation 1 and around 3 standard deviations from the mean in estimation 2 are removed. This reduces the sample size used in Estimation 1 to 745 auctions, and all of the outliers occurred before the change in the definition of auction concession by the DMO in 2014. In Estimation 2 in which the concession is measured by the pre-2014 definition, 19 auctions are considered as outliers.

The results of the estimation of the coefficients of equation (2) are given in Table 5.[18] For Estimation 1, It is notable that the debt issuance is more expensive during the phases of QE by around £1.17 million per auction. This could be explained by two ways. First of all, QE can increase the concession cost through a supply channel. In fact, issuing more gilts puts pressure on the inventories of GEMMs to absorb more issuance which results in a downward pressure on gilts prices, which will increase the issuance cost, all other things being equal. It is also possible that the use of QE demonstrates a commitment to low interest rates and monetary easing more generally, and this is likely to reduce the demand for gilts, and so it is harder for GEMMs to unwind their expanding inventories. Furthermore, the larger the size of the auction the greater the concession that is incurred which is consistent with evidence in Nyborg et al. (2002) who show that larger auctions tend to result in higher auction discounts from the investor's perspective—implying that the government must offer more favourable pricing, thus incurring a greater cost of issuance. We observe that the turnover of GEMM market is (highly) significant in the model, and raises the issuance premium by around £2.93 million, in line with the DMO's statement that the GEMM's activity improve the liquidity in the gilt-edged market. The benchmark status of a gilt is insignificant in the model, and this could be explained by the huge increase in the gilt issuance activity in the recent years which diminishes the importance of the issuance benchmark status. Volatility exerts a negative effect on the cost of issuance increasing the concession by around 19 million per auction, which is consistent with the results of Goldreich (2007) finding that the volatility is positively related to the under-pricing. We observe that the Post Auction Option Facility (PAOF) increases the issuance premium. This could also could be explained by improving the liquidity of the gilt market. Further, the time to maturity raises the concession cost, which means the longer-duration gilts are more expensive, aligned with Albuquerque et al. (2024) statement that that longer-

[18] Insignificant variables are remaining in the results tables to provide a complete picture of the effects of variables whose potential explanatory power is motivated by theory, dropping some insignificant variables did not enhance the significance of others to any great degree, indicating that the reported results are stable to such modelling changes.

duration bonds, due to their higher interest rate risk, are more susceptible to price volatility. This could be explained by the fact that the proportion of long-term gilts in total issuance is lower than for other durations, consequently leading to reduced liquidity in the long-term market, which can pose challenges for investors and market participants. Although the effect of the bid to cover ratio for the previous auction is insignificance, it is positively associated with the issuance premium, which is in line with the findings from Klingler and Sundaresan (2023) that the major factor influencing Treasury bill yields in the U.S. is the dealers' excessive demand in auctions. Other variables, *ACT*, *LIQ*, and *FCI* do not have a statistically significant predictive power in the estimation. This might happen since the effect of these variable are captured by other variables in the model. *ACT* is a measure of market activity and demand which is included within *DEM*. The impact of liquidity is adequately represented by other measures so *LIQ* is not significant. *FCI* is mostly capturing the crisis that is also captured to some extent by the *QEDUM* variable.

Applying the pre-2014 DMO definition of concession cost throughout the sample period in Estimation 2 reveals that the variables *SIZE*, *TGEMMs*, *MAT*, and *QEDUM* have a statistically significant impact. Consistent with estimation 1, *PAOF* has a positive influence on the issuance premium, but does not reach statistical significance. Comparing estimations 1 and 2 reveals that in estimation 1, more variables are statistically significant with stronger estimated effects. This suggests the new DMO definition captures features of gilts and market conditions more effectively, potentially enabling auction design to better manage issuance costs.

The average concession cost for the whole sample period is approximately 0.059% of the average auction size, using the first definition of concession cost. The average auction size over this period was around £2,881 million. However, the economic significance of these costs has increased markedly in recent years. During the COVID-19 pandemic, the Bank of England expanded its Asset Purchase Facility from £445 billion to £895 billion, while the UK Debt Management Office tripled the planned issuance for 2020/21. In the second quarter of 2020 alone, conventional debt issuance peaked at £127.1 billion, 2.56 times higher than the previous peak. Given the dramatic increase in both the scale of issuance and the volume of gilt purchases, even modest reductions in concession costs can now translate into substantial savings for the government. Therefore, understanding and minimizing issuance concessions has become increasingly important for debt management policy, particularly in periods of large-scale fiscal interventions.

Table 5: Determinants of Auction Concession

This table has the estimated coefficients of equation (2) being used to identify the determinants of issuance cost (-) premium (+) for gilt auctions between May 1987 and December 2022 inclusive. The concession cost, measured in £ million, is the difference between the average accepted price at the auction and the price that the gilts could have otherwise been sold in the secondary (or when-issued) market, multiplied by the size of auction. In estimation 1, From 2002 to 2014, the DMO measured the secondary market price as the closing clean price on the day before the auction. After 2014, the DMO measured the secondary market price by the mid-price at the time of the auction. In estimation 2, the concession cost is measure by using the pre-2014 definition of concession used by the DMO to calculate the concession cost throughout the entire sample period. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. VOL is the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract; the implied volatility is expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. BENCH is a dummy variable equal to 1 if the issuance is into a 5-, 10-, or 20-year benchmark line, and 0 otherwise (indicator variable). PAOF equals 1 if the Post Auction Option Facility was available, and 0 otherwise (indicator variable). ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days. MAT is the time to maturity, calculated as the number of days from the auction to the gilt's maturity date divided by 365.25, and expressed in years. LIQ is the ratio of the size of the gilt being auctioned (including the auctioned amount) to the average outstanding size of all other conventional gilts on the auction day; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover ratio of the previous auction, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). QEDUM is a dummy equal to 1 during the Bank of England's Asset Purchase Facility (QE) periods, and 0 otherwise (indicator variable). FCI equals 1 when the Financial Conditions Index identifies systemic financial stress, and 0 otherwise (indicator variable). We applied clustered standard errors, and the clusters are defined by the gilt issuance's frequency. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels.

$$Y_i = c + b_1QEDUM_i + b_2SIZE_i + b_3LIQ_i + b_4BENCH_i + b_5VOL_i + b_6ACT_i + b_7MAT_i + b_8DEM_i + b_9TGMMs_i + b_{10}PAOF_i + b_{11}UKFCI_i + \varepsilon_i$$

	Estimation 1	Estimation 2
QEDUM	-1.17***	-1.27*
	(-3.24)	(-1.99)
SIZE	-3.09***	-2.39**
	(-3.65)	(-2.23)
TGEMMs	2.93***	2.08**
	(5.68)	(2.44)
VOL	-16.57**	-18.48
	(-2.63)	(-1.66)
BENCH	0.24	-0.18
	(0.39)	(-0.33)
PAOF	1.38*	1.55
	(1.93)	(1.64)
ACT	-0.03	0.10
	(-0.09)	(0.26)
MAT	-0.07*	-0.10**
	(-1.9)	(-2.47)
LIQ	0.11	0.58
	(0.24)	(0.96)
DEM	0.70	0.14
	(1.74)	(0.2)
FCI	0.31	0.24
	(0.65)	(0.45)
Constant	10.06	9.05
	(1.13)	(0.89)
No. Observations	745	737
R-squared	0.12	0.05

3.6. An Analysis of Secondary Issuance

In this section, we apply the model specified in Equation (2) to auctions involving secondary issuance. In this context, secondary issuance refers to the re-opening of previously issued gilts—bonds that have already been introduced to the market but are auctioned again to raise additional funds. This contrasts with primary issuance, which involves newly created gilts being issued for the first time.

This analysis is motivated by several considerations. First, the results of Scalia (1998b) suggest that the purpose of reopening is to enhance the liquidity and accessibility of each security by enabling data aggregation on the secondary market to happen quickly after the initial auction, to the benefit of all subsequent auctions of the same security. Moreover, regular reopening additionally minimises the likelihood of short squeezes in post-issue auctions by increasing the quantity of each asset outstanding. These market structure differences suggest that pricing behaviour and investor demand in secondary issuance may differ significantly from primary issuance.

Second, secondary issuance provides a methodological advantage in terms of data availability and timing. For primary issuance, some auction-related data is only available on the day of the auction, which risks being contaminated by the auction process itself. In contrast, for secondary issuance, we are able to observe all explanatory variables on the day before the auction, reducing potential endogeneity and measurement bias. This makes secondary issuance an ideal setting to test the robustness of the results and investigate whether auction dynamics are consistent across different types of issuance.

Third, this section aims to explore whether market characteristics and responses to QE differ for secondary issuance. Given that secondary issuances typically involve bonds with an established trading history, more reliable pricing signals, and potentially higher liquidity, it is possible that investors respond differently to macroeconomic factors and policy interventions—such as Quantitative Easing—than they would in primary markets. Understanding these dynamics is essential for assessing how issuance strategy interacts with monetary policy tools and market conditions.

In terms of model specification, two explanatory variables have been redefined to better reflect bond-specific dynamics. The liquidity variable (*LIQ*), in the baseline model, is measured as the size of the outstanding gilt being auctioned (including the auctioned amount) divided by the average size outstanding of all other conventional gilts. To focus solely on pre-auction market conditions in secondary issuance, this variable is redefined to exclude the auctioned amount and instead represent liquidity as of the day before the auction. Similarly, the activity variable (*ACT*) is adjusted to reflect the log of the number of days since the last issuance of the same gilt, rather than any gilt—a refinement that captures the unique auction cycle for re-opened bonds. All other variables are consistent with those used in the baseline regression model in Section 4.

The results from the secondary issuance model are broadly consistent with expectations. The stronger QE effect observed for secondary issuances was also anticipated, given that long-term bonds are more sensitive to interest rate changes and account for a higher proportion of secondary auctions during the QE period. Key variables such as auction size (*SIZE*), the number of GEMMs (*TGEMMs*), and the QE dummy (*QEDUM*) remain statistically significant, in line with the findings for the full sample. The refined specification of the *ACT* variable—now bond-specific—also shows a strong and significant effect, highlighting the importance of issue timing for reopened bonds. One notable difference is that the effect of *PAOF*, although positive, is not statistically significant in this subsample. This is expected, as primary issuances tend to be less liquid and therefore more sensitive to the liquidity-enhancing role of the *PAOF*. In contrast, secondary issuances involve bonds that have already been traded and typically enjoy greater market liquidity. These findings confirm that, while core relationships remain robust, the dynamics of secondary issuance auctions exhibit nuances that justify their separate treatment.

Table 6 gives information about summary statistics of the main variables for 694 auctions that were secondary issuance. No outlier removal was performed for the summary statistics presented here. The summary statistics of variables without the observations that correspond to the outlier dates for the Concession 1 and Concession 2 are reported in the appendix (Table 24 and Table 25). It is worth noting that the majority of auctions in the sample fall under the category of secondary issuance. This is important, as it highlights the significance of understanding pricing dynamics for these types of auctions, particularly given their potential differences from primary issuance in terms of investor behaviour and liquidity. As shown in Table 6, the average concession cost under Concession 1 for secondary issuance is approximately £0.195 million higher per auction than the average concession across all issuances. This indicates that primary issuance is generally more expensive, likely due to the lower liquidity and market familiarity of new bonds. The t-test comparison of means (table 7) supports this conclusion: it shows a statistically significant difference, with a t-statistic of -2.63 (754 degrees of freedom), and an average concession cost difference of £-2.414 million, confirming that primary issuance incurs a higher cost relative to secondary issuance. The fact that there is a significant difference between secondary and primary issuance costs, even when the proportion of primary issuance auctions is only a small proportion of the overall sample, further points to the importance of separately modelling the secondary issuance auctions.

Table 6: Summary statistics of main variables for auctions that were secondary issuance

This table contains the summary statistics for nine variables across 694 auctions that were secondary issuance from May 1987 to December 2022. The concession cost, measured in £ million, is the difference between the average accepted price at the auction and the price that the gilts could have otherwise been sold in the secondary (or when-issued) market, multiplied by the size of auction. In concession 1, From 2002 to 2014, the DMO measured the secondary market price as the closing clean price on the day before the auction. After 2014, the DMO measured the secondary market price by the mid-price at the time of the auction. In concession 2, the concession cost is measure by using the pre-2014 definition of concession used by the DMO to calculate the concession cost throughout the entire sample period. SIZE is the natural log of the auction size, representing the total amount of gilts issued in each auction, measured in £ million. LIQ is the size of the outstanding gilt being auctioned (excluding the auctioned amount) divided by the average outstanding size of all other conventional gilts on the auction day; a value greater than 1.0 indicates that the gilt being reissued is larger than average and likely more liquid (liquidity ratio). ACT is the natural log of the number of days since the last issuance of the specific gilt being auctioned, and is measured in days. VOL is the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract; the implied volatility is expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. DEM is the bid-to-cover ratio of the previous auction, where a value of 1.0 indicates that the total bids equalled the amount offered, and a value of 2.0 means the bids were twice the auctioned amount (demand ratio). TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. MAT is the time to maturity, calculated as the number of days from the auction date to the gilt's maturity date divided by 365.25, and is expressed in years. Mean is the sample mean of the variable, SD is the sample standard deviation, Min and Max are the minimum and maximum observations, and p25, p50, and p75 indicate the observation in percentile 25, 50, or 75, respectively.

Variable	Observation	Mean	SD	Min	P25	P50	P75	Max
Concession 1	694	-0.44	6.73	-44.18	-1.50	0.90	2.09	32.78
Concession 2	694	-1.60	9.14	-44.18	-6.53	-0.81	3.40	32.78
SIZE	694	7.91	0.31	6.62	7.72	7.92	8.14	8.66
LIQ	694	0.76	0.40	0.08	0.46	0.73	1.03	2.73
ACT	694	3.89	1.05	1.79	3.14	3.68	4.26	8.36
VOL	694	0.07	0.02	0.02	0.05	0.07	0.08	0.15
DEM	694	2.10	0.48	0.93	1.74	2.08	2.39	4.81
TGEMMs	694	4.82	0.55	2.74	4.50	4.97	5.21	5.72
MAT	694	15.57	12.08	2.12	5.45	10.12	24.04	53.37

Table 7: t-test comparison of means of Concession 1

This table contains the results of t-test comparison of means of concession, measured in £ million, cost between secondary and primary issuance. The concession cost is the difference between the average accepted price at the auction and the price that the gilts could have otherwise been sold in the secondary (or when-issued) market, multiplied by the size of auction. From 2002 to 2014, the DMO measured the secondary market price as the closing clean price on the day before the auction. After 2014, the DMO measured the secondary market price by the mid-price at the time of the auction.

Group	Observation	Mean	Std. errs.	Std. dev.	[95% conf.	interval]
Primary	62	-2.851	1.122	8.836	-5.095	-0.607
Secondary	694	-0.437	0.255	6.726	-0.938	0.064
Combined	756	-0.635	0.253	6.948	-1.131	-0.139
diff		-2.414	0.917		-4.215	-0.614
Diff = mean (Primary) - mean (Secondary)					T = -2.63	
H0: Diff = 0					Degree of freedom = 754	

Table 8: t-test comparison of means of Concession 2

This table contains the results of t-test comparison of means of concession, measured in £ million, cost between secondary and primary issuance. The concession cost is the difference between the average accepted price at the auction and the price that the gilts could have otherwise been sold in the secondary (or when-issued) market, multiplied by the size of auction. The secondary market price is measured as the closing clean price on the day before the auction throughout the entire sample period.

Group	Observation	Mean	Std. errs.	Std. dev.	[95% conf.	interval]
Primary	62	-2.826	1.241	9.771	-5.308	-0.345
Secondary	694	-1.597	0.347	9.136	-2.278	-0.916
Combined	756	-1.698	0.334	9.189	-2.354	-1.042
diff		-1.229	1.218		-3.620	1.162
Diff = mean (Primary) - mean (Secondary)					T =-1.009	
H0: Diff = 0					Degree of freedom = 754	

Following the approach of the previous section, this section presents results for the two alternative definitions of concession. Estimation 1 replicates the DMO's methodology with two definitions: the difference between the auction's average accepted price and the secondary market price (measured as closing clean price on day-before for 2002-2014 and mid-price at auction time for 2014 onwards), multiplied by the auction size. Estimation 2 applies the pre-2014 DMO concession definition to the entire sample period.

Removing outliers (auctions with concessions or premiums exceeding £25) reduces the sample size of Estimation 1 to 685 and of Estimation 2 to 677 auctions.

Table 9 presents the results obtained from modelling the secondary issuance. Interestingly, the outcome of secondary issuance model closely resembles the findings for the combined sample of primary and secondary auctions confirming that the results are robust. What stands out in the Table 9 is that the issuance is more expensive during the phases of QE. As before, the variables *SIZE* and *TGEMM* are highly significant in Estimation1, consistent with the results of the estimation for all issuance. The variable volatility is significant which means the gilt issuance is more expensive when market volatility is high. Interestingly, the alternative measure for market activity and demand (*ACT*, now measured on a bond specific basis) is highly significant in the secondary issuance model. As a result, an increase in the natural log of the number of days since the previous auction for that specific gilt expand the concession cost by £0.64 million. Furthermore, the results illustrate that gilts with longer maturity are more expensive than short term bonds, although the it loses the statistical significance in the estimation of secondary issuance. The higher bid to cover ratio of the previous auction increases the issuance premium by around £0.64 million but it is insignificant. The study found that *PAOF* has a positive effect on issuance premiums for secondary issues, raising them by an average of around £1 million. However, the it is not significant for the secondary issuance, suggesting that the primary issuance dropped from the estimation is more sensitive to the existence of the PAOF to improve the liquidity of gilt being auctioned. Another reason for this could be the increase of the proportion of long-term gilts in the secondary auction estimation, since 82% of primary issuance dropped from the estimation for secondary issuance are short and medium term.[19] Later results, in section 7, (An Analysis of Maturity Segmentation) show that the variable *PAOF* is significant for only short-term gilts, which is consistent with this finding. Since QE is designed to depress bond yields, longer term bonds (which would lock in a lower yield for a longer period) are likely to be in lower demand than short- or medium-term gilts, all other things equal. Thus, the existence of a facility to buy more longer bonds may be less relevant to longer term gilt auctions. So, when the use of the secondary issuance sample increases the proportion of longer-term gilts, it might be expected that the PAOF is less significant. It is notable that the variable *LIQ* remains insignificant even when measured ahead of the auction.

Estimation 2 confirms the findings of the model for all issuance now also just for secondary issuance, with both models showing statistically significant effects of the variables *SIZE*, *TGEMMs*, *MAT*, and *QEDUM*. For both Estimation 1 and 2, the impact of QE activity is more statistically significant for secondary issuance alone than it was when also including primary issuance. And the fact that QE activity is significant in all of these estimations, further points to the robustness of the findings.

[19] The maturity segments use the standard market convention of Short (< 7 years), Medium (7 to 15 years), and Long (>15 years).

Table 9: Determinants of Auction Concession for secondary issuance

This table has the estimated coefficients of equation (2) being used to identify the determinants of issuance cost (-) premium (+) for secondary issuance between May 1987 and December 2022 inclusive. The concession cost, measured in million £, is the difference between the average accepted price at the auction and the price that the gilts could have otherwise been sold in the secondary (or when-issued) market, multiplied by the size of auction. In estimation 1, From 2002 to 2014, the DMO measured the secondary market price as the closing clean price on the day before the auction. After 2014, the DMO measured the secondary market price by the mid-price at the time of the auction. In estimation 2, the concession cost is measure by using the pre-2014 definition of concession used by the DMO to calculate the concession cost throughout the entire sample period. SIZE is the natural log of the auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. VOL is the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract; the implied volatility is expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. BENCH is a dummy variable equal to 1 if the gilt is issued into a 5-, 10-, or 20-year benchmark line, and 0 otherwise (indicator variable). PAOF is a dummy variable equal to 1 if the auction includes the Post Auction Option Facility, and 0 otherwise (indicator variable). ACT is the natural log of the number of days since the last issuance of the specific gilt, measured in days. MAT represents the time to maturity, calculated as the number of days from the auction to the gilt's maturity date divided by 365.25, and is expressed in years. LIQ is the size of the outstanding gilt being auctioned (excluding the auction amount) divided by the average outstanding size of all other conventional gilts on the auction day; a value above 1.0 implies that the gilt being reissued is larger than average and potentially more liquid (liquidity ratio). DEM is the bid-to-cover ratio of the previous auction, where a value of 1.0 indicates that total bids equalled the amount offered, and 2.0 means the bids were twice the offer (demand ratio). QEDUM is a dummy variable equal to 1 during the periods in which the Bank of England operated its Asset Purchase Facility under Quantitative Easing, and 0 otherwise (indicator variable). FCI is a dummy variable equal to 1 when the Financial Conditions Index identifies systemic episodes of financial stress, and 0 otherwise (indicator variable). We applied clustered standard errors, and the clusters are defined by the gilt issuance's frequency. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels.

$$Y_i = c + b_1 QEDUM_i + b_2 SIZE_i + b_3 LIQ_i + b_4 BENCH_i + b_5 VOL_i + b_6 ACT_i + b_7 MAT_i + b_8 DEM_i + b_9 TGMMs_i + b_{10} PAOF_i + b_{11} UKFCI_i + \varepsilon_i$$

	Estimation 1	Estimation 2
QEDUM	-1.53^{***}	-1.66^{**}
	(-5.58)	(-2.84)
SIZE	-3.23^{***}	-2.33^{*}
	(-3.64)	(-1.96)
TGEMMs	2.96^{***}	2.22^{***}
	(9.44)	(4.36)
VOL	-12.47^{**}	-12.91
	(-2.74)	(-1.36)
BENCH	0.23	0.12
	(0.4)	(0.21)
PAOF	0.98	0.98
	(1.64)	(1.17)
ACT	-0.64^{***}	0.02
	(-5.02)	(0.09)
MAT	-0.05	-0.09^{*}
	(-1.54)	(-2.07)
LIQ	0.23	0.41
	(0.62)	(0.54)
DEM	0.64	0.32
	(1.66)	(0.43)
FCI	0.24	0.06
	(0.59)	(0.11)
Constant	13.42	7.66
	(1.52)	(0.7)
No. Observations	685	677
R-squared	0.13	0.04

3.7. Alternative measures of QE

Previous researches have revealed the impact of QE on the gilt yields around announcements and purchases. Their evidence suggest that yields of individual gilts fall in response to the announcements of QE activity, such as decisions to raise the threshold, and also the purchase auctions.[20]

20 There are some studies of the effects of the first round of QE including: Meaning and Zhu (2011) , Joyce et al. (2011), Glick and Leduc (2012), Joyce and Tong (2012), and Further papers illustrate the impact of the QE second phase, such as Churm et al. (2021), Meaning and Zhu (2011), Goodhart and Ashworth (2012))

A number of contributions find evidence for the effect of QE on the secondary market liquidity.[21] This is crucial for bond issuance since a decline in secondary market liquidity could lead to a decrease in primary market liquidity, which would escalate the issuance costs. It is therefore natural to explore whether QE activity affects the cost of issuing debt. Hence, in this subsection we extend the baseline regression by including two variables related to the QE activity described below.

The BOE debt holding ratio and the APF variable are related but measure different aspects of QE activity. While the BOE debt holding ratio reflects the total proportion of gilts held by the Bank of England at any given time, capturing the cumulative effect of all purchases over time, the APF variable measures the frequency and recency of those purchases by calculating the number of days since the last purchase. This distinction is important because the APF captures the timing and recency of QE purchases, which could have a more immediate effect on market expectations and issuance costs, while the BOE debt holding ratio reflects the overall stock of assets the Bank holds over a longer period. Both measures provide complementary information, with the APF focusing on short-term effects and the BOE debt holding ratio reflecting longer-term QE impacts.

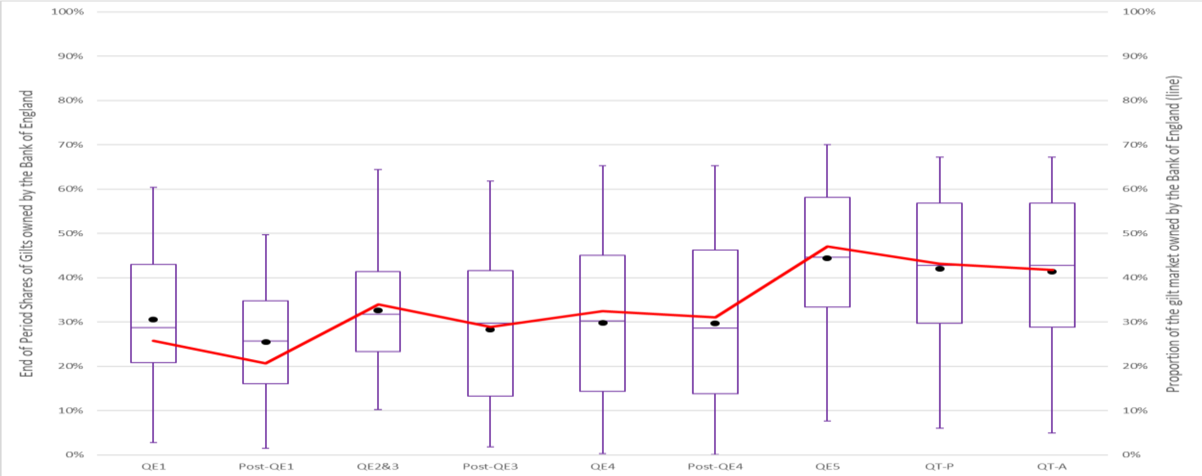
3.7.1. BOE debt holding ratio

The variable BOE debt holding ratio is the share of the gilt owned by the Bank of England, purchased under the Asset Purchase Scheme, at the point of the auction. The primary objective of the Asset Purchase Scheme is to stimulate economic activity by increasing the demand for government securities, which raises their prices and lowers their yields. In doing so, the Bank aims to reduce borrowing costs across the economy and support broader monetary easing. It is probable that BOE debt purchases that occurred on or around dates of gilt auctions have affected the cost of their issuance. Beetsma et al. (2020) present a number of explanations for this. First of all, the increased demand for a gilt in the secondary market before an auction pushes up the prices in both the secondary market and the primary market because of the perfect (or high for newly-issued) degree of substitutability between re-opening bond and the bond traded in the secondary market. Additionally, if primary dealers anticipate further central bank purchases following the auction, it could also drive up the price of debt. The evolution of BOE shares can be seen in Figure 13. The graph highlights that the BOE ownership shares grow during QE phases, and increase sharply during QE5 phase to 70% for some gilts but less than 50 percent of all conventional gilts.

21 Steeley (2015), Benos and Zikes (2016) , Boneva et al. (2020), Grimaldi et al. (2021), Christensen and Gillan (2022), Ferdinandusse et al. (2017), Song and Zhu (2018), Schlepper et al. (2020).

Figure 13: Bank of England Ownership Shares

This figure displays the distribution of ownership shares of individual conventional gilts held by the Bank of England at the end of each sub-period between March 2009 and December 2022. The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive.The box plots show the dispersion of end-of-period ownership shares across gilts, where each box represents the interquartile range (IQR), the horizontal line indicates the median, and the whiskers extend to the furthest data points within 1.5 IQR of the outer quartiles. Black dots represent the mean ownership share within each sub-period. The red line (right-hand axis) shows the overall proportion of the conventional gilt market held by the Bank of England across the same sub-periods. The left y-axis is labelled "End of Period Share of Gilts Owned by the Bank of England (%)" and the right y-axis is labelled "Proportion of the Gilt Market Owned by the Bank of England (line, %)." Data sources: Bank of England and UK Debt Management Office (UK DMO).

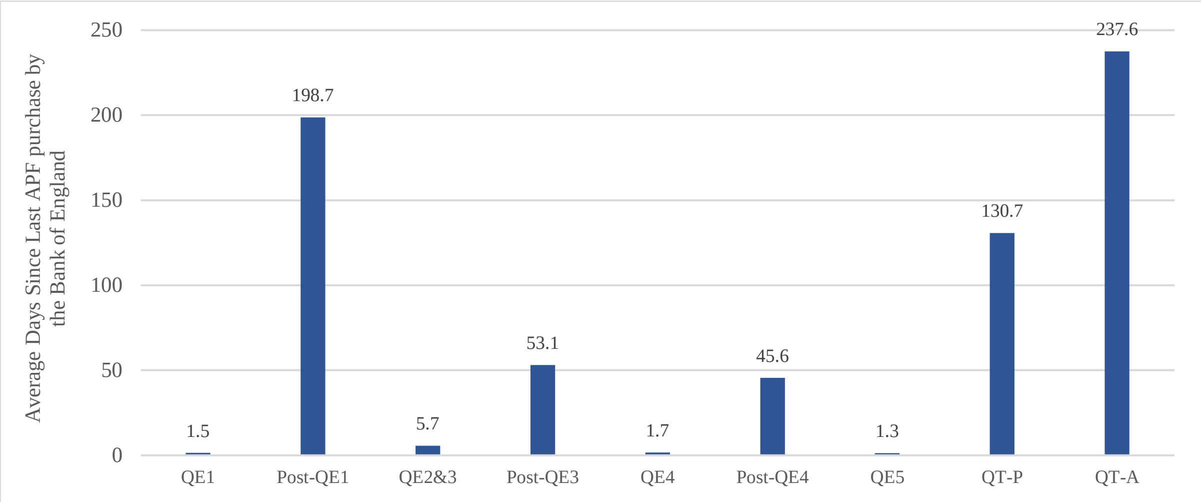


3.7.2. Asset Purchase Activity

We apply this variable to capture any effects of the purchase activity that has increased in scale and frequency throughout QE, and particularly in recent times. This is motivated by Joyce and Tong (2012) confirming the reduction of gilt yields under the effect of QE activity announcements. Therefore, a variable, named *APF*, is designed to measure the effect of QE activity on the cost of debt issuance, and calculated by the natural log of the number of (working) days since a previous APF purchase by the Bank of England. Figure 14 compares the average days since previous APF purchase between different sub-periods. The bar graph illustrates high frequency of QE activity during the QE5 phase. The relatively lower APF throughout the phases of post-QE3 and post-QE4 is the result of reinvesting the maturing assets. However, the considerable growth after phase of QE5 could be explained by the MPC announcement to begin to reduce the stock of UK government bond purchases by ceasing to repurchasing maturing gilts.

Figure 14: Asset Purchase Facility Activity

This figure shows the annual average number of days since the last Asset Purchase Facility (APF) gilt purchase by the Bank of England across different sub-periods between March 2009 and December 2022. Each bar represents one sub-period, with the y-axis capturing the average number of days between purchases within that period. The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive. A higher value indicates less frequent purchase activity. The sub-periods are defined by quantitative easing (QE) and quantitative tightening (QT) phases, including QE1, Post-QE1, QE2and3, Post-QE3, QE4, Post-QE4, QE5, QT-Passive, and QT-Active. The Post-QE5 period is short and combined with QT-Passive. The y-axis is labelled "Average Days Since Last APF Purchase by the Bank of England," and the x-axis shows the sub-periods. Data source: UK Debt Management Office (UK DMO).



3.7.3. Number of Gilt-Edged Market Makers

This variable is designed to reflect the effect of primary dealer's demand in auctions, and measured as the number of Gilt-Edged Market Makers on the auction day. This is inspired by Beetsma et al. (2020) who provide the evidence for statically significant negative impact of the number of primary dealers for specific maturities on the current bid-to-cover ratio, although it is mentioned that the outcome should not be over-interpreted due to the quite low fluctuation in the number of primary dealers across the sample. We extract the data on the number of GEMMs from the DMO's announcements.[22] Since the only data for this variable is available from 2006 to 2022, it is not possible to include this variable in the baseline estimation covering the period from 1987 to 2022. Thus, despite the fact that the variable is not specific to the asset purchase activity period, we include it only in the regression augmented for analysing the influence of QE activity. Figure 15 presents the number of GEMMs from 2009 to 2022. According to the graph below, this variable increased significantly between 2009 and 2011, going from 15 to 22 dealers, and reached its highest level, and after year 2011, it decreases steadily.

[22]https://www.dmo.gov.uk/publications

Figure 15: Number of Gilt-Edged Market Makers

This figure shows the number of Gilt-Edged Market Makers (GEMMs) operating in the UK government bond market from March 2009 to December 2022. The y-axis is labelled "Number of Gilt-Edged Market Makers," and the x-axis represents time. Data source: UK Debt Management Office (UK DMO).

Table 10 provides information about the summary statistics for explanatory variables applied in the estimation designed to evaluate the impact of QE on the gilt market. The average of auction Concession 1 changed to a premium for the time period 2009 to 2022. It is positive and it is higher than the average auction cost for the full sample between 1987 to 2022 by around £1 million per auction which is shown in Table 11 indicating that this increase is significant. The average auction concession, calculated using the pre-2014 definition (Concession 2), is also higher compared to the 1987-2022 sample, but the means are not statistically different from each other. The purpose of comparing these sub-periods is to explore whether auction pricing changed following the introduction of QE. The 2009–2022 period was selected as it broadly corresponds with the timeline of QE implementation. However, this period also includes phases without QE activity, so the observed differences may reflect a range of underlying market or policy-related factors. Using the shorter sample ensures that nothing in the 1987-2009 period, when QE had not been initiated, is having an undue impact on the full sample (1987-2022) results regarding the impact of QE and other significant factors. It is also notable that the average maturity decreased from 15.3 years for the full sample period to 14.79 years after the first phase of QE in 2009. The average of bid to cover ratio for the previous auction increased from 2.08 to 2.12. However, the means are not statistically different from each other.

Table 10:Summary statistics for QE and the gilt market

This table contains the summary statistics for eleven variables across 571 auctions from March 2009 to December 2022. The concession cost, measured in million £, is the difference between the average accepted price at the auction and the price that the gilts could have otherwise been sold in the secondary (or when-issued) market, multiplied by the size of auction. In concession 1, From 2002 to 2014, the DMO measured the secondary market price as the closing clean price on the day before the auction. After 2014, the DMO measured the secondary market price by the mid-price at the time of the auction. In concession 2, the concession cost is measure by using the pre-2014 definition of concession used by the DMO to calculate the concession cost throughout the entire sample period. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. VOL is the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract; the implied volatility is expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days. MAT is the time to maturity, calculated as the number of days from the auction to the gilt's maturity date divided by 365.25, and expressed in years. LIQ is the ratio of the size of the gilt being auctioned (including the auctioned amount) to the average outstanding size of all other conventional gilts on the auction day; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover ratio of the previous auction, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). BOE is the share of the gilt owned by the Bank of England under the Asset Purchase Scheme at the time of the auction, expressed as a percentage. APF is the natural log of the number of working days since the previous APF gilt purchase by the Bank of England, measured in days. NGEMMs is the number of Gilt-Edged Market Makers active on the auction day, measured as a count. Mean is the sample mean of the variable, SD is the sample standard deviation, Min and Max are the minimum and maximum observations, and p25, p50, and p75 indicate the observation in percentile 25, 50, or 75, respectively.

Variable	Observation	Mean	SD	Min	P25	P50	P75	Max
Concession1	571	0.40	5.85	-44.18	0.22	1.07	2.12	32.78
Concession2	571	-1.00	9.20	-44.18	-5.58	-0.45	3.75	32.78
SIZE	571	7.96	0.31	6.91	7.74	8.01	8.18	8.66
LIQ	571	0.77	0.38	0.08	0.47	0.76	1.04	1.81
ACT	571	1.48	0.79	0.00	1.10	1.61	2.08	3.09
VOL	571	0.07	0.02	0.02	0.05	0.07	0.07	0.15
DEM	571	2.12	0.44	0.93	1.79	2.11	2.41	3.85
TGEMMs	571	5.06	0.29	4.14	4.88	5.09	5.28	5.72
MAT	571	14.79	11.70	2.12	5.43	9.97	22.31	53.37
BOE	571	0.17	0.19	0.00	0.00	0.10	0.28	0.75
APF	571	2.09	2.15	0.00	0.00	1.10	4.26	6.05
NGEMMs	571	18.61	1.63	15.00	18.00	18.00	20.00	22.00

Table 11: t-test comparison of means for Concession 1

This table contains the results of t-test comparison of means of concession cost, measured in million £, between baseline model and QE activity. The concession cost is the difference between the average accepted price at the auction and the price that the gilts could have otherwise been sold in the secondary (or when-issued) market, multiplied by the size of auction. From 2002 to 2014, the DMO measured the secondary market price as the closing clean price on the day before the auction. After 2014, the DMO measured the secondary market price by the mid-price at the time of the auction.

Group	Observation	Mean	Std. errs.	Std. dev.	[95% conf.	interval]
Concession 1 (2009-2022)	571	0.404	0.24	5.85	-0.08	0.89
Concession 1 (1987-2022)	756	-0.635	0.25	6.95	-1.13	-0.14
diff		-1.039	0.36		-1.75	-0.33
Diff = mean (Concession (2009-2022)) - mean (Concession (1987-2022))					T = -2.88	
H0: Diff = 0					Degree of freedom = 1325	

Table 12: t-test comparison of means for Concession 2

This table contains the results of t-test comparison of means of concession cost, measured in million £, between baseline model and QE activity. The concession cost is the difference between the average accepted price at the auction and the price that the gilts could have otherwise been sold in the secondary (or when-issued) market, multiplied by the size of auction. The secondary market price is measured as the closing clean price on the day before the auction throughout the entire sample period.

Group	Observation	Mean	Std. errs.	Std. dev.	[95% conf.	interval]
Concession 2 (2009-2022)	571	-1.003	0.385	9.198	-1.760	-0.247
Concession 2 (1987-2022)	756	-1.698	0.334	9.189	-2.354	-1.042
diff		-0.695	0.510		-1.694	0.305
Diff = mean (Concession (2009-2022)) - mean (Concession (1987-2022))					T = -1.36	
H0: Diff = 0					Degree of freedom = 1325	

3.7.4. Results for the Modified Regression Model

In this subsection we extend the baseline regression, in equation (2), by including the BOE share, APF, and the number of GEMMs. The variable *QEDUM* is excluded from the model due to the presence of other variables *BOE* and *APF* related to the QE activity. This leads us to the following regression equation:

$$Y_i = c + b_1 BOE_i + b_2 APF_i + b_3 SIZE_i + b_4 LIQ_i + b_5 BENCH_i + b_6 VOL_i + b_7 ACT_i + b_8 MAT_i + b_9 DEM_i + b_{10} TGMMs_i + b_{11} PAOF_i + b_{12} NGEMMs_i + b_{13} UKFCI_i + \varepsilon_i \quad (3)$$

The results of two estimation techniques are presented in this section, which builds on the "Empirical Results" section. Estimation 1 mirroring the DMO's approach with adjusted concession definitions, and estimation 2 applying the pre-2014 DMO definition throughout. Removing the outliers with concessions or premiums exceeding £25 results in a reduced sample size for both estimations: 565 auctions for Estimation 1 and 557 auctions for Estimation 2.

The results for equation 3 are shown in Table 13. We observe that the size of issuance features a negative coefficient estimate, indicating that cost of issuance increases in the case of larger issuance, but weaker significance than 1987-2022 sample period for both measures of concession. The results show that the QE activity has a negative effect on the issuance cost. The BOE share is highly significant with negative impact, and this could be explained by the fact that the increase in the BOE shares is associated with future drops in liquidity of gilts in the secondary market.[23] Moreover, the variable *APF* indicates that less frequency in QE activity increases issuance premium by around £0.22 million. As we explained above, more activity related to the asset purchase facility demonstrates a commitment to low interest rates and monetary easing more generally, and this is likely to reduce the demand for debt market.[24] The sub-periods "crisis" and "pre-crisis", featuring noticeably lower the auction size compared with the subsequent sub-periods (Figure 4), are not included in the analysis of QE activity, and this could weaken the impact of auction size, due to its reduced variability. In line with the theoretical framework of literature, the volatility exerts a negative effect on the issuance cost of debt. As in the full-sample, the two variables *PAOF* and *TGEMMs* show positive effects on issuance premium which is consistent with our theorical prediction. However, the effect of *PAOF* is not statistically significant. The variable *MAT* is no longer significant in this time period, and one reason for this could be that the decline in the average of time to maturity in the gilt market weakens the sensitivity of auction concession to the maturity of gilt.

[23] This finding aligns with studies such as Beetsma et al. (2020), which also report a negative impact on demand. Furthermore, according to Ferdinandusse et al. (2020), QE reduces gilt supply by lowering the number of sellers while simultaneously raising demand through central bank purchases. However, they also highlight that this dual mechanism can adversely affect market functionality due to liquidity constraints.

[24] If this analysis is repeated for only periods of QE, the sign of the APF variable flips showing that more APF activity is helpful (reduces concession) all other things equal, and then in the long run, the reduction in liquidity measured by BOEShare dominates, to produce the overall negative effect seen when using only QEDum.

So that time to maturity is measured in years, calculated as the number of days remaining until the gilt's maturity date divided by 365.25. This approach ensures consistency across the sample period. In Figure 10, the values are also reported in years to match this definition.

Based on figure 10, the largest peaks of the average of gilt maturity occurred in the first two sub-periods which are not included in this estimation. The coefficient on the number of GEMMs gets weaker, and the coefficient is not in line with our theorical prediction that an increase in the number of primary dealers pushes up the demand for the gilt being auctioned since the number of competitive bidders is higher. A potential explanation for this could be the limitation of variation in the number of primary dealers over the sample. The variable liquidity is statistically stronger compared to the 1987-2022 sample period. This might happen since we exclude two sub-periods, pre-crisis and crisis, from the 2009-2022 sample period, and liquidity exhibited high levels of dispersion during pre-crisis and crisis sub-periods. The variables *BENCH*, *ACT*, and *DEM* are insignificant.

Estimation 2 confirms that variables *TGEMMs* and *BOE* play a statistically significant role in influencing the auction concession. Furthermore, using Concession 2 reinforces the significance of variables *SIZE*, *MAT*, and *LIQ* at the 10% level.

Table 13: Determinants of Auction Concession under the impact of QE

This table has the estimated coefficients of equation (3) being used to identify the determinants of issuance cost (-) premium (+) for gilt auctions between March 2009 and December 2022 inclusive. The concession cost, measure in million £, is the difference between the average accepted price at the auction and the price that the gilts could have otherwise been sold in the secondary (or when-issued) market, multiplied by the size of auction. In estimation 1, From 2002 to 2014, the DMO measured the secondary market price as the closing clean price on the day before the auction. After 2014, the DMO measured the secondary market price by the mid-price at the time of the auction. In estimation 2, the concession cost is measure by using the pre-2014 definition of concession used by the DMO to calculate the concession cost throughout the entire sample period. BOE is the share of the gilt owned by the Bank of England under the Asset Purchase Scheme at the time of the auction, expressed as a percentage. APF is the natural log of the number of working days since the previous APF gilt purchase by the Bank of England, measured in days. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. VOL is the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract; the implied volatility is expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. BENCH is a dummy variable equal to 1 if the issuance is into a 5-, 10-, or 20-year benchmark line, and 0 otherwise (indicator variable). PAOF equals 1 if the Post Auction Option Facility was available, and 0 otherwise (indicator variable). ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days. MAT is the time to maturity, calculated as the number of days from the auction to the gilt's maturity date divided by 365.25, and expressed in years. LIQ is the ratio of the size of the gilt being auctioned (including the auctioned amount) to the average outstanding size of all other conventional gilts on the auction day; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover ratio of the previous auction, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). NGEMMs is the number of Gilt-Edged Market Makers active on the auction day, measured as a count. FCI equals 1 when the Financial Conditions Index identifies systemic financial stress, and 0 otherwise (indicator variable). We applied clustered standard errors, and the clusters are defined by the gilt issuance's frequency. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels.

$$Y_i = c + b_1BOE_i + b_2APF_i + b_3SIZE_i + b_4LIQ_i + b_5BENCH_i + b_6VOL_i + b_7ACT_i + b_8MAT_i + b_9DEM_i + b_{10}TGMMs_i + b_{11}PAOF_i + b_{12}NGEMMs_i + b_{13}UKFCI_i + \varepsilon_i$$

	Estimation 1	Estimation 2
BOE	-3.93^{**}	-3.65^{**}
	(-2.86)	(-2.9)
APF	0.22^{**}	0.11
	(2.4)	(0.6)
SIZE	-2.32^{**}	-2.93^{*}
	(-2.83)	(-1.81)
TGEMMs	4.03^{***}	3.40^{**}
	(5.06)	(2.74)
VOL	-19.98^{***}	-21.53
	(-3.75)	(-1.53)
BENCH	-0.43	-0.94
	(-0.83)	(-1.42)
PAOF	0.90	1.45
	(1.71)	(1.65)
ACT	0.19	0.42
	(0.86)	(1.25)
MAT	-0.01	-0.09^{*}
	(-0.61)	(-1.86)
LIQ	0.86	1.72^{*}
	(1.72)	(1.81)
DEM	0.20	-0.86
	(0.51)	(-0.79)
NGEMMs	-0.32^{**}	-0.32
	(-2.22)	(-1.6)
FCI	-0.04	-0.23
	(-0.07)	(-0.39)
Constant	4.29	13.69
	(0.43)	(0.79)
No. Observations	565	557
R-squared	0.10	0.04

3.7.5. Results for Secondary Issuance

This subsection explores the impact of QE on the cost of issuance only for auctions that were secondary issuance. The reason for re-estimating the model to secondary issuance is explained in the section 5 (An Analysis of Secondary Issuance). Similar to the earlier analysis of secondary issuance for the full sample period, we redefine two of the explanatory variables on the day before auction. The variable *LIQ* depicts liquidity on the day before auction by excluding the auctioned amount from the outstanding gilt that is being auctioned. Also, the variable *ACT* is changed to the log of the number of days since the last conventional gilt issuance for that specific gilt.

The results are reported in Table 14. The variables related to QE activity exhibit consistent results with regression for all issuance, as visually illustrated in Table 13. expanding the frequency of asset purchase under QE program and the share of BOE increase the cost of issuance debt. The results from estimation 1 demonstrate the impact of variables *SIZE* and *TGEMMs* on the auction concession with statistically equivalent significance. Additionally, variable *VOL* negatively influences the auction concession but with lower statistical significance (t = -2.48) which is in line with our theorical predicts that information asymmetries as a cause of under-pricing is less in the presence of an active when-issued or secondary market which leads lower volatility and dispersion of bids. Variable *ACT*, with a highly significant impact (t=-5.02) in Table 9, is no longer significant here (t=-1.65). This could be explained by excluding subperiods crisis and pre-crisis, where the significantly higher values of variable *ACT*, shown in Figure 8, might weaken the impact of *ACT*. Redefining *LIQ* on the day before auction by excluding the auctioned amount from the outstanding gilt that is being auctioned does not alter the significance of *LIQ's* impact.

Estimation 2 confirms the impact of variables *TGEMM*, *MAT*, and *BOE* on the cost of issuance for auctions that were secondary issuance, similar in direction and statistical significance to the regression results of all issuance. Variable *FCI* impacts auction concession at 10% level, making the issuance of gilt more expensive during episodes of financial stress identified by *FCI*. The variable *FCI* is not significant in the baseline model, covering from 1987 to 2022, possibly due to its enhanced ability to identify financial stress after 2009. This improvement might be related to the limited data availability for certain variables used in *FCI's* development before that year. A possible explanation for the insignificance of APF in Estimation 2 is in its use of the pre-2014 definition of concession, which may be less sensitive to short-term variations in market conditions and central bank activity. Additionally, this definition may understate the impact of APF purchases when the timing and measurement of secondary market prices do not fully align with auction dynamics. As a result, the effect of QE captured through APF may appear more muted in this specification.

Table 14: Determinants of Auction Concession under the impact of QE for secondary issuance

This table has the estimated coefficients of equation (3) being used to identify the determinants of issuance cost (-) premium (+) for secondary issuance between March 2009 and December 2022 inclusive. The concession cost, measured in million £, is the difference between the average accepted price at the auction and the price that the gilts could have otherwise been sold in the secondary (or when-issued) market, multiplied by the size of auction. In estimation 1, From 2002 to 2014, the DMO measured the secondary market price as the closing clean price on the day before the auction. After 2014, the DMO measured the secondary market price by the mid-price at the time of the auction. In estimation 2, the concession cost is measure by using the pre-2014 definition of concession used by the DMO to calculate the concession cost throughout the entire sample period. BOE is the share of the gilt owned by the Bank of England under the Asset Purchase Scheme at the time of the auction, expressed as a percentage. APF is the natural log of the number of working days since the previous APF gilt purchase by the Bank of England, measured in days. SIZE is the natural log of the auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. VOL is the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract; the implied volatility is expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. BENCH is a dummy variable equal to 1 if the gilt is issued into a 5-, 10-, or 20-year benchmark line, and 0 otherwise (indicator variable). PAOF is a dummy variable equal to 1 if the auction includes the Post Auction Option Facility, and 0 otherwise (indicator variable). ACT is the natural log of the number of days since the last issuance of the specific gilt, measured in days. MAT represents the time to maturity, calculated as the number of days from the auction to the gilt's maturity date divided by 365.25, and is expressed in years. LIQ is the size of the outstanding gilt being auctioned (excluding the auction amount) divided by the average outstanding size of all other conventional gilts on the auction day; a value above 1.0 implies that the gilt being reissued is larger than average and potentially more liquid (liquidity ratio). DEM is the bid-to-cover ratio of the previous auction, where a value of 1.0 indicates that total bids equalled the amount offered, and 2.0 means the bids were twice the offer (demand ratio). NGEMMs is the number of Gilt-Edged Market Makers on the auction day, measured as a count. FCI is a dummy variable equal to 1 when the Financial Conditions Index identifies systemic episodes of financial stress, and 0 otherwise (indicator variable). We applied clustered standard errors, and the clusters are defined by the gilt issuance's frequency. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels.

$$Y_i = c + b_1 BOE_i + b_2 APF_i + b_3 SIZE_i + b_4 LIQ_i + b_5 BENCH_i + b_6 VOL_i + b_7 ACT_i + b_8 MAT_i + b_9 DEM_i + b_{10} TGMMs_i + b_{11} PAOF_i + b_{12} NGEMMs_i + b_{13} UKFCI_i + \varepsilon_i$$

	Estimation 1	Estimation 2
BOE	-3.05*	-4.93***
	(-2.07)	(-3.17)
APF	0.25**	0.11
	(2.47)	(0.5)
SIZE	-2.16**	-2.95
	(-2.61)	(-1.67)
TGEMMs	3.84***	3.61**
	(4.88)	(2.87)
VOL	-11.42**	-16.65
	(-2.48)	(-1.25)
BENCH	-0.33	-0.32
	(-0.63)	(-0.41)
PAOF	0.47	0.95
	(1.1)	(1.25)
ACT	-0.25	0.71
	(-1.65)	(1.64)
MAT	-0.01	-0.10*
	(-0.45)	(-1.89)
LIQ	0.81	1.82
	(1.39)	(1.75)
DEM	0.48	-0.65
	(0.99)	(-0.56)
NGEMMs	1.96*	-0.26
	(1.79)	(-1.35)
FCI	-0.57	-0.77*
	(-1.46)	(-1.89)
Constant	-1.74	9.49
	(-0.19)	(0.5)
No. Observations	527	519
R-squared	0.10	0.04

3.8. An Analysis of Maturity Segmentation

In this section, we apply the model in equations (2) across the different maturity segments to see whether there are segmentation premia in different sectors of the conventional gilt market in regard to the issuance cost. This is inspired by the preferred habitat and segmentation theories of Culbertson et al. (1957), Modigliani and Sutch (1966), Vayanos et al. (2009) and Greenwood and Vayanos (2010), where investors have preference for a particular range of maturities along the yield curve, implies that an imperfect substitutability may exist also within the bond market itself. Furthermore, J. Allen et al. (2020) find evidence that compared to the demand for longer bonds, demand for shorter bonds is typically less price-sensitive.

In Table 15, we show the average concession (if negative, or premium if positive) and average auction size for conventional gilt auctions that are divided into three maturity segments, and the sample period has been divided into eleven partitions. The maturity segments use the standard market convention of Short (< 7 years), Medium (7 to 15 years), and Long (>15 years). Comparing the auction concession between different maturity segments over eleven sub-periods in figure 16, it is notable that there is more fluctuation in the auction concession of long-term gilts. The gilt issuance is more expensive during the crisis period, specially the issuance cost for long-term bonds reached a low of around £11 million per auction. However, we can see the auction concession recovered during the first phase of QE, and this could be explained by the increase of demand for debt market since the investors preferred the less risky markets after the financial crisis even though the bank rate decreased during the first QE. It is worth emphasizing that sharp rise of the auction concession as a percentage of the average auction size for long-term gilts in compare to the other maturities during QE1 and post-QE1 can be explained by the decline in long-term issuance which means less supply in the market. It is also worth noting that the significant increase in auction premium for long-term gilts in 2022 might be influenced by changes in investor expectations regarding future inflation and interest rate stability. While the Bank of England raised the Bank Rate considerably during this period, which might typically reduce demand for long-term bonds, the increase in long-term gilt demand could reflect a preference for locking in yields in anticipation of continued economic uncertainty or expectations that rates would peak and eventually decline. This behaviour is consistent with a flight-to-duration strategy, where investors seek long-term assets to hedge against future rate volatility. To compare the effect of changing the definition of auction concession by DMO in 2014 on different maturity segments, we recalculated the auction concession by applying only the pre-2014 definition over the entire sample period (figure on the right side and Table 16). The results show that the trend during different sub-period is almost same, but the variation is less when we apply the new definition of DMO after 2014.

Using a between-subjects ANOVA to compare the average concession throughout various maturity segments, we find that, when applying Concession 1 ($p=0.321$,), the average concession remains constant across the maturity segments. Conversely, using Concession 2 revealed significant difference between the average of auction concession over different maturity segments ($p=0.045$). We also apply the Tukey HSD tests to make pair-wise comparisons for gilts within maturity segments. Since the variation in auction concession is higher for long-term gilts, we find more significant difference in the average of auction concession for long-term gilts over different sub-periods. Long-term gilts have statistically significant higher concession cost during the crisis than during pre-crisis, post-QE1, post-QE3, QE4, QE5, and QT ($p<0.01$). Furthermore, we find a reduction in concession cost during post-QE4 and QE5 in comparison with QE1 and pre-crisis ($p<0.01$). Although there is no significant difference for short-term gilts, we observe that the average of concession cost is higher for medium-term gilts during QE2and3 than post-QE4 and QE5 ($p<0.10$). Employing Concession 2 in pair-wise comparisons over different maturity segments, we find evidence that the average of concession cost for long-term gilts is significantly higher during crisis than post-QE3 (p=0.001) and QE5 (p=0.056). Additionally, there is a significant reduction in concession cost for long-term gilts during post-QE3 in compare to the pre-crisis (p<0.10). The details of the ANOVA analysis and all of the accompanying pairwise mean tests are in the Appendix, Tables 28-33.

Table 15: Auction Concession and Auction Size for Different Maturity Segments

This table contains the average auction size (£ million), the number of auctions, the average auction concession (£ million) and the issuance cost (-) or premium (+) as a percentage of the average auction size for three maturity segments. For the time-period 1987 to 2014, the concession cost is measured by multiplying the size of auction by the difference between the average price at auction and the clean close price on the day before auction. After 2014, the concession cost is measured by the difference between the average price at auction and the mid-price at the time of the auction, multiplied by the auction size. Since the data provided by DMO is only available from 2002 to 2022, we obtained the data from Data-Stream before 2002. The maturity buckets use the standard market convention of Short (< 7 years), Medium (7 to 15 years), and Long (>15 years). The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive.

Maturity	Statistic	Pre-crisis	Crisis	QE1	Post-QE1	QE2 and 3	Post-QE3	QE4	Post-QE4	QE5	QT-P	QT-A	Full Sample
Short	Average Auction Size (£m)	2540	3559	4896	4421	4297	4073	2945	3035	3509	3429	3904	3538
	Average Concession (£m)	-1.330	-2.028	0.789	0.334	-2.548	-0.545	1.139	0.884	0.505	0.748	0.034	-0.187
	Percent cost (-) premium (+)	-0.05%	-0.06%	0.02%	0.008%	-0.06%	-0.01%	0.04%	0.03%	0.01%	0.02%	0.001%	-0.005%
	Number of Auctions	38	17	14	20	14	34	5	35	60	10	4	251
Medium	Average Auction Size (£m)	2504	2865	3785	3376	3361	3270	2602	2758	3061	3133	3250	3006
	Average Concession (£m)	-2.949	-4.504	-0.053	0.496	-6.470	-0.073	0.914	1.098	0.958	1.181	1.417	-0.588
	Percent cost (-) premium (+)	-0.12%	-0.16%	0.001%	0.01%	-0.19%	0.002%	0.04%	0.04%	0.03%	0.04%	0.04%	-0.020%
	Number of Auctions	41	13	15	21	11	32	6	30	53	10	3	235
Long	Average Auction Size (£m)	2322	2176	2306	2213	1904	2026	2236	2276	1989	2370	2625	2164
	Average Concession (£m)	-4.412	-10.94	-6.927	-1.589	-3.238	0.984	2.700	2.192	2.214	1.903	5.610	-1.093
	Percent cost (-) premium (+)	-0.19%	-0.50%	-0.30%	-0.07%	-0.17%	0.05%	0.12%	0.10%	0.11%	0.08%	0.21%	-0.050%
	Number of Auctions	59	17	11	18	13	39	6	30	65	9	3	270

Table 16: Auction Concession (pre-2014 definition) and Auction Size for Different Maturity Segments

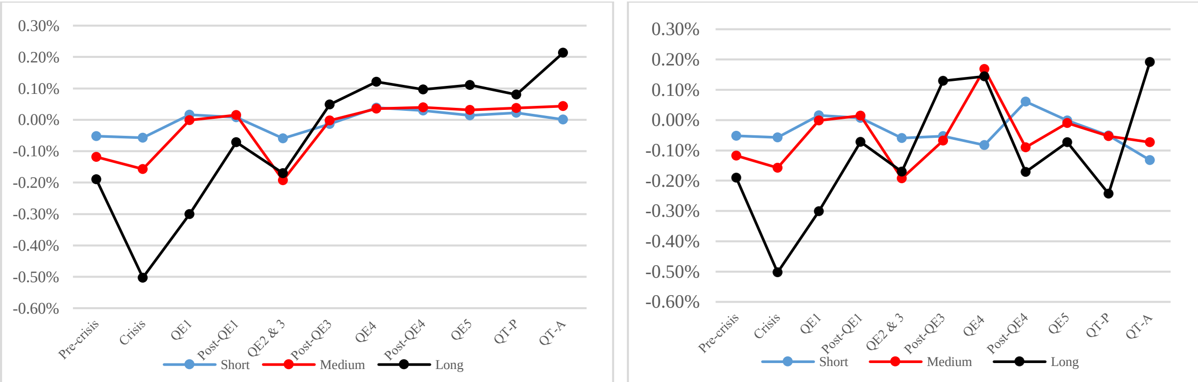
This table contains the average auction size (£ million), the number of auctions, the average auction concession (£ million) and the issuance cost (-) or premium (+) as a percentage of the average auction size for three maturity segments. The concession cost is measured by multiplying the size of auction by the difference between the average price at auction and the clean close price on the day before auction. Since the data provided by DMO is only available from 2002 to 2022, we obtained the data from Data-Stream before 2002. The maturity buckets use the standard market convention of Short (< 7 years), Medium (7 to 15 years), and Long (>15 years). The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive.

Maturity	Statistic	Pre-crisis	Crisis	QE1	Post-QE1	QE2 and 3	Post-QE3	QE4	Post-QE4	QE5	QT-P	QT-A	Full Sample
Short	Average Auction Size (£m)	2540	3559	4896	4421	4297	4073	2945	3035	3509	3429	3904	3538
	Average Concession (£m)	-1.330	-2.028	0.789	0.334	-2.548	-2.137	-2.420	1.854	-0.054	-1.761	-5.155	-0.654
	Percent cost (-) premium (+)	-0.05%	-0.06%	0.02%	0.008%	-0.06%	-0.05%	-0.08%	0.06%	0.00%	-0.05%	-0.13%	-0.018%
	Number of Auctions	38	17	14	20	14	34	5	35	60	10	4	251
Medium	Average Auction Size (£m)	2504	2865	3785	3376	3361	3270	2602	2758	3061	3133	3250	3006
	Average Concession (£m)	-2.949	-4.504	-0.053	0.496	-6.470	-2.218	4.389	-2.487	-0.311	-1.651	-2.385	-1.704
	Percent cost (-) premium (+)	-0.12%	-0.16%	0.00%	0.01%	-0.19%	-0.07%	0.17%	-0.09%	-0.01%	-0.05%	-0.07%	-0.057%
	Number of Auctions	41	13	15	21	11	32	6	30	53	10	3	235
Long	Average Auction Size (£m)	2322	2176	2306	2213	1904	2026	2236	2276	1989	2370	2625	2164
	Average Concession (£m)	-4.412	-10.940	-6.927	-1.589	-3.238	2.621	3.239	-3.887	-1.449	-5.761	5.045	-2.663
	Percent cost (-) premium (+)	-0.19%	-0.50%	-0.30%	-0.07%	-0.17%	0.13%	0.14%	-0.17%	-0.07%	-0.24%	0.19%	-0.123%
	Number of Auctions	59	17	11	18	13	39	6	30	65	9	3	270

Figure 16: The Auction Concession as A Percentage of the Average Auction Size

For the time-period 1987 to 2014, the concession cost is measured by multiplying the size of auction by the difference between the average price at auction and the clean close price on the day before auction. After 2014, the concession cost is measured by the difference between the average price at auction and the mid-price at the time of the auction, multiplied by the auction size. The y-axis is labelled "Auction Concession (% of Average Auction Size)," and the x-axis displays the sub-periods. The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive. Data source: UK Debt Management Office (UK DMO).

In this panel, the auction concession is recalculated by applying only the pre-2014 definition of the DMO during the entire sample period which is the difference between the average price at auction and the clean close price on the day before auction multiplied by the size of auction. The y-axis is labelled "Auction Concession (% of Average Auction Size)," and the x-axis displays the sub-periods. The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive. Data source: UK Debt Management Office (UK DMO).



According to the data presented in figure 17, the issuance of short-term gilts increased from 2008Q2 corresponding to the period of the financial crisis before the onset of QE1, Figure 18 also shows the increase of the short-term gilt issuance as a proportion of total gilt issuance from 28% in pre-crisis sub-period to 45%. During the first phase of QE, the share of long-term gilt issuance reached a low of 17%, but this raised gradually until the end of QE4 phase. It is notable that the share of short-term gilts issuance decreased steadily from QE1 until the end of QE5. However, this increased sharply during QT-active phase and this could be explained by the increase of bank rate from 0.1% to 3.5%. The fluctuation in the maturity of gilt issuance might be due to the changes in the bank rate determined by the MPC. The higher proportion of short-term gilt issuance could be the secondary goal of QE program to significantly change the average maturity of the debt. This would be similar to "operation twist," in which sales of short-term debt are used to support the acquisition of longer-term debt, with the goal of reducing the average maturity of outstanding debt and possibly decreasing long-term yields. (Swanson, 2011).

Figure 17: Gilt Issuance (£ million)

This figure shows the annual gross issuance of conventional gilts through auctions from May 1987 to December 2022, disaggregated by maturity segment. Issuance is measured in millions of pounds (£ million), with the y-axis displayed in thousands (£000s). The maturity categories follow standard market conventions: Short-term gilts (< 7 years), Medium-term gilts (7 to 15 years), and Long-term gilts (> 15 years). The stacked bar format allows comparison of both total issuance and shifts in maturity preference over time. The y-axis is labelled gilt issuance and the x-axis shows the year of issuance. Data source: UK Debt Management Office (UK DMO).

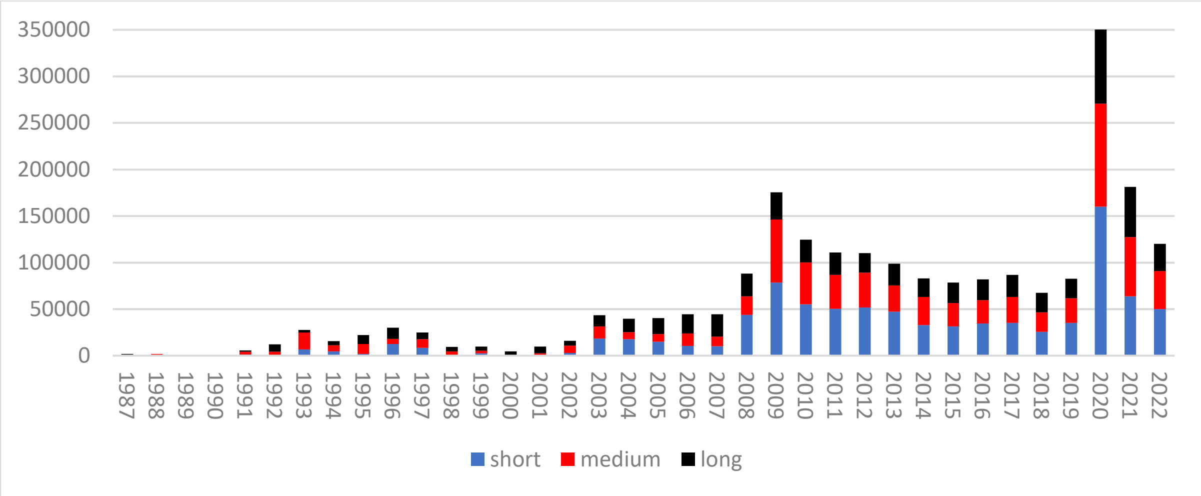
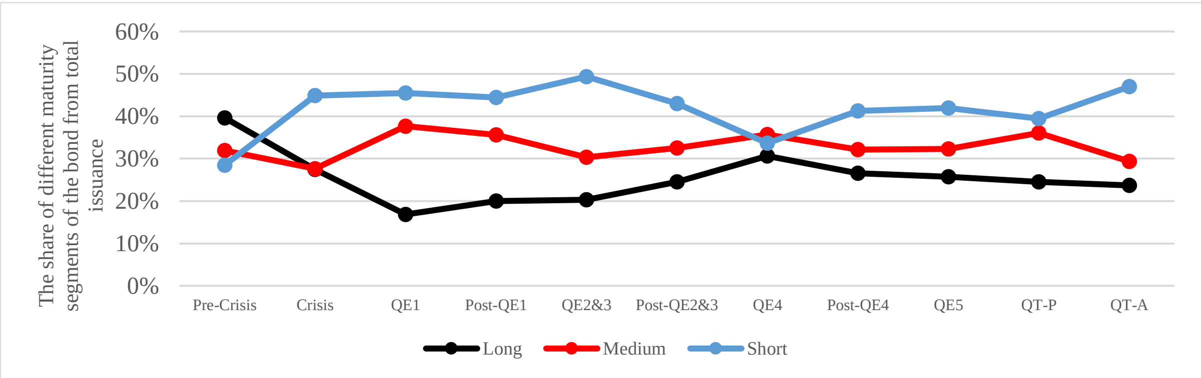


Figure 18: The share of different maturity segments of the bond from total issuance

figure shows the average share of conventional gilt issuance allocated to different maturity segments during each sub-period from May 1987 to December 2022. The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive. The maturity buckets follow standard market convention: Short-term (< 7 years), Medium-term (7 to 15 years), and Long-term (>15 years). Each line represents one maturity category, illustrating shifts in the UK government's issuance strategy over time. The y-axis is labelled "Share of Different Maturity Segments of the Bond from Total Issuance (%)," and the x-axis displays the sub-periods. Data source: UK Debt Management Office (UK DMO)



3.8.1. Results for Baseline Regression

In this sub-section, we applied the equation (2) separately for three different maturity from May 1987 to December 2022 to evaluate the gilts within their individual maturity segment. In this section, the variables are not measured on a maturity basis, and we applied the same set of variables in three estimations. However, we applied variables re-defined based on maturity segmentation in the appendix section 9.2.

According to the results of the estimation 1 of the coefficients given in Table 17, the variable *QEDUM* has a substantial negative impact on the issuance cost, increasing it by £2 million for long-term and £1.5 million for medium-term gilts. This impact is clearly statistically significant for long-term segment, while the effect for medium-term gilts is not significance. As we discussed previously, the strong impact of QE on long-term gilts driven by two reasons. Firstly, because long-term gilts have a longer duration than short-term gilts, they are more susceptible to changes in interest rates. Therefore, the demand and price of long-term gilts are more strongly impacted by the QE phase, which is an indication of monetary easing and a lower interest rate. Moreover, over the examined period, the long-term gilts' ratio of total QE purchases to total issuance was higher than that of the other durations (47% for long-term, 44% for medium-term, and 40% for short-term gilts). Consequently, a larger proportion of long-term gilts are owned by BOE, which lowers the gilts' market liquidity. Furthermore, compared to shorter maturities, a larger dampening effect on the cost of issuance for longer-dated gilts is produced by the concentration of QE purchase activities in the long-term sector.

the variable *TGEMMs* is highly significant for long- and short-term gilts. This might be due to the higher turnover of gilt-edged market makers in medium-term gilts which is shown in figure 19, rendering medium-term gilts less sensitive to changes in primary dealers' activity due to improved market liquidity conditions. The variable volatility is only significant for long-term gilts, which is in line with theorical prediction that gilts with a longer maturity typically carry a larger interest rate risk, making them more likely to affect the volatility of dealers' profits. This is also clear in figure 16, suggesting more volatility for gilts with longer maturity.

It is remarkable that variable *Bench* is only significant in long-term segmentation, and this might be the result of less issuance of long-term gilts which is obvious in figure 16. In fact, the increase in the issuance of the medium- and short-term gilt weakened the importance of the issuance benchmark status. Another reason could be that the range covered by each maturity, it might weaken their relationships with the benchmark status. Based on the definition of maturity buckets, short-term bucket comprises the gilts with maturity less than 7 years, and the gilts with maturity between 7 and 15 years are categorized as medium-term, and finally all of gilts with maturity more than 15 years are considered as long-term gilts. Therefore, long-term bucket covers a wider range of maturities since this bucket has an average maturity of around 30 years, with the longest maturity of 53 years. As a result of this, long term gilts are more sensitive to the benchmark status.

The variable *PAOF* is highly significant for short-term gilts. The variable *ACT* increase the issuance premium for medium-term gilts by around £1.13 million per auction, but increase the issuance cost for short-term gilts around £1.07 million. While the number of auctions is close over different maturities and Figure 21 similarly reveals no significant variation in the number of days since previous issuance across maturities, these factors alone cannot explain the observed inverse impact of *ACT* on auction concession across different maturities. An increase in market activity can lead to improvements in liquidity, potentially resulting in a decrease in auction concession, as observed for medium-term gilts.

While short-term gilts exhibit a significantly negative relationship between market activity and the auction concession, this observation appears inconsistent with the similar frequency of issuance values across maturity segments. This discrepancy may be explained by the significantly higher auction size and, consequently, the total issuance, observed for short-term gilts which means more activity increase the supply of short-term gilts in the market. On the other hand, in contrast to medium-term gilts, the turnover of primary dealer is significantly lower for short-term gilts which means less demand in the market. Therefore, more activity and issuance for short-term gilts increase the cost of issuance throughout demand and supply channel. This observation suggests the potential for minimizing the cost of issuance debt for government through strategic debt structure design by increasing the activity in short-term gilts and reducing the frequency of issuance for medium-term gilts.

The variable *DEM* is only significant for long-term issuance. It is also notable that *FCI* increases the issuance premium for long-term gilts. *FCI* is an indicator variable that take value one if the episodes of financials stress have been identified. Government bonds are frequently referred to as a “safe haven” since they are viewed as safer investments than other kinds of investments. They can help with portfolio diversification and act as a hedge during a crisis. During times of crisis, assets perceived as safe havens tend to perform better as investors seek to replace their riskier stock holdings with safer ones. This tendency is known as the "flight to quality". [25] This could explain the positive impact of *FCI* on issuance premium.

25 See Nasir et al (2023).

Table 17: Determinants of Auction Concession for Maturity Segments

This table has the estimated coefficients of equation (2) being used to identify the determinants of issuance cost (-) premium (+) for gilt auctions in three different maturity segments between May 1987 and December 2022 inclusive. The concession cost, measured in million £, is the difference between the average accepted price at the auction and the price that the gilts could have otherwise been sold in the secondary (or when-issued) market, multiplied by the size of auction. In estimation 1, From 2002 to 2014, the DMO measured the secondary market price as the closing clean price on the day before the auction. After 2014, the DMO measured the secondary market price by the mid-price at the time of the auction. In estimation 2, the concession cost is measure by using the pre-2014 definition of concession used by the DMO to calculate the concession cost throughout the entire sample period. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. VOL is the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract; the implied volatility is expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. BENCH is a dummy variable equal to 1 if the issuance is into a 5-, 10-, or 20-year benchmark line, and 0 otherwise (indicator variable). PAOF equals 1 if the Post Auction Option Facility was available, and 0 otherwise (indicator variable). ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days. MAT is the time to maturity, calculated as the number of days from the auction to the gilt's maturity date divided by 365.25, and expressed in years. LIQ is the ratio of the size of the gilt being auctioned (including the auctioned amount) to the average outstanding size of all other conventional gilts on the auction day; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover ratio of the previous auction, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). QEDUM is a dummy equal to 1 during the Bank of England's Asset Purchase Facility (QE) periods, and 0 otherwise (indicator variable). FCI equals 1 when the Financial Conditions Index identifies systemic financial stress, and 0 otherwise (indicator variable). The maturity buckets use the standard market convention of Short (< 7 years), Medium (7 to 15 years), and Long (>15 years). We applied clustered standard errors, and the clusters are defined by the gilt issuance's frequency. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels.

$$Y_i = c + b_1 QEDUM_i + b_2 SIZE_i + b_3 LIQ_i + b_4 BENCH_i + b_5 VOL_i + b_6 ACT_i + b_7 MAT_i + b_8 DEM_i + b_9 TGEMMs_i + b_{10} PAOF_i + b_{11} UKFCI_i + \varepsilon_i$$

	Estimation 1	Estimation 2	Estimation 1	Estimation 2	Estimation 1	Estimation 2
	Short	Short	Medium	Medium	Long	Long
QEDUM	-0.08	-0.33	-1.50	-0.32	-2.01**	-3.04
	(-0.15)	(-0.5)	(-1.59)	(-0.26)	(-2.45)	(-1.56)
SIZE	-2.13	-1.92	-3.58	-4.32	-3.09	-0.50
	(-1.64)	(-1.72)	(-1.62)	(-1.46)	(-1.23)	(-0.15)
TGEMMs	2.30***	1.66	0.97	1.29	5.31***	2.85
	(3.96)	(1.33)	(0.83)	(1.12)	(4.23)	(1.33)
VOL	-0.71	-19.97	-9.41	29.80	-43.00**	-54.47*
	(-0.04)	(-0.99)	(-0.91)	(0.89)	(-2.37)	(-2.09)
BENCH	-0.14	0.04	-0.24	-0.11	5.71***	3.24
	(-0.31)	(0.08)	(-0.21)	(-0.1)	(3.17)	(1.7)
PAOF	1.60***	1.05	1.58	2.40	0.54	1.29
	(2.23)	(1.74)	(1.46)	(1.56)	(0.49)	(0.75)
ACT	1.07***	0.69	-1.13**	-0.40	0.36	0.11
	(3.31)	(1.31)	(-1.99)	(-0.64)	(0.55)	(0.13)
MAT	-0.35	-0.30	-0.10	-0.16	-0.03	-0.10**
	(-1.71)	(-0.86)	(-0.46)	(-0.52)	(-0.59)	(-2.17)
LIQ	0.77	1.08	-1.37	0.24	0.39	-0.85
	(0.97)	(1.16)	(-0.97)	(0.17)	(0.36)	(-0.56)
DEM	-0.01	0.16	0.77	0.55	1.97***	0.43
	(-0.01)	(0.16)	(0.92)	(0.42)	(4.15)	(0.42)
FCI	0.25	0.03	0.11	-0.67	1.17*	1.34
	(0.34)	(0.04)	(0.08)	(-0.44)	(2.05)	(0.8)
Constant	4.42	6.90	26.25	24.67	-3.67	-5.25
	(0.43)	(0.83)	(1.12)	(0.83)	(-0.17)	(-0.2)
No. Observations	248	248	233	231	264	258
R-squared	0.10	0.054	0.11	0.040	0.25	0.08

Figure 19: Turnover of Gilt Market for Different Maturity segments

This figure presents the quarterly aggregate turnover in the secondary gilt market by Gilt-Edged Market Makers (GEMMs), broken down by maturity segment, from Q4 2008 to Q4 2022. Turnover is measured in million £, and represents the total nominal trading volume for each segment per quarter. Maturity categories follow standard market convention: Short-term (< 7 years), Medium-term (7 to 15 years), and Long-term (>15 years). The y-axis is labelled "Turnover of Gilt Market by Maturity (million £)," and the x-axis shows calendar quarters. Data source: UK Debt Management Office (UK DMO).

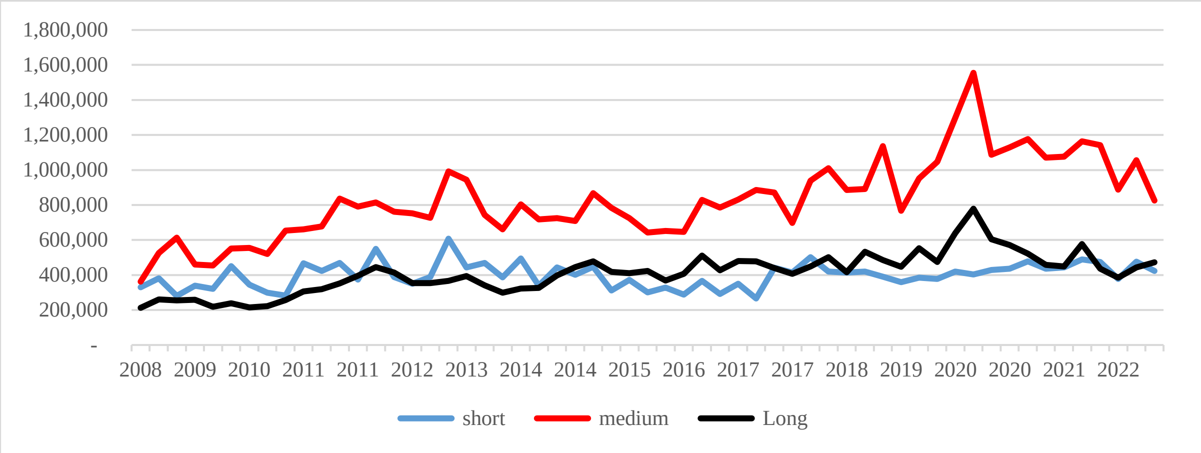


Figure 20: Average size of auction for different maturity segments

This figure presents the average auction size of conventional gilts for different maturity segments across eleven sub-periods from 1987 to 2022. The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive. The maturity buckets follow standard market definitions: Short-term (< 7 years), Medium-term (7 to 15 years), and Long-term (>15 years). The chart illustrates how the average issuance amount per auction has varied over time for each segment, reflecting shifts in issuance strategy and market demand. Auction sizes are measured in millions of pounds (£ million). The y-axis is labelled "Average Auction Size (£ million)," and the x-axis shows the sub-periods. Data source: UK Debt Management Office (UK DMO).

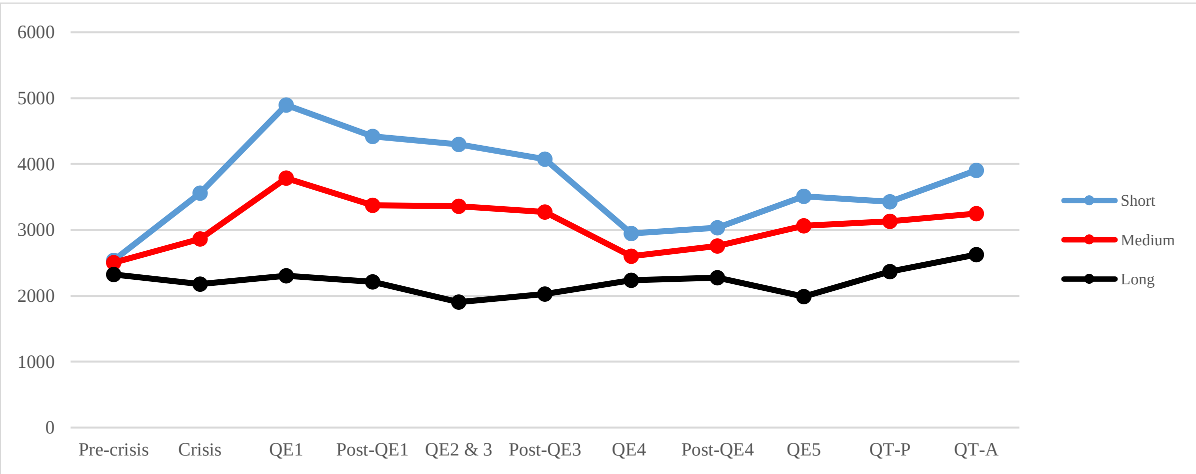
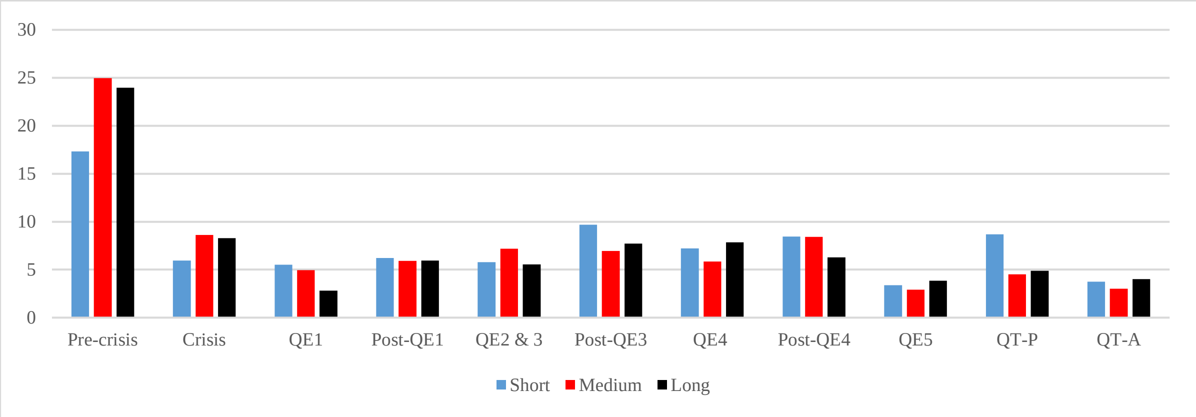


Figure 21: Average number of days since previous issuance for different maturities

figure shows the average number of days between successive auctions for conventional gilts, disaggregated by maturity segment, across eleven sub-periods from 1987 to 2022. The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive. The maturity categories follow standard market definitions: Short-term (< 7 years), Medium-term (7 to 15 years), and Long-term (>15 years). The metric reflects the frequency of issuance within each segment, with higher values indicating less frequent auctions. The y-axis is "Average Number of Days (trading days)," and the x-axis displays the sub-periods. Data source: UK Debt Management Office (UK DMO).



3.8.2. Results for Secondary Issuance

In this section, we apply the model in equation (2) to secondary issuance auctions across different maturity segments separately. The motivation for re-estimating the model for secondary issuance is elaborated in Section 5 (An Analysis of Secondary Issuance). As in that analysis of secondary issuance, one of the explanatory variables use data on the day preceding the auction. The variable *LIQ* now represents liquidity on the day before the auction by excluding the auctioned amount from the outstanding gilt being auctioned. Additionally, the variable *ACT* is again transformed into the natural logarithm of the number of days since the last conventional gilt issuance for that specific gilt, rather than since the last issuance of any gilt.

The results are reported in Table 18, representing almost same findings to those obtained from the estimation for all issuances. The effect of *QEDUM* is negative, but only significant for long term gilts for Estimation 1, as was found in table 17. The negative impact of size on the cost of issuance is stronger in the estimation for secondary issuance within different maturity segments; however, the impact of size on the cost of issuance for medium-term exhibits an insignificant impact (=-1.62), the higher turnover of primary dealers within this maturity bucket may offer a preliminary explanation for their decreased sensitivity to variations in auction size. It is noteworthy that the turnover of the GEMM market is becoming significant for medium-term gilts in the estimation of secondary issuance. This might be because removing primary issuance from the model revealed the impact of primary dealers' activity more clearly, as the average of auction concession for primary issuance (£-2.3 million per auction) is significantly lower than the average for secondary issuance (£-0.69 million per auction). The impact of *TGEMM* is statistically weaker for secondary issuance in the short-term maturity, and in the short-term maturity bucket the average of auction concession for primary issuance excluded from the estimation (£-0.14 million per auction) is higher than the average for secondary issuance (£-0.29 million per auction). For long-term maturity, both variables *VOL* and *BENCH* play a significant role in influencing auction concession of secondary issuance. Notably, the effect of variable *BENCH* achieved a level of significance in estimation 2 indicating its specific importance for this maturity. The effect of *PAOF* is weaker for secondary issuance which is in line with our expectation since the primary issuance is more sensitive to the liquidity condition. The variable *ACT* which is measured on a bond specific basis for the estimation of secondary issuance exerts a negative impact on the issuance cost of gilts in long maturity bucket. We found same impact for gilts with short and medium maturity, but weaker significance, suggesting measuring the activity and demand in the market by the number of days since previous issuance of that specific gilt might be easier to interpret. The impact of time to maturity is weaker for secondary issuance consistent with the results of section 5 (An Analysis of Secondary Issuance), indicting the primary issuance is more sensitive to the duration. The variable *LIQ* is significant for gilts with short maturity and indicates the positive impact of liquidity on the issuance premium, suggesting that measuring the liquidity of outstanding issue on the day before the auction by excluding the auction amount for short-term gilts is a better proxy than on the day of auction. The positive correlation between *DEM* and issuance premium is confirmed in the estimation of secondary issuance for long-term gilts, and it changed to be significant for gilts with medium maturity.

Overall, the analysis confirms that long-term bonds play a central role in shaping the cost dynamics of government debt issuance, particularly under unconventional monetary policy interventions such as QE. Across both baseline and secondary issuance estimations, long-term gilts consistently exhibit stronger and more statistically significant relationships with key variables including QE activity (*QEDUM*), volatility, and benchmark status. This reflects their heightened sensitivity to macroeconomic signals and policy measures due to their extended duration and greater exposure to interest rate risk. Moreover, the concentration of QE purchases in the long-term segment further amplifies their importance, as it affects both (secondary market) supply and liquidity in the gilt market. These findings underscore the strategic importance of long-term gilts in sovereign debt management, particularly in the design of policies aimed at balancing cost, risk, and investor demand.

Table 18: Determinants of Auction Concession for Secondary Issuance in Different Maturity Segments

This table has the estimated coefficients of equation (2) being used to identify the determinants of issuance cost (-) premium (+) for secondary gilt auctions in three different maturity segments between May 1987 and December 2022 inclusive. The concession cost, measured in million £, is the difference between the average accepted price at the auction and the price that the gilts could have otherwise been sold in the secondary (or when-issued) market, multiplied by the size of auction. In estimation 1, From 2002 to 2014, the DMO measured the secondary market price as the closing clean price on the day before the auction. After 2014, the DMO measured the secondary market price by the mid-price at the time of the auction. In estimation 2, the concession cost is measure by using the pre-2014 definition of concession used by the DMO to calculate the concession cost throughout the entire sample period. SIZE is the natural log of the auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. VOL is the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract; the implied volatility is expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. BENCH is a dummy variable equal to 1 if the gilt is issued into a 5-, 10-, or 20-year benchmark line, and 0 otherwise (indicator variable). PAOF is a dummy variable equal to 1 if the auction includes the Post Auction Option Facility, and 0 otherwise (indicator variable). ACT is the natural log of the number of days since the last issuance of the specific gilt, measured in days. MAT represents the time to maturity, calculated as the number of days from the auction to the gilt's maturity date divided by 365.25, and is expressed in years. LIQ is the size of the outstanding gilt being auctioned (excluding the auction amount) divided by the average outstanding size of all other conventional gilts on the auction day; a value above 1.0 implies that the gilt being reissued is larger than average and potentially more liquid (liquidity ratio). DEM is the bid-to-cover ratio of the previous auction, where a value of 1.0 indicates that total bids equalled the amount offered, and 2.0 means the bids were twice the offer (demand ratio). QEDUM is a dummy variable equal to 1 during the periods in which the Bank of England operated its Asset Purchase Facility under Quantitative Easing, and 0 otherwise (indicator variable). FCI is a dummy variable equal to 1 when the Financial Conditions Index identifies systemic episodes of financial stress, and 0 otherwise (indicator variable). The maturity buckets use the standard market convention of Short (< 7 years), Medium (7 to 15 years), and Long (>15 years). We applied clustered standard errors, and the clusters are defined by the gilt issuance's frequency. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels.

$$Y_i = c + b_1 QEDUM_i + b_2 SIZE_i + b_3 LIQ_i + b_4 BENCH_i + b_5 VOL_i + b_6 ACT_i + b_7 MAT_i + b_8 DEM_i + b_9 TGMMs_i + b_{10} PAOF_i + b_{11} UKFCI_i + \varepsilon_i$$

	Estimation 1	Estimation 2	Estimation 1	Estimation 2	Estimation 1	Estimation 2
	Short	Short	Medium	Medium	Long	Long
QEDUM	-0.84	-1.00	-1.54	-0.52	-2.99**	-3.74
	(-1.56)	(-1.43)	(-1.64)	(-0.43)	(-3.05)	(-1.77)
SIZE	-2.20	-2.25*	-2.74	-3.29	-4.43*	-1.79
	(-1.75)	(-2.08)	(-1.72)	(-1.08)	(-1.97)	(-0.56)
TGEMMs	1.53**	1.46	2.42**	2.14**	4.59***	2.82
	(2.85)	(1.62)	(2.53)	(2.48)	(5.84)	(1.7)
VOL	-15.38	-27.48	1.08	38.27	-29.57***	-44.13*
	(-0.95)	(-1.25)	(0.1)	(1.09)	(-3.3)	(-1.9)
BENCH	-0.38	0.07	-0.11	0.47	6.32***	3.44*
	(-0.72)	(0.13)	(-0.09)	(0.4)	(3.43)	(1.8)
PAOF	1.20*	0.78	0.65	1.27	0.67	0.91
	(1.88)	(1.32)	(0.95)	(1.02)	(0.59)	(0.52)
ACT	-0.38	0.024	-0.84	-0.05	-1.34**	-0.43
	(-1.76)	(0.09)	(-1.34)	(-0.06)	(-3.06)	(-0.86)
MAT	-0.21	-0.25	0.02	-0.06	-0.05	-0.10*
	(-0.91)	(-0.67)	(0.08)	(-0.18)	(-0.91)	(-2.13)
LIQ	1.63*	1.51	-1.36	0.67	-0.08	-1.69
	(1.85)	(1.44)	(-0.91)	(0.33)	(-0.07)	(-0.98)
DEM	-0.25	0.01	1.43**	1.33	1.46**	0.31
	(-0.33)	(0.01)	(2.86)	(1.3)	(2.44)	(0.25)
FCI	-0.58	-0.36	0.75	-0.14	0.89	0.73
	(-1.27)	(-0.48)	(0.48)	(-0.08)	(1.32)	(0.48)
Constant	13.09	12.51	10.62	8.57	17.69	7.37
	(1.28)	(1.65)	(0.67)	(0.32)	(0.9)	(0.27)
No. Observations	221	221	211	209	253	247
R-squared	0.09	0.06	0.13	0.04	0.24	0.08

3.9. Conclusion

This chapter has investigated the determinants of the cost of issuing UK government debt through auctions, spanning from the inception of the gilt auction market in 1987 to the end of 2022. The analysis covers major monetary policy interventions, including the phases of Quantitative Easing (QE), and periods of economic and financial turbulence such as the global financial crisis and the COVID-19 pandemic. By modelling issuance costs across different maturity segments and issuance types (primary and secondary), this study provides novel insights into the complex interactions between auction characteristics, bond features, market conditions, and unconventional monetary policy.

A key result is the finding that issuance costs increased during QE phases, particularly for long-term gilts. This contrasts with much of the secondary market literature—such as Joyce et al. (2011), Breedon et al. (2012), and Joyce and Tong (2012) —which shows that QE reduced yields and supported secondary market prices. However, our results are not inconsistent when considering structural differences between primary and secondary markets. QE appears to exert distinct impacts at the point of issuance compared to its effects in the broader trading environment.

Two central theoretical mechanisms—the portfolio rebalancing and signalling channels—help to interpret these findings. The portfolio rebalancing channel suggests that by reducing the supply of gilts available to private investors, QE raises bond prices and lowers yields in secondary markets (Tobin, 1969; Vayanos and Vila, 2009). However, from a primary market perspective, central bank accumulation of bonds decreases the free float, which over time reduces liquidity and auction competitiveness. As highlighted by Ferdinandusse et al. (2020), QE initially boosts market liquidity by facilitating transactions, but prolonged asset holdings by the Bank of England create scarcity, reducing liquidity and pushing up issuance costs.

Similarly, the signalling channel implies that QE announcements reinforce expectations of a lower future interest rate environment. While this initially supports bond valuations, it may also reduce investors' urgency to acquire long-term debt at issuance, anticipating further favourable conditions ahead. Consequently, QE can paradoxically weaken primary market demand even as it strengthens secondary market valuations.

This tension reflects a price-liquidity trade-off inherent in QE. As discussed by Spronsen and Beetsma (2022) and Beetsma et al. (2020), large-scale asset purchases can lower auction competitiveness, suppress bid-to-cover ratios, and alter auction dynamics, especially for long-term securities. Our finding that QE raised issuance costs for long-term gilts is consistent with Beetsma et al. (2020) who observed a negative impact of Eurosystem asset purchases on auction demand for long-term debt.

Furthermore, the concentration of QE purchases on long-term gilts (47% of QE purchases directed toward long maturities) is a key factor amplifying segmentation effects. Consistent with the preferred habitat theory (Culbertson et al. ,1957; Modigliani and Sutch ,1966), long-term bonds exhibited stronger sensitivity to liquidity, volatility, and QE variables, reflecting their greater exposure to interest rate risk and policy uncertainty. Compared to shorter maturities, long-term issuance is therefore more vulnerable to shifts in liquidity conditions and central bank interventions.

Additional insights arise from our findings regarding the pace of asset purchases. As Bailey et al. (2020) and Froemel et al. (2022) suggest, the speed of QE implementation can significantly influence liquidity conditions and yield expectations. The accelerated pace of purchases in 2020, aimed at restoring market functioning during the COVID-19 shock, likely mitigated some issuance cost pressures. However, slower-than-expected purchasing or uncertainty regarding future purchase stock can increase yields, adding further complexity to auction outcomes.

Our segmentation analysis further reveals that while all maturity segments show some responsiveness to auction characteristics and market factors, the long-term segment is consistently the most sensitive. Variables such as volatility, benchmark status, liquidity, and GEMM turnover exert stronger and more significant effects on long-dated gilts. This suggests that sovereign debt managers should pay particular attention to long-term issuance strategies during periods of unconventional monetary policy.

Finally, comparing primary and secondary issuance results indicates that primary auctions are more sensitive to immediate market conditions and auction design variables. The stronger sensitivity of primary issuance underscores the importance of careful issuance planning, particularly when market liquidity is distorted by central bank interventions.

In summary, this chapter provides evidence that QE, while lowering yields and supporting prices in the secondary market, increased issuance costs in the primary market through liquidity depletion, scarcity effects, and altered demand dynamics. These results contribute to the literature by highlighting the nuanced effects of QE across different segments of the government bond market, offering valuable insights for policymakers aiming to manage debt issuance efficiently during periods of extraordinary monetary intervention.

Based on the findings of this chapter, the following policy recommendations are proposed to optimise debt issuance strategies and minimise issuance costs during periods of unconventional monetary policy:

➢ Reduce the issuance of long-term gilts during QE phases to mitigate the higher issuance costs driven by lower liquidity and heightened sensitivity to interest rate changes;

➢ Monitor and manage the size of auctions carefully, particularly during QE periods, to avoid increasing the issuance cost through supply pressures on GEMM inventories;

➢ Enhance the turnover of Gilt-Edged Market Makers (GEMMs) across all maturities, especially in the long-term and short-term segments, to strengthen market liquidity and issuance premiums;

➢ Focus on maintaining or promoting benchmark status, especially for long-term gilts, as it can help reduce issuance costs where issuance volumes are lower;

➢ Encourage market activity for medium-term gilts by increasing auction frequency, while exercising caution for short-term gilts where higher activity may lead to increased issuance costs;

➢ Make greater use of the Post Auction Option Facility (PAOF), especially for short-term gilts, to improve liquidity and support higher issuance premiums;

➢ Recognize that volatility significantly impacts the issuance cost of long-term gilts, and therefore, consider limiting long-term issuance during periods of heightened financial market stress;

➢ Acknowledge that while QE initially supports bond prices in secondary markets, its liquidity-scarcity effects can raise issuance costs in primary auctions, particularly over longer durations, and adjust issuance strategies accordingly.

3.10. Appendix

3.10.1. Correlations

Table 19: Correlations

The table reports the Pearson correlations among the independent variables across the 779 auctions from 1987 to 2022, and no outlier removal was performed for the summary statistics presented here. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. VOL is the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract; the implied volatility is expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. BENCH is a dummy variable equal to 1 if the issuance is into a 5-, 10-, or 20-year benchmark line, and 0 otherwise (indicator variable). PAOF equals 1 if the Post Auction Option Facility was available, and 0 otherwise (indicator variable). ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days. MAT is the time to maturity, calculated as the number of days from the auction to the gilt's maturity date divided by 365.25, and expressed in years. LIQ is the ratio of the size of the gilt being auctioned (including the auctioned amount) to the average outstanding size of all other conventional gilts on the auction day; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover ratio of the previous auction, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). QEDUM is a dummy equal to 1 during the Bank of England's Asset Purchase Facility (QE) periods, and 0 otherwise (indicator variable). FCI equals 1 when the Financial Conditions Index identifies systemic financial stress, and 0 otherwise (indicator variable). *, **, *** correspond to significance levels of 10%, 5%, and1%, respectively.

	MAT	SIZE	ACT	VOL	BENCH	TGEMMs	PAOF	LIQ	DEM	QEDUM	FCI
MAT	1										
SIZE	-0.66***	1									
ACT	0.02	-0.13***	1								
VOL	-0.01	0.06*	0.05	1							
BENCH	-0.42***	0.28***	0.05	-0.11***	1						
TGEMMs	-0.01	0.19***	-0.59***	-0.34***	-0.04	1					
PAOF	0.01	0.23***	-0.28***	-0.21***	-0.01	0.45***	1				
LIQ	-0.09***	-0.07*	0.18***	0.13***	0.05	-0.42***	-0.16***	1			
DEM	0.05	-0.08**	-0.26***	-0.05	-0.13***	0.24***	0.07*	0.01	1		
QEDUM	0.01	0.07**	-0.45***	-0.21***	-0.08**	0.44***	0.23***	-0.08***	0.33***	1	
FCI	-0.06*	0.10***	-0.19***	0.10***	0.01	0.17***	0.03	-0.03	-0.03	0.12***	1

Table 20: Correlations Without Outliers in Auction Concession 1

The table reports the Pearson correlations among the main variables across the 745 auctions from 1987 to 2022, where we use the data that excludes observations on dates corresponding to the concession outliers (in Estimation 1) and the missing data prior to 2002 for primary issuance. The concession cost, measured in million £, is the difference between the average accepted price at the auction and the price that the gilts could have otherwise been sold in the secondary (or when-issued) market, multiplied by the size of auction. In Concession 1, From 2002 to 2014, the DMO measured the secondary market price as the closing clean price on the day before the auction. After 2014, the DMO measured the secondary market price by the mid-price at the time of the auction. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. VOL is the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract; the implied volatility is expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. BENCH is a dummy variable equal to 1 if the issuance is into a 5-, 10-, or 20-year benchmark line, and 0 otherwise (indicator variable). PAOF equals 1 if the Post Auction Option Facility was available, and 0 otherwise (indicator variable). ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days. MAT is the time to maturity, calculated as the number of days from the auction to the gilt's maturity date divided by 365.25, and expressed in years. LIQ is the ratio of the size of the gilt being auctioned (including the auctioned amount) to the average outstanding size of all other conventional gilts on the auction day; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover ratio of the previous auction, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). QEDUM is a dummy equal to 1 during the Bank of England's Asset Purchase Facility (QE) periods, and 0 otherwise (indicator variable). FCI equals 1 when the Financial Conditions Index identifies systemic financial stress, and 0 otherwise (indicator variable). *, **, *** correspond to significance levels of 10%, 5%, and1%, respectively.

	Concession 1	MAT	SIZE	ACT	VOL	BENCH	TGEMMs	PAOF	LIQ	DEM	QEDUM	FCI
Concession	1											
MAT	-0.03	1										
SIZE	-0.01	-0.67***	1									
ACT	-0.14***	0.01	-0.12***	1								
VOL	-0.17***	-0.03	0.08**	0.05	1							
BENCH	0.01	-0.42***	0.28***	0.08**	-0.11***	1						
TGEMMs	0.29***	-0.01	0.18***	-0.56***	-0.34***	-0.08**	1					
PAOF	0.19***	0.02	0.22***	-0.25***	-0.21***	-0.03	0.43***	1				
LIQ	-0.12***	-0.09**	-0.09**	0.21***	0.13***	0.05	-0.49***	-0.19***	1			
DEM	0.10***	0.05	-0.10***	-0.24***	-0.04	-0.13***	0.22***	0.05	0.01	1		
QEDUM	0.07*	0.01	0.06*	-0.44***	-0.21***	-0.09***	0.43***	0.21***	-0.10***	0.32***	1	
FCI	0.04	-0.06	0.09**	-0.18***	0.10***	0.002	0.16***	0.02	-0.03	-0.05	0.11***	1

Table 21: Correlations Without Outliers in Auction Concession 2

The table reports the Pearson correlations among the main variables across the 737 auctions from 1987 to 2022, where we use the data that excludes observations on dates corresponding to the concession outliers (in Estimation 2) and the missing data prior to 2002 for primary issuance. The concession cost, measured in million £, is the difference between the average accepted price at the auction and the price that the gilts could have otherwise been sold in the secondary (or when-issued) market, multiplied by the size of auction. In Concession 2, the concession cost is measure by using the pre-2014 definition of concession used by the DMO to calculate the concession cost throughout the entire sample period. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. VOL is the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract; the implied volatility is expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. BENCH is a dummy variable equal to 1 if the issuance is into a 5-, 10-, or 20-year benchmark line, and 0 otherwise (indicator variable). PAOF equals 1 if the Post Auction Option Facility was available, and 0 otherwise (indicator variable). ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days. MAT is the time to maturity, calculated as the number of days from the auction to the gilt's maturity date divided by 365.25, and expressed in years. LIQ is the ratio of the size of the gilt being auctioned (including the auctioned amount) to the average outstanding size of all other conventional gilts on the auction day; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover ratio of the previous auction, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). QEDUM is a dummy equal to 1 during the Bank of England's Asset Purchase Facility (QE) periods, and 0 otherwise (indicator variable). FCI equals 1 when the Financial Conditions Index identifies systemic financial stress, and 0 otherwise (indicator variable). *, **, *** correspond to significance levels of 10%, 5%, and1%, respectively.

	Concession 1	MAT	SIZE	ACT	VOL	BENCH	TGEMMs	PAOF	LIQ	DEM	QEDUM	FCI
Concession	1											
MAT	-0.09**	1										
SIZE	0.04	-0.67***	1									
ACT	-0.05	0.01	-0.13***	1								
VOL	-0.10***	-0.02	0.07*	0.06	1							
BENCH	0.02	-0.41***	0.28***	0.08**	-0.11***	1						
TGEMMs	0.14***	-0.02	0.18***	-0.57***	-0.35***	-0.07*	1					
PAOF	0.13***	0.01	0.22***	-0.25***	-0.22***	-0.03	0.43***	1				
LIQ	-0.03	-0.08**	-0.09**	0.21***	0.14***	0.04	-0.49***	-0.18***	1			
DEM	0.03	0.05	-0.10***	-0.24***	-0.05	-0.13***	0.22***	0.05	0.01	1		
QEDUM	0.01	0.02	0.06*	-0.45***	-0.22***	-0.10***	0.44***	0.22***	-0.10***	0.32	1	
FCI	0.02	-0.06	0.09**	-0.17***	0.09**	0.002	0.15***	0.00	-0.03	-0.06	0.11***	1

Table 22: Summary statistics of main variables without outliers in Estimation 1

This table is similar to Table 4, but it presents summary statistics for the same variables using data that excludes observations on dates corresponding to the concession outliers (in Estimation 1) and the missing data prior to 2002 for primary issuance.

Variable	**Observation**	**Mean**	**SD**	**Min**	**P25**	**P50**	**P75**	**Max**	**Skewness**	**Kurtosis**	**Pr(S)**	**Pr(K)**	**Ha: mean=0 Pr (|T| > |t|)**
SIZE	745	7.92	0.31	6.62	7.72	7.92	8.14	8.66	-0.44	3.56	0	0	0.00
LIQ	745	0.88	0.49	0.08	0.51	0.83	1.17	2.98	0.85	4	0	0	0.00
ACT	745	1.73	0.94	0	1.1	1.61	2.3	4.37	-0.02	2.80	0.79	0.27	0.00
VOL	745	0.07	0.02	0.02	0.05	0.07	0.09	0.15	1.22	4.29	0	0	0.00
DEM	745	2.09	0.48	0.93	1.73	2.07	2.38	4.81	0.72	4.97	0	0	0.00
TGEMMs	745	4.82	0.54	2.74	4.49	4.97	5.21	5.72	-1.14	4.15	0	0	0.00
MAT	745	15.23	11.96	2.12	5.46	10.13	23.1	53.3	1.07	3.17	0	0.29	0.00

Table 23: Summary statistics of main variables without outliers in Estimation 2

This table is similar to Table 4, but it presents summary statistics for the same variables using data that excludes observations on dates corresponding to the concession outliers (in Estimation 2) and the missing data prior to 2002 for primary issuance.

Variable	**Observation**	**Mean**	**SD**	**Min**	**P25**	**P50**	**P75**	**Max**	**Skewness**	**Kurtosis**	**Pr(S)**	**Pr(K)**	**Ha: mean=0 Pr (|T| > |t|)**
SIZE	737	7.92	0.31	6.62	7.72	7.93	8.14	8.66	-0.45	3.59	0	0	0.00
LIQ	737	0.88	0.49	0.08	0.51	0.83	1.17	2.98	0.85	3.98	0	0	0.00
ACT	737	1.74	0.94	0	1.1	1.61	2.3	4.37	-0.03	2.81	0.77	0.30	0.00
VOL	737	0.07	0.02	0.02	0.05	0.07	0.09	0.15	1.20	4.26	0	0	0.00
DEM	737	2.09	0.48	0.93	1.73	2.08	2.39	4.81	0.71	4.94	0	0	0.00
TGEMMs	737	4.81	0.54	2.74	4.49	4.96	5.2	5.72	-1.15	4.15	0	0	0.00
MAT	737	15.11	11.89	2.12	5.43	10.1	22.77	53.37	1.09	3.24	0	0.18	0.00

Table 24: Summary statistics of main variables for auctions that were secondary issuance without outliers in Estimation 1

This table is similar to Table 6, however it shows the summary statistics for the same variables in which we apply the data without the observations on dates corresponding to the dates of the concession outliers (in Estimation 1).

Variable	**Observation**	**Mean**	**SD**	**Min**	**P25**	**P50**	**P75**	**Max**
Concession 1	685	-0.46	5.75	-22.05	-1.42	0.9	2.05	19.2
SIZE	685	7.91	0.31	6.62	7.72	7.92	8.14	8.66
LIQ	685	0.94	0.47	0.16	0.59	0.88	1.2	2.98
ACT	685	1.71	0.95	0	1.1	1.61	2.3	4.37
VOL	685	0.07	0.02	0.02	0.05	0.07	0.08	0.15
DEM	685	2.1	0.48	0.93	1.74	2.08	2.39	4.81
TGEMMs	685	4.82	0.55	2.74	4.5	4.97	5.22	5.72
MAT	685	15.53	12.05	2.12	5.46	10.13	23.82	53.37

Table 25: Summary statistics of main variables for auctions that were secondary issuance without outliers in Estimation 2

This table is similar to Table 6, however it shows the summary statistics for the same variables using the data without the observations on dates corresponding to the dates of the concession outliers (in Estimation 2).

Variable	**Observation**	**Mean**	**SD**	**Min**	**P25**	**P50**	**P75**	**Max**
Concession 2	677	-1.43	7.8	-24.93	-6	-0.75	3.33	23.31
SIZE	677	7.91	0.31	6.62	7.72	7.92	8.14	8.66
LIQ	677	0.94	0.47	0.16	0.59	0.89	1.2	2.98
ACT	677	1.71	0.95	0	1.1	1.61	2.3	4.37
VOL	677	0.07	0.02	0.02	0.05	0.07	0.08	0.15
DEM	677	2.1	0.49	0.93	1.74	2.08	2.4	4.81
TGEMMs	677	4.81	0.55	2.74	4.5	4.97	5.21	5.72
MAT	677	15.39	11.99	2.12	5.43	10.1	23.42	53.37

Table 26: Summary statistics for QE and the gilt market without outliers in Estimation 1

This table is similar to Table 10, however it shows the summary statistics for the same variables using the data without the observations on dates corresponding to the dates of the concession outliers (in Estimation 1).

Variable	Observation	Mean	SD	Min	P25	P50	P75	Max
Concession2	565	0.33	4.84	-22.05	0.24	1.07	2.11	18.9
SIZE	565	7.96	0.31	6.91	7.74	8.01	8.18	8.66
LIQ	565	0.77	0.38	0.08	0.47	0.76	1.04	1.81
ACT	565	1.48	0.79	0	1.1	1.61	2.08	3.09
VOL	565	0.07	0.02	0.02	0.05	0.07	0.07	0.15
DEM	565	2.12	0.43	0.93	1.8	2.12	2.41	3.85
TGEMMs	565	5.06	0.29	4.14	4.88	5.09	5.28	5.72
MAT	565	14.83	11.72	2.12	5.46	9.98	22.31	53.37
BOE	565	0.17	0.19	0	0	0.1	0.28	0.75
APF	565	2.07	2.15	0	0	1.1	4.26	6.04
NGEMMs	565	18.6	1.62	15	18	18	20	22

Table 27: Summary statistics for QE and the gilt market without outliers in Estimation 2

This table is similar to Table 10, however it shows the summary statistics for the same variables, using the data without the observations on dates corresponding to the dates of the concession outliers (in Estimation 2).

Variable	Observation	Mean	SD	Min	P25	P50	P75	Max
Concession2	557	-0.83	7.78	-24.93	-5.39	-0.4	3.6	23.31
SIZE	557	7.96	0.31	6.91	7.74	8.01	8.18	8.66
LIQ	557	0.77	0.38	0.08	0.47	0.76	1.04	1.81
ACT	557	1.48	0.79	0	1.1	1.61	2.08	3.09
VOL	557	0.07	0.02	0.02	0.05	0.07	0.07	0.15
DEM	557	2.12	0.44	0.93	1.8	2.12	2.41	3.85
TGEMMs	557	5.05	0.29	4.14	4.88	5.08	5.28	5.72
MAT	557	14.66	11.62	2.12	5.43	9.97	21.57	53.37
BOE	557	0.17	0.19	0	0	0.1	0.28	0.75
APF	557	2.07	2.15	0	0	1.1	4.26	6.04
NGEMMs	557	18.61	1.62	15	18	18	20	22

Table 28: One-Way ANOVA for Concession 1

This tables contains the results for the one-way ANOVA, indicating whether there is a statistically significant difference throughout three maturity segments, short, medium, and long-term gilts (in the left side), and also eleven sub-periods (in the right side). The dependent variable is the concession cost (in million £) measured as the difference between the average accepted price at the auction and the price that the gilts could have otherwise been sold in the secondary (or when-issued) market, multiplied by the size of auction. From 2002 to 2014, the DMO measured the secondary market price as the closing clean price on the day before the auction. After 2014, the DMO measured the secondary market price by the mid-price at the time of the auction. The dataset contains 756 auctions from 1987 to 2022.

Maturity Segmentation						**Sub-periods**					
Source	SS	df	MS	F	Prob >F	Source	SS	df	MS	F	Prob >F
Between groups	107.41	2	53.70	1.11	0.329	Between groups	3995.80	10	399.58	9.17	0.000
Within groups	36336.34	753	48.26			Within groups	32447.95	745	43.55		
Total	36443.75	755	48.27			**Total**	36443.75	755	48.27		

Table 29: One-Way ANOVA for Concession 2

This tables contains the results for the one-way ANOVA, indicating whether there is a statistically significant difference throughout three maturity segments, short, medium, and long-term gilts (in the left side), and also eleven sub-periods (in the right side). The dependent variable is the concession cost (in million £) measured as the difference between the average accepted price at the auction and the closing clean price on the day before the auction, multiplied by the size of auction. The dataset contains 756 auctions from 1987 to 2022.

Maturity Segmentation						**Sub-periods**					
Source	SS	df	MS	F	Prob > F	Source	SS	df	MS	F	Prob > F
Between groups	524.79	2	262.40	3.12	0.045	Between groups	2116.59	10	211.66	2.56	0.005
Within groups	63229.30	753	83.97			Within groups	61637.50	745	82.73		
Total	63754.09	755	84.44			**Total**	63754.09	755	84.44		

Table 30: Pairwise Comparisons of Means over QE Phases (Concession 1)

This table reports the comparisons as contrasts (differences) of margins along with significance tests or confidence intervals for the contrasts as output of Tukey's honestly significant difference test. The variable is Concession 1 (in million £) measured as the difference between the average accepted price at the auction and the price that the gilts could have otherwise been sold in the secondary (or when-issued) market, multiplied by the size of auction. From 2002 to 2014, the DMO measured the secondary market price as the closing clean price on the day before the auction. After 2014, the DMO measured the secondary market price by the mid-price at the time of the auction. The dataset contains 756 auctions from 1987 to 2022. *, **, *** correspond to significance levels of 10%, 5%, and1%, respectively. The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive.

	Pre-crisis	Crisis	QE1	Post-QE1	QE2 and 3	Post-QE3	QE4	Post-QE4	QE5	QT-P
Crisis	-2.81									
QE1	1.48	4.29*								
Post-QE1	2.93	5.74***	1.45							
QE2 and 3	-0.79	2.02	-2.27	-3.72						
Post-QE3	3.30***	6.10***	1.82	0.36	4.09**					
QE4	4.74	7.55***	3.26	1.81	5.53	1.44				
Post-QE4	4.49***	7.30***	3.01	1.56	5.28***	1.20	-0.25			
QE5	4.39***	7.20***	2.91	1.46	5.18***	1.10	-0.35	-0.10		
QT-P	4.38**	7.19***	2.90	1.45	5.18*	1.09	-0.35	-0.11	-0.01	
QT-A	5.25	8.06**	3.77	2.32	6.04	1.96	0.51	0.76	0.86	0.87

Table 31: Pairwise Comparisons of Means over QE Phases (Concession 2)

This table reports the comparisons as contrasts (differences) of margins along with significance tests or confidence intervals for the contrasts as output of Tukey HSD. The variable is Concession 2 (in million £) measured as the difference between the average accepted price at the auction and the closing clean price on the day before the auction, multiplied by the size of auction. The dataset contains 756 auctions from 1987 to 2022. *, **, *** correspond to significance levels of 10%, 5%, and1%, respectively. The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive.

	Pre-crisis	Crisis	QE1	Post-QE1	QE2 and 3	Post-QE3	QE4	Post-QE4	QE5	QT-P
Crisis	-2.81									
QE1	1.48	4.29								
Post-QE1	2.93	5.74*	1.45							
QE2 and 3	-0.79	2.02	-2.27	-3.72						
Post-QE3	2.73	5.54**	1.25	-0.20	3.53					
QE4	5.11	7.92*	3.63	2.18	5.90	2.37				
Post-QE4	1.80	4.61	0.32	-1.14	2.59	-0.94	-3.31			
QE5	2.49	5.30**	1.01	-0.44	3.28	-0.25	-2.62	0.69		
QT-P	0.16	2.97	-1.32	-2.77	0.96	-2.57	-4.94	-1.63	-2.32	
QT-A	1.86	4.67	0.38	-1.07	2.66	-0.87	-3.24	0.07	-0.62	1.70

Table 32: Pairwise Comparisons of Means over QE Phases and Maturity Segments (Concession 1)

This table reports the comparisons as contrasts (differences) of margins along with significance tests or confidence intervals for the contrasts as output of Tukey HSD within different maturity segments. The variable is Concession 1 (in million £) measured as the difference between the average accepted price at the auction and the price that the gilts could have otherwise been sold in the secondary (or when-issued) market, multiplied by the size of auction. From 2002 to 2014, the DMO measured the secondary market price as the closing clean price on the day before the auction. After 2014, the DMO measured the secondary market price by the mid-price at the time of the auction. The dataset contains 756 auctions from 1987 to 2022. The maturity buckets use the standard market convention of Short (< 7 years), Medium (7 to 15 years), and Long (>15 years). *, **, *** correspond to significance levels of 10%, 5%, and1%, respectively. The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive.

Sub-period	Maturity	Pre-crisis	Crisis	QE1	Post-QE1	QE2 and 3	Post-QE3	QE4	Post-QE4	QE5	QT-P
Crisis	long	-6.53**									
	medium	-1.56									
	short	-0.70									
QE1	long	-2.52	4.01								
	medium	2.90	4.45								
	short	2.12	2.82								
Post-QE1	long	2.82	9.35***	5.34							
	medium	3.45	5.00	0.55							
	short	1.66	2.36	-0.46							
QE2 and 3	long	1.17	7.70	3.69	-1.65						
	medium	-3.52	-1.97	-6.42	-6.97						
	short	-1.22	-0.52	-3.34	-2.88						
Post-QE3	long	5.40	11.92***	7.91**	2.57	4.22					
	medium	2.88	4.43	-0.02	-0.57	6.40					
	short	0.78	1.48	-1.33	-0.88	2.00					
QE4	long	7.11	13.64***	9.63	4.29	5.94	1.72				
	medium	3.86	5.42	0.97	0.42	7.38	0.99				
	short	2.47	3.17	0.35	0.80	3.69	1.68				
Post-QE4	long	6.60***	13.13	9.12**	3.78	5.43	1.21	-0.51			
	medium	4.05	5.60	1.15	0.60	7.57*	1.17	0.18			
	short	2.21	2.91	0.10	0.55	3.43	1.43	-0.25			
QE5	long	6.63***	13.15***	9.14***	3.80	5.45	1.23	-0.49	0.02		
	medium	3.91	5.46	1.01	0.46	7.43**	1.03	0.04	-0.14		
	short	1.83	2.53	-0.28	0.17	3.05	1.05	-0.63	-0.38		
QT-P	long	6.31	12.84***	8.83	3.49	5.14	0.92	-0.80	-0.29	-0.31	
	medium	4.13	5.69	1.23	0.68	7.65	1.25	0.27	0.08	0.22	
	short	2.08	2.78	-0.04	0.41	3.30	1.29	-0.39	-0.14	0.24	
QT-A	long	10.02	16.55**	12.54	7.20	8.85	4.63	2.91	3.42	3.40	3.71
	medium	4.37	5.92	1.47	0.92	7.89	1.49	0.50	0.32	0.46	0.24
	short	1.36	2.06	-0.76	-0.30	2.58	0.58	-1.10	-0.85	-0.47	-0.71

Table 33: Pairwise Comparisons of Means over QE Phases and Maturity Segments Concession 2)

This table reports the comparisons as contrasts (differences) of margins along with significance tests or confidence intervals for the contrasts as output of Tukey HSD within different maturity segments. The variable is Concession 2 measured as the difference between the average accepted price at the auction and the closing clean price on the day before the auction, multiplied by the size of auction. The dataset contains 756 auctions from 1987 to 2022. The maturity buckets use the standard market convention of Short (< 7 years), Medium (7 to 15 years), and Long (>15 years). *, **, *** correspond to significance levels of 10%, 5%, and1%, respectively. The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive.

Sub-period	Maturity	Pre-crisis	Crisis	QE1	Post-QE1	QE2 and 3	Post-QE3	QE4	Post-QE4	QE5	QT-P
Crisis	long	-6.53									
	medium	-1.56									
	short	-0.70									
QE1	long	-2.52	4.01								
	medium	2.90	4.45								
	short	2.12	2.82								
Post-QE1	long	2.82	9.35	5.34							
	medium	3.45	5.00	0.55							
	short	1.66	2.36	-0.46							
QE2 and 3	long	1.17	7.70	3.69	-1.65						
	medium	-3.52	-1.97	-6.42	-6.97						
	short	-1.22	-0.52	-3.34	-2.88						
Post-QE3	long	7.03*	13.56***	9.55	4.21	5.86					
	medium	0.73	2.29	-2.16	-2.71	4.25					
	short	-0.81	-0.11	-2.93	-2.47	0.41					
QE4	long	7.65	14.18	10.17	4.83	6.48	0.62				
	medium	7.34	8.89	4.44	3.89	10.86	6.61				
	short	-1.09	-0.39	-3.21	-2.75	0.13	-0.28				
Post-QE4	long	0.52	7.05	3.04	-2.30	-0.65	-6.51	-7.13			
	medium	0.46	2.02	-2.43	-2.98	3.98	-0.27	-6.88			
	short	3.18	3.88	1.06	1.52	4.40	3.99	4.27			
QE5	long	2.96	9.49*	5.48	0.14	1.79	-4.07	-4.69	2.44		
	medium	2.64	4.19	-0.26	-0.81	6.16	1.91	-4.70	2.18		
	short	1.28	1.97	-0.84	-0.39	2.49	2.08	2.37	-1.91		
QT-P	long	-1.35	5.18	1.17	-4.17	-2.52	-8.38	-9.00	-1.87	-4.31	
	medium	1.30	2.85	-1.60	-2.15	4.82	0.57	-6.04	0.84	-1.34	
	short	-0.43	0.27	-2.55	-2.09	0.79	0.38	0.66	-3.61	-1.71	
QT-A	long	9.46	15.98	11.97	6.63	8.28	2.42	1.81	8.93	6.49	10.81
	medium	0.56	2.12	-2.33	-2.88	4.09	-0.17	-6.77	0.10	-2.07	-0.73
	short	-3.82	-3.13	-5.94	-5.49	-2.61	-3.02	-2.73	-7.01	-5.10	-3.39

3.10.2. Baseline Results with Maturity Based Explanatory Variables

As another robustness check, we investigate whether the results change if we re-define three of the explanatory variables based on maturity segmentation. Thus, the variable *ACT* is the natural log of the number of days since the last public issuance in a gilt in the same maturity segment. *LIQ* is measured as the size of the outstanding gilt that is being auctioned (including the auctioned amount) divided by the average size outstanding of other (conventional) gilts in the same maturity segment. DEM is the bid-to-cover of the previous auction in the same maturity segment. Redefining the turnover of the gilt market based on maturity segments is not feasible due to data limitations. The only maturity-based turnover data available on the DMO website dates back to 2001 and is aggregated quarterly. For the summary statistics shown in Table 34, no outlier elimination was undertaken for the 776 auctions in the first section of the table, which covers the years 1987 to 2022. The second section gives summary statistics for 743 auctions, excluding the observations that correspond to Concession 1's outlier dates. The final section includes summary statistics for 735 auctions, removing observations corresponding to Concession 2's outlier dates. The correlation between the maturity-based variables and other variables is presented in table 34.

Table 34: Summary statistics of the variables based on maturity segmentation

This table contains the summary statistics for three variables constructed based on the maturity segmentation. The first part of table contains 776 auctions between 1987 to 2022, and no outlier removal was performed for the summary statistics presented here. The second part contains the summary statistics for 743 auctions without the observations corresponding to the outlier dates of Concession 1. The last part contains the summary statistics for 735 auctions excluding the observations corresponding to the outlier dates of Concession 2. The variable ACT is the natural log of the number of days since the last public issuance in a gilt in the same maturity segment, measured in days. LIQ is measured as the size of the outstanding gilt that is being auctioned (including the auctioned amount) divided by the average size outstanding of other (conventional) gilts in the same maturity segment; a value above 1.0 indicates that the gilt is larger than the average in the same maturity segment and likely more liquid (liquidity ratio). DEM is the bid-to-cover of the previous auction in the same maturity segment, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). Mean is the sample mean of the variable, SD is the sample standard deviation, Min and Max are the minimum and maximum observations, and p25, p50, and p75 indicate the observation in percentile 25, 50, or 75, respectively. Skewness essentially is a commonly used measure in descriptive statistics that characterizes the asymmetry of a data distribution, while kurtosis determines the heaviness of the distribution tails. Skewness is a descriptive statistics measure that characterises the asymmetry of a data distribution. Kurtosis determines the heaviness of the distribution tails. P(S) shows the P-value for skewness, and P(K) shows the P-value for kurtosis. The last column shows the means are statistically significantly different from zero.

Variable	Observation	Mean	SD	Min	P25	P50	P75	Max	Skewness	Kurtosis	Pr(S)	Pr(K)	Ha: mean=0 Pr (|T| > |t|)
DEM	776	2.07	0.47	0.93	1.72	2.06	2.37	4.81	0.69	5.07	0	0	0
ACT	779	1.25	0.41	0	1	1.3	1.49	2.83	-0.14	3.84	0.094	0	0
LIQ	779	0.84	0.47	0.08	0.51	0.81	1.1	3.02	0.98	4.91	0	0	0
DEM	743	2.07	0.47	0.93	1.73	2.07	2.37	3.02	0.7	5.17	0	0	0
ACT	743	1.22	0.4	0	1	1.28	1.48	743	-0.26	3.82	0	0	0
LIQ	743	0.84	0.47	0.08	0.51	0.81	1.1	3.02	0.99	4.96	0	0	0
DEM	735	2.07	0.47	0.93	1.73	2.06	2.37	4.81	0.71	5.17	0	0	0
ACT	735	1.23	0.4	0	1	1.28	1.48	2.83	0.26	3.81	0	0	0
LIQ	735	0.84	0.47	0.08	0.51	0.82	1.1	3.02	0.99	4.93	0	0	0

Table 35: Correlation with maturity-based variables

The table reports the Pearson correlations among maturity-based variables and other variables from 1987 to 2022. The concession cost, measured in million £, is the difference between the average accepted price at the auction and the price that the gilts could have otherwise been sold in the secondary (or when-issued) market, multiplied by the size of auction. In Concession 1, From 2002 to 2014, the DMO measured the secondary market price as the closing clean price on the day before the auction. After 2014, the DMO measured the secondary market price by the mid-price at the time of the auction. In Concession 2, the concession cost is measure by using the pre-2014 definition of concession used by the DMO to calculate the concession cost throughout the entire sample period. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. VOL is the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract; the implied volatility is expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. BENCH is a dummy variable equal to 1 if the issuance is into a 5-, 10-, or 20-year benchmark line, and 0 otherwise (indicator variable). PAOF equals 1 if the Post Auction Option Facility was available, and 0 otherwise (indicator variable). ACT is the natural log of the number of days since the last public issuance in a gilt in the same maturity segment, measured in days. MAT is the time to maturity, calculated as the number of days from the auction to the gilt's maturity date divided by 365.25, and expressed in years. LIQ is measured as the size of the outstanding gilt that is being auctioned (including the auctioned amount) divided by the average size outstanding of other (conventional) gilts in the same maturity segment, a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover of the previous auction in the same maturity segment, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). QEDUM is a dummy equal to 1 during the Bank of England's Asset Purchase Facility (QE) periods, and 0 otherwise (indicator variable). FCI equals 1 when the Financial Conditions Index identifies systemic financial stress, and 0 otherwise (indicator variable). *, **, *** correspond to significance levels of 10%, 5%, and1%, respectively.

	Concession 1	Concession 2	SIZE	ACT	VOL	BENCH	TGEMMs	PAOF	LIQ	DEM	QEDUM	FCI
Concession	1	1										
SIZE	-0.01	0.03	1									
ACT	-0.17***	-0.06*	-0.07***	1								
VOL	-0.17***	-0.10***	0.08	0.09***	1							
BENCH	0.01	0.02	0.28***	0.20***	-0.10***	1						
TGEMMs	0.28***	0.14***	0.16***	-0.61***	-0.34***	-0.08	1					
PAOF	0.19***	0.13***	0.22***	-0.27***	-0.21***	-0.04	0.43***	1				
LIQ	-0.06*	0.007	-0.11***	0.10**	0.12***	0.05*	-0.43***	-0.14***	1			
DEM	0.11***	0.06	-0.01	-0.25***	-0.01	-0.04	0.24***	0.07**	0.05	1		
QEDUM	0.06*	0.01	0.06**	-0.61***	-0.21***	-0.10**	0.44***	0.21***	-0.07	0.30***	1	
FCI	0.04	0.02	0.09***	-0.16***	0.09***	0.00	0.15***	0.00	-0.01	-0.08	0.11***	1

Similar to the baseline estimation, all auctions with a concession or premium greater than £25 million are removed from the estimation. The number of observations is two fewer than the baseline regression, as defining the DEM based on the bid-to-cover of the previous auction in the same maturity segment results in missing data for the first auction in each maturity bucket. Given the missing auction concession for the primary issuance before 2002 in baseline estimation, the first auction in the short maturity bucket was categorized as missing data since it is primary issuance. Interestingly, the results represented in Table 36 are consistent with baseline results in section 4 (Empirical Results). The variable *ACT* which was insignificant in the baseline estimation achieved the significance level as we redefine it to measure the market activity by the number of days from the previous issuance within each maturity bucket. This research highlights that using not maturity segmented variables does not matter. The results show that measuring the demand and liquidity based on the maturity segments does not affect the output of estimation.

Table 36: Baseline Results with Maturity Based Explanatory Variables

This table has the estimated coefficients of equation (2) being used to identify the determinants of issuance cost (-) premium (+) for gilt auctions between May 1987 and December 2022 inclusive. The concession cost, measured in million £, is the difference between the average accepted price at the auction and the price that the gilts could have otherwise been sold in the secondary (or when-issued) market, multiplied by the size of auction. In estimation 1, From 2002 to 2014, the DMO measured the secondary market price as the closing clean price on the day before the auction. After 2014, the DMO measured the secondary market price by the mid-price at the time of the auction. In estimation 2, the concession cost is measure by using the pre-2014 definition of concession used by the DMO to calculate the concession cost throughout the entire sample period. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. VOL is the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract; the implied volatility is expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. BENCH is a dummy variable equal to 1 if the issuance is into a 5-, 10-, or 20-year benchmark line, and 0 otherwise (indicator variable). PAOF equals 1 if the Post Auction Option Facility was available, and 0 otherwise (indicator variable). ACT is the natural log of the number of days since the last public issuance in a gilt in the same maturity segment, measured in days. MAT is the time to maturity, calculated as the number of days from the auction to the gilt's maturity date divided by 365.25, and expressed in years. LIQ is measured as the size of the outstanding gilt that is being auctioned (including the auctioned amount) divided by the average size outstanding of other (conventional) gilts in the same maturity segment, a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover of the previous auction in the same maturity segment, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). QEDUM is a dummy equal to 1 during the Bank of England's Asset Purchase Facility (QE) periods, and 0 otherwise (indicator variable). FCI equals 1 when the Financial Conditions Index identifies systemic financial stress, and 0 otherwise (indicator variable). ***, **, * indicate statistical significance at the 1%, 5% and 10% levels.

$$Y_i = c + b_1 QEDUM_i + b_2 SIZE_i + b_3 LIQ_i + b_4 BENCH_i + b_5 VOL_i + b_6 ACT_i + b_7 MAT_i + b_8 DEM_i + b_9 TGMMs_i + b_{10} PAOF_i + b_{11} UKFCI_i + \varepsilon_i$$

	Estimation 1	Estimation 2
QEDUM	-1.46***	-1.46*
	(-3.27)	(-2.02)
SIZE	-3.06***	-2.34*
	(-3.06)	(-1.87)
TGEMMs	2.74***	1.89**
	(6.14)	(2.27)
VOL	-18.73**	-20.21
	(-2.69)	(-1.65)
BENCH	0.27	-0.19
	(0.45)	(-0.31)
PAOF	1.33*	1.52
	(1.86)	(1.62)
ACT	-0.94*	-0.34
	(-1.88)	(-0.48)
MAT	-0.06*	-0.10**
	(-1.78)	(-2.22)
LIQ	0.45	0.85
	(0.9)	(1.38)
DEM	0.53	0.17
	(0.78)	(0.15)
FCI	0.25	0.19
	(0.53)	(0.37)
Constant	12.16	10.13
	(1.26)	(0.73)
No. Observations	743	735
R-squared	0.12	0.05

3.10.3. QE Period Results with Maturity Based Explanatory Variables

We also examine whether the findings for the period starting in 2009 differ if the explanatory variables are defined according to maturity segmentation as an additional robustness check. Similar to previous section, the variables *ACT*, *DEM*, and *LIQ* are defined based on maturity. In this subsection, we additionally construct the variable *APF* based on maturity, which is the natural logarithm of the number of (working) days since the BOE last purchased a gilt in the same maturity segment through an APF operation.

After removing auctions with a concession or premium greater than £25 million, the number of observations is 4 fewer than the estimation of modified regression model in section 3.7.4, which is because, when we consider the number of days since the BOE last purchased a gilt within same maturity segment, four observations in long-term maturity bucket fall before 11th August 2009, the date of the first purchase for long-term gilt.

On the evidence of Table 37, the results align with the findings of the QE period without maturity-based variables reported in Section 3.7.4). Segmenting the *LIQ* and *APF* by maturity reveals the impact of these variables with greater statically significance. However, we could not find any improvement for measuring the variables *DEM* and *ACT* based on maturity.

Table 37: QE Period Results with Maturity Based Explanatory Variables

BOE is the share of the gilt owned by the Bank of England under the Asset Purchase Scheme at the time of the auction, expressed as a percentage. PF is the natural log of the number of (working) days since a previous APF purchase of a gilt in the same maturity segment by the BOE, measured in days. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. VOL is the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract; the implied volatility is expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. BENCH is a dummy variable equal to 1 if the issuance is into a 5-, 10-, or 20-year benchmark line, and 0 otherwise (indicator variable). PAOF equals 1 if the Post Auction Option Facility was available, and 0 otherwise (indicator variable). ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days. MAT is the time to maturity, calculated as the number of days from the auction to the gilt's maturity date divided by 365.25, and expressed in years. LIQ is measured as the size of the outstanding gilt that is being auctioned (including the auctioned amount) divided by the average size outstanding of other (conventional) gilts in the same maturity segment; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover ratio of the previous auction in the same maturity segment, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). NGEMMs is the number of Gilt-Edged Market Makers active on the auction day, measured as a count. FCI equals 1 when the Financial Conditions Index identifies systemic financial stress, and 0 otherwise (indicator variable). We applied clustered standard errors, and the clusters are defined by the gilt issuance's frequency. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels.

$$Y_i = c + b_1 BOE_i + b_2 APF_i + b_3 SIZE_i + b_4 LIQ_i + b_5 BENCH_i + b_6 VOL_i + b_7 ACT_i + b_8 MAT_i + b_9 DEM_i + b_{10} TGMMs_i + b_{11} PAOF_i + b_{12} NGEMMs_i + b_{13} UKFCI_i + \varepsilon_i$$

	Estimation 1	Estimation 2
BOE	-4.56***	-3.74**
	(-4.19)	(-2.71)
APF	0.63***	0.28
	(3.41)	(0.74)
SIZE	-2.59***	-3.10
	(-3.25)	(-1.55)
TGEMMs	3.47**	2.70
	(2.92)	(1.57)
VOL	-19.08***	-21.24
	(-3.37)	(-1.36)
BENCH	-0.41	-0.93
	(-0.8)	(-1.35)
PAOF	0.83	1.43
	(1.58)	(1.69)
ACT	-0.61	0.59
	(-1.03)	(0.46)
MAT	-0.02	-0.10
	(-0.88)	(-1.6)
LIQ	1.00**	1.81*
	(2.14)	(1.95)
DEM	0.27	0.03
	(0.34)	(0.02)
NGEMMs	-0.29	-0.20
	(-1.58)	(-0.97)
FCI	0.12	-0.13
	(0.21)	(-0.22)
Constant	9.46	14.48
	(1.08)	(0.63)
No. Observations	561	553
R-squared	0.10	0.03

3.10.4. An analysis of Outliers

All Auctions with concession or premium more than £25 million are considered as outliers in our estimation. Applying the pre-2014 definition throughout the entire sample period to measure the auction concession, we found nineteen outliers, and we explain the possible reasons of occurring these outliers in this sub-section. The following table presents the values for the variables explained previously for these outliers to find whether the variables used in the model caused the larger premium or concession at auctions. While Table 38 presents variables *SIZE* and *TGEMMs* without natural logarithms to enhance the comprehension to determine the presence and magnitude of significant values. From nineteen outliers, twelve auctions have long-term maturity suggesting that designing the issuance of gilts with long-term duration needs more effort to decrease the cost of issuance. Comparing individual variable values to the average in Table 38 revealed no significant factor consistently leading to higher premium or concession at auction. Therefore, we investigate in policies and news published around the days of auction to find whether the investors' behaviour changed because of policy decisions and market condition.

Table 38: List of Outliers:

The auction concession cost (if negative, or premium if positive) is measured by multiplying the size of auction by the difference between the average price at auction and the clean close price on the day before auction, measured in million SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. VOL is the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract; the implied volatility is expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. BENCH is a dummy variable equal to 1 if the issuance is into a 5-, 10-, or 20-year benchmark line, and 0 otherwise (indicator variable). PAOF equals 1 if the Post Auction Option Facility was available, and 0 otherwise (indicator variable). ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days. MAT is the time to maturity, calculated as the number of days from the auction to the gilt's maturity date divided by 365.25, and expressed in years. LIQ is the ratio of the size of the gilt being auctioned (including the auctioned amount) to the average outstanding size of all other conventional gilts on the auction day; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover ratio of the previous auction, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). QEDUM is a dummy equal to 1 during the Bank of England's Asset Purchase Facility (QE) periods, and 0 otherwise (indicator variable). FCI equals 1 when the Financial Conditions Index identifies systemic financial stress, and 0 otherwise (indicator variable). We applied clustered standard errors, and the clusters are defined by the gilt issuance's frequency. Secondary is an indicator that takes value unity if the issuance is secondary and zero if it is primary issuance.

Auction Date	Auction Concession	Secondary	Maturity	MAT	SIZE	ACT	VOL	BENCH	LIQ	DEM	TGEMMs	PAOF	FCI
28/05/2003	-30.06	1	Long	33	2250	10	0.121	0	0.761	2.85	50.2	0	0
02/07/2003	-27.80	1	Long	33	2250	4	0.116	0	1.065	1.76	63.9	0	0
06/02/2007	26.77	1	Long	40	2250	20	0.103	0	1.093	2.3	85.2	0	0
02/09/2008	-25.65	0	Long	41	2250	19	0.103	0	0.195	1.58	63.4	0	0
04/03/2009	-37.03	0	Long	31	2250	1	0.112	0	0.144	2.86	122.7	0	1
03/06/2009	28.70	1	Medium	10	3850	1	0.102	1	1.605	2.3	95.2	1	1
09/06/2009	25.00	1	Short	5	5490	4	0.103	1	1.401	2.51	90.0	1	1
04/10/2011	31.20	1	Medium	10	3575	5	0.075	1	0.920	1.29	170.5	1	1
20/06/2013	-44.18	1	Short	5	4750	5	0.066	1	0.739	1.45	165.5	0	0
10/09/2013	-29.98	1	Long	30	3018	17	0.064	0	0.751	1.48	124.7	1	0
19/09/2013	32.78	1	Short	5	5084	5	0.064	1	1.127	1.59	148.6	1	0
07/01/2016	25.41	1	Long	44	1500	2	0.047	0	0.842	1.62	138.7	0	0
15/02/2018	-35.57	1	Long	39	2563	20	0.062	0	0.446	2.07	184.3	1	0
01/10/2019	-27.40	1	Long	18	2250	15	0.068	0	1.022	1.94	246.8	0	0
10/03/2020	-43.02	1	Medium	11	2587	4	0.056	1	1.423	1.75	273.3	1	1
17/03/2020	-40.30	1	Long	29	2300	5	0.070	0	0.681	2.23	260.7	1	1
21/04/2020	25.26	1	Long	35	1875	3	0.069	0	0.408	2.4	234.0	1	1
08/03/2022	-28.34	1	Long	29	1875	4	0.070	0	0.573	1.91	205.9	1	0
05/10/2022	-28.83	1	Medium	9	3750	1	0.144	0	0.835	1.97	229.7	1	1

➢ **28/05/2003 and 02/07/2003 (4¼% Treasury Stock 203)**

Between end-March 2003 and end-March 2004 yields on conventional gilts rose along the curve. During the second quarter of 2003, yields continued to increase as investors' views that interest rates had bottomed out strengthened in response to better economic data from the US, the UK, and the Eurozone as well as a robust rebound in equity market indices. But even with a string of encouraging economic reports, especially from the US, the market believed that the global recovery was only partially underway. Central banks started downplaying expectations of impending rate hikes, and bond markets had a small uptick in mid-September.

Figure 22: Conventional benchmark nominal yields 2003-2004

This figure presents the daily nominal yields of selected UK government bonds (gilts) across various maturities from March 2003 to March 2004. Each line represents a benchmark gilt—such as the 5% 2004, 5% 2008, and 4¼% 2032 issues—highlighting how yields evolved over time for different tenors. The y-axis is labelled "Yield (% per annum)," reflecting the annualised return an investor would expect, while the x-axis shows the timeline in monthly intervals. This visualisation captures market expectations for interest rates and inflation over short, medium, and long horizons. Data source: UK Debt Management Office (DMO).

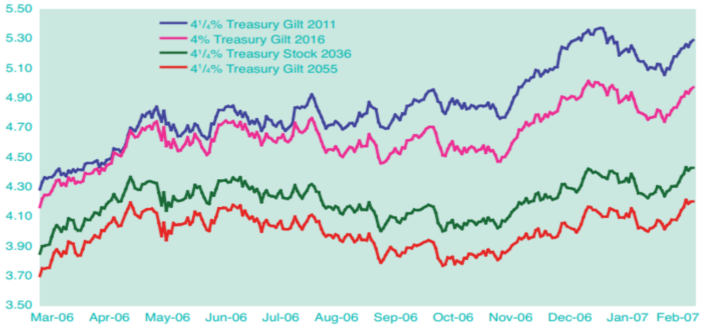
➢ **06/02/2007 (4¼% Treasury Gilt 2046)**

Figure 23 shows how the gilt yield curve significantly inverted between 2006 and 2007. While yields increased across all asset classes, short-dated gilts significantly underperformed long maturities, which was expected given the context of rising interest rates. An additional interest rate rise in November 2006 was expected by the market as a result of the economic data continuing to beat forecasts in the autumn 2006 and the exceptionally high house prices. On 9th November 2006, the MPC did rise UK rates, but because the decision was widely expected, the gilt market observed tight movement. In December 2006, gilt rates surged another time due to the persistence of positive economic indicators and growing concerns regarding the possibility of inflation staying higher than goal. Because of the continued geopolitical tensions in the Middle East, oil prices were volatile during this period, raising concerns about inflationary pressures for many central banks. Market expectations increased for another rise in UK interest rates in early 2007. As a result, on January 11th, the MPC increased rates by 25 basis points, and yields dramatically increased across all maturity buckets, especially at the short end. Long yields decreased as short yields increased, indicating the persistence of strong demand at the long end of the curve, which was said to be indicative of Liability Driven Investment (LDI) intentions. In the meantime, uncertainties over rising oil prices and ongoing merger and acquisition activity kept the

FTSE-100 rocketing. It was stated that investors switched from stocks to gilts as a result of this. This could explain the larger premium of long-term gilt being auctioned on 6th February 2007.

Figure 23: Conventional benchmark nominal yields 2006-2007

This figure shows the daily nominal yields of selected UK government bonds (gilts) across various maturities from March 2006 to February 2007. Each line represents a benchmark gilt, including the 4¼% Treasury Gilt 2011, 4% Treasury Gilt 2016, 4½% Treasury Stock 2036, and 4¼% Treasury Gilt 2055. The y-axis is labelled "Yield (% per annum)," reflecting the annualised return investors expect over the life of each bond, and the x-axis displays the date range in monthly intervals. This chart illustrates market expectations for interest rates and inflation over short-, medium-, and long-term horizons. Data source: UK Debt Management Office (DMO).



- **02/09/2008 (4¼% Treasury Gilt 2049), 04/03/2009 (4¼% Treasury Gilt 2039):**

Figure 24 illustrates that gilt yields decreased sharply at the short end of the nominal par curve and increased at the long end during 2008–09. This was mostly due to Bank Rate decreases that were made in reaction to the macroeconomic situation. Gilt yields fell significantly at the short-end of the nominal par curve and rose at the long-end in 2008-09 as shown in Figure 24. This reflected primarily reductions in Bank Rate implemented in response to prevailing macroeconomic conditions. Volatility in financial markets increased in late September 2008 as Lehman Brothers filed for bankruptcy and AIG received support from the US Government. The outliers here could be due to high uncertainty, in that it was difficult to sell a long bond around the time of Lehman collapsing and at the time of the start of QE. This was followed by public sector support for a number of banks in the US, UK and Europe. The demand for government bonds, reflecting "flight-to-quality", led to a fall in yields at the short-end. Other factors such as the unwillingness of stock lenders to lend gilts, also contributed to the downward trend in gilt yields through the quarter. Another reason could be that both of gilts are primary issuance which is riskier than secondary issuance.

Figure 24: Conventional benchmark nominal yields 2008-2009

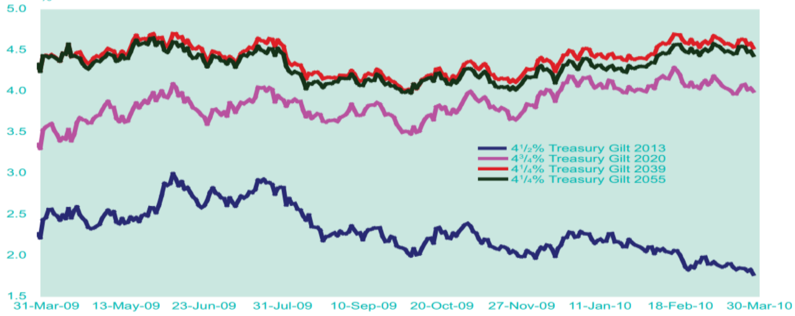
This figure displays the daily nominal yields of selected UK government bonds (gilts) from March 2008 to March 2009, covering the onset of the Global Financial Crisis. The chart includes benchmark gilts such as the 5¼% 2012, 4% 2016, 4¾% 2038, and 4¼% 2055, representing a range of maturities. The y-axis is labelled "Yield (% per annum)," indicating the annualised return expected by investors, while the x-axis shows the date range. The figure illustrates how market expectations for interest rates and inflation shifted sharply during a period of heightened financial stress. Data source: UK Debt Management Office (DMO).

- **03/06/2009 (4½% Treasury Gilt 2019), and 09/06/2009 (5% Treasury Stock 2014)**

In 2009-10, government bond markets were volatile due to uncertainty in the domestic and global economy. In most of the G10 economies, expectations for the evolution of monetary conditions were still dominated by downside risks to GDP, especially in the second quarter of year. Meanwhile, flows out of riskier assets continued to support the rise of government bond markets. Therefore, the demand for assets with less risk increased which could explain the larger premium of two gilts being auctioned with medium and short maturities in September. This is also clear in Figure 25 showing a decrease in gilt's yield in the start of September. Another possible explanation could be that these bonds were benchmarks, so maybe that caused high demand resulting in a high premium. This could also explain why Breedon found that BENCH is significant and we did not. That is, he was not careful to remove outliers.

Figure 25: Conventional benchmark nominal yields 2009-2010

figure shows the daily nominal yields of selected UK government bonds (gilts) across various maturities from March 2009 to March 2010. The bonds included are the 4½% Treasury Gilt 2013, 4¾% Treasury Gilt 2020, 4¼% Treasury Gilt 2039, and 4¼% Treasury Gilt 2055. Each line represents one bond's yield, capturing investor expectations for returns over different time horizons during the early post-crisis monetary policy environment. The y-axis is labelled "Yield (% per annum)," and the x-axis shows the date. Data source: UK Debt Management Office (DMO).

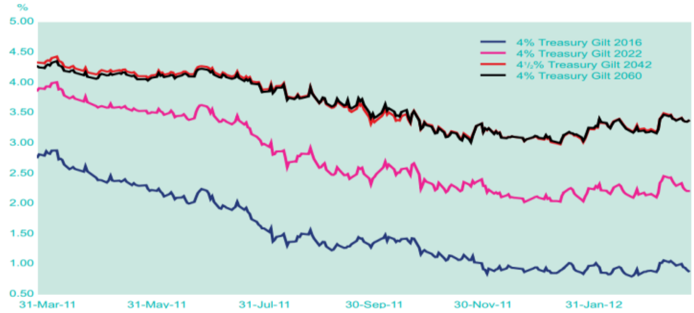


- **04/10/2011 (3¾% Treasury Gilt 2021)**

During the period 2011–12, yields declined sharply over the nominal yield curve, particularly in the 5–10 year maturity range. This decline was driven by worsening domestic and European economic outlooks, as well as concerns about the sovereign debt and banking sectors of the Euro area. Against a backdrop of growing these concerns, the UK government bond market benefited from greater flight to safety flows during 2011–12. Again, this bond was a benchmark. It was also issued just a week ahead of the start of QE2, and so may have been affected by the prospect of a willing buyer waiting to start buying.

Figure 26: Conventional benchmark nominal yields 2010-2011

This figure presents the daily nominal yields of selected UK government bonds (gilts) from March 2011 to February 2012. The chart includes benchmark gilts such as the 4% Treasury Gilt 2016, 4% Treasury Gilt 2022, 4¼% Treasury Gilt 2042, and 4% Treasury Gilt 2060, capturing yield movements across short-, medium-, and long-term maturities. The y-axis is labelled "Yield (% per annum)," indicating the expected annualised return, while the x-axis shows the date. The chart highlights a declining yield environment across all maturities during this period. Data source: UK Debt Management Office (DMO).

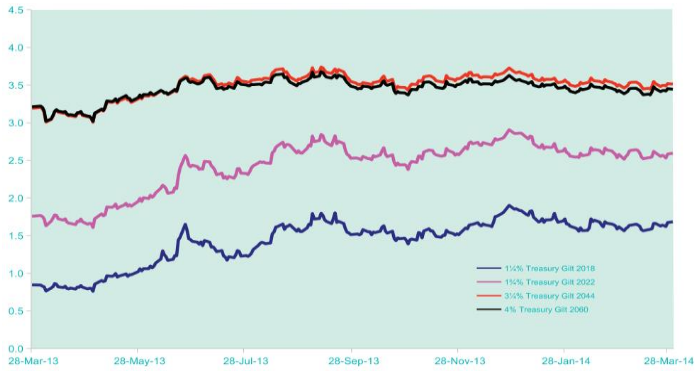


- **20/06/2013 (1¼% Treasury Gilt 2018), 10/09/2013 (3¼% Treasury Gilt 2044), 19/09/2013 (1¼% Treasury Gilt 2018)**

The gilt with a short maturity being auctioned on June 20, 2013, featured a significant concession cost. This could be explained by the increase of Consumer Price Index (CPI) inflation from 2.4% at the end of March to a financial year peak of 2.9% in June which is a sign of rising the interest rate in the market. As a result, when investors anticipated an increase in interest rates, they were not motivated to purchase gilts. In response to financial stability conditions, the Monetary Policy Committee stated in August 2013 that it would not increase the bank rate or reduce the stock of assets purchased until the Labour Force Survey (LFS) headline measure of unemployment rate dropped to 7.0%. Following the publication of promising unemployment data, market rates started to suggest that the first Bank Rate increase might happen sooner than initially anticipated.

Figure 27: Conventional benchmark nominal yields 2013-2014

This figure displays the daily nominal yields of selected UK government bonds (gilts) from March 2013 to March 2014. The chart includes benchmark gilts such as the 1¾% Treasury Gilt 2018, 1½% Treasury Gilt 2022, 3½% Treasury Gilt 2044, and 4¼% Treasury Gilt 2060, representing a range of maturities. The y-axis is labelled "Yield (% per annum)," indicating the expected annualised return for each bond, and the x-axis shows the timeline in monthly intervals. This visual illustrates the yield curve dynamics across short-, medium-, and long-term gilts during a period of relative market stability. Data source: UK Debt Management Office (DMO).



- **07/01/2016 (4% Treasury Gilt 2060)**

This outlier could be the result of Brexit referendum a period of heightened financial market volatility.

➢ **15/02/2018 (1¾% Treasury Gilt 2057)**

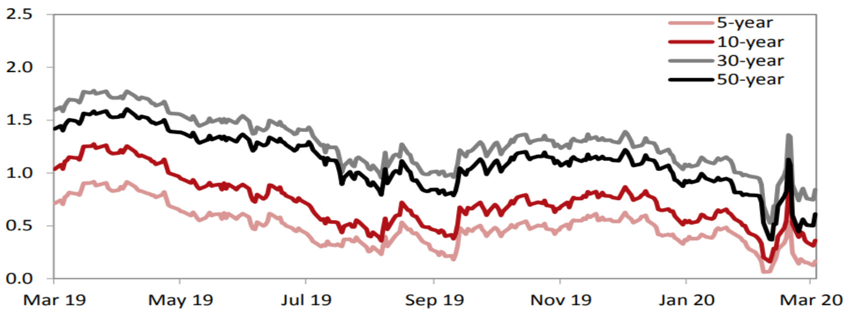
In general, since the MPC's last meeting and the November Inflation Report, the rates on government bonds had increased globally. According to Inflation Reports and MPC minutes, the MPC stated that inflation increased in 2017 and reach a top of 3.0%. The twelve-month CPI inflation rate in November was 3.1%, 1.1 percentage points more than the target of 2%, in line with that estimate. Therefore, the increase of Bank Rate in November and the inflation rate were a sign of increasing Bank rate for traders which reduce their interests in long-term gilts.

➢ **10/03/2020 (4¾% Treasury Gilt 2030), 17/03/2020 (1¾% Treasury Gilt 2049)**

Covid-19's increasing effects in the first quarter of 2020 caused a dramatic decline in economic activity, an acceleration of safe haven flows, and a sharp decline in bond yields. Before coordinated central bank, intervention restored market equilibrium, the gilt (and other government bond) market had become dysfunctional in early to mid-March 2020. Chart 3 illustrates the impact.

Figure 28: Conventional benchmark nominal yields 2019-2020

This figure presents the daily nominal yields of UK government bonds (gilts) across four maturity benchmarks—5-year, 10-year, 30-year, and 50-year—from March 2019 to March 2020. The chart illustrates how gilt yields evolved in the lead-up to and during the early stages of the COVID-19 pandemic, reflecting shifts in investor expectations for interest rates and risk. The y-axis is labelled "Yield (% per annum)," representing the annualised return expected by investors, and the x-axis displays the timeline in monthly intervals. Data source: UK Debt Management Office (DMO).

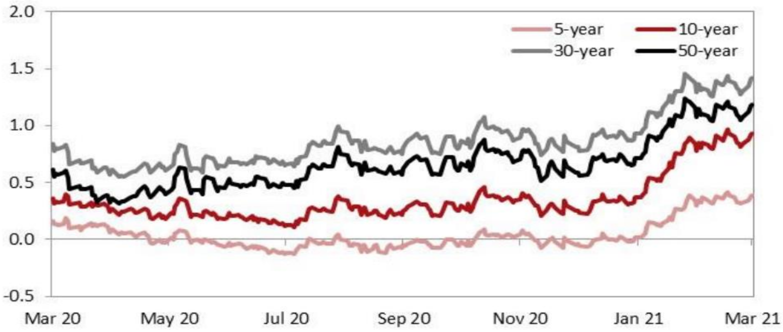


➢ **21/04/2020 (1 5/8% Treasury Gilt 2054)**

In March 2020, the Pandemic Emergency purchase programme (PEPP), a temporary purchase programme of securities from the public and private sectors, was announced. Targeting longer-term financing operations, this plan supplemented other non-standard measures already in place, such as the ECB's asset purchase programme (APP), which continued at a net purchase rate of €20 billion per month. With respect to the effect of asset purchases, gilt yields experienced a notable decline, and it was announced that the MPC has the ability to increase asset purchases if necessary. Therefore, the asset purchase program was a sign of monetary easing and lower interest rate, which drew investors' attention to long-term gilts.

Figure 29: Conventional benchmark nominal yields 2020-2021

figure shows the daily nominal yields of UK government bonds (gilts) across four benchmark maturities—5-year, 10-year, 30-year, and 50-year—from March 2020 to March 2021. The chart captures market conditions during the COVID-19 recovery phase, highlighting the gradual upward shift in yields as economic and inflation expectations adjusted. The y-axis is labelled "Yield (% per annum)," indicating the expected annualised return on each bond, and the x-axis displays the timeline in monthly intervals. Data source: UK Debt Management Office (DMO).



- **08/03/2022 (1¼% Treasury Gilt 2051)**

This might have been affected by the combination of very long maturity and a low yield that really no one wanted.

Figure 30: Conventional benchmark nominal yields 2021-2022

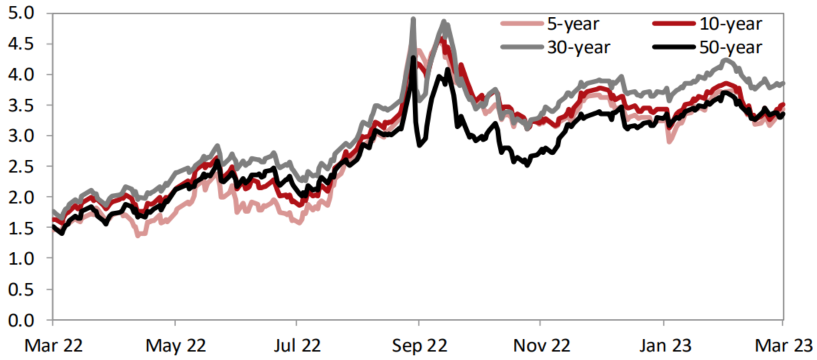
This figure presents the daily nominal yields of UK government bonds (gilts) across four benchmark maturities—5-year, 10-year, 30-year, and 50-year—from March 2021 to March 2022. The chart captures the upward movement in yields during this period, reflecting rising inflation expectations and tightening monetary policy. The y-axis is labelled "Yield (% per annum)," indicating the annualised return expected by investors, while the x-axis shows the timeline in monthly intervals. Data source: UK Debt Management Office (DMO).

- **05/10/2022 (1% Treasury Gilt 2032)**

The price of food and drink and home energy expenditures continued to grow, causing the UK Consumer Prices Index (CPI) to jump from 7.0% in March 2022 to 11.1% in October 2022. The Monetary Policy Committee (MPC) of the Bank of England increased the bank rate in response, raising it from 0.75% in March 2022 to 2.25% in September 2022. The committee resolved to accelerate the process of balance sheet normalization by actively selling bonds starting in October, following its decision to stop reinvesting the proceeds from maturing gilts from the Asset Purchase Facility (APF) in February 2022. By the end of September 2023, the stock of gilt purchases, which are funded by the issuance of central bank reserves, was expected to be reduced by £80 billion through a combination of active sales and redemptions, to reach a total of £758 billion. This could account for October's increased issuance costs.

Figure 31: Conventional benchmark nominal yields 2022-2023

This figure shows the daily nominal yields of UK government bonds (gilts) for four benchmark maturities—5-year, 10-year, 30-year, and 50-year—from March 2022 to March 2023. The chart reflects the sharp rise in yields during this period, driven by inflationary pressures and monetary tightening, including market volatility around the September 2022 UK fiscal announcement. The y-axis is labelled "Yield (% per annum)," indicating the expected annualised return, and the x-axis shows the timeline in monthly intervals. Data source: UK Debt Management Office (DMO).



3.10.5. Financial Condition Index

Our analysis of 20 UK financial indicators covering key areas, including default free spread, corporate bonds spread, Asset prices, Lending, and Broad money and debt level, aims to provide a holistic view of potential financial stability risks. Therefore, in order to select the variables from each section, we examine the power of indicators to explain the variance of economic activity measured by GDP growth. The following sub-sections explain the variables in each key area. First, we assess the stationarity of each variable at the 5% significance level using the Augmented Dickey-Fuller (ADF) test in EViews software. For those indicators exhibiting non-stationarity at their levels, we apply first differencing to achieve stationarity.

➢ **Default Free Spread**

To capture the risk inherent in the default-free spread, we consider five variables: spread of 3-month LIBOR and 3-month T-bill, spread of 2-year gilt and 3-month T-bill, spread of 10-year gilt and 3-month T-bill, spread of 3-month T-bill and Bank Rate, spread of 3-month LIBOR and Overnight index swap (OIS). We collected monthly data for all variables from the BOE's website and Data-Stream, spanning the period from 1987 to 2022. However, for the variable OIS, the data was available only from 2009. The subsequent table presents the number of lags required for each variable to achieve stationarity.

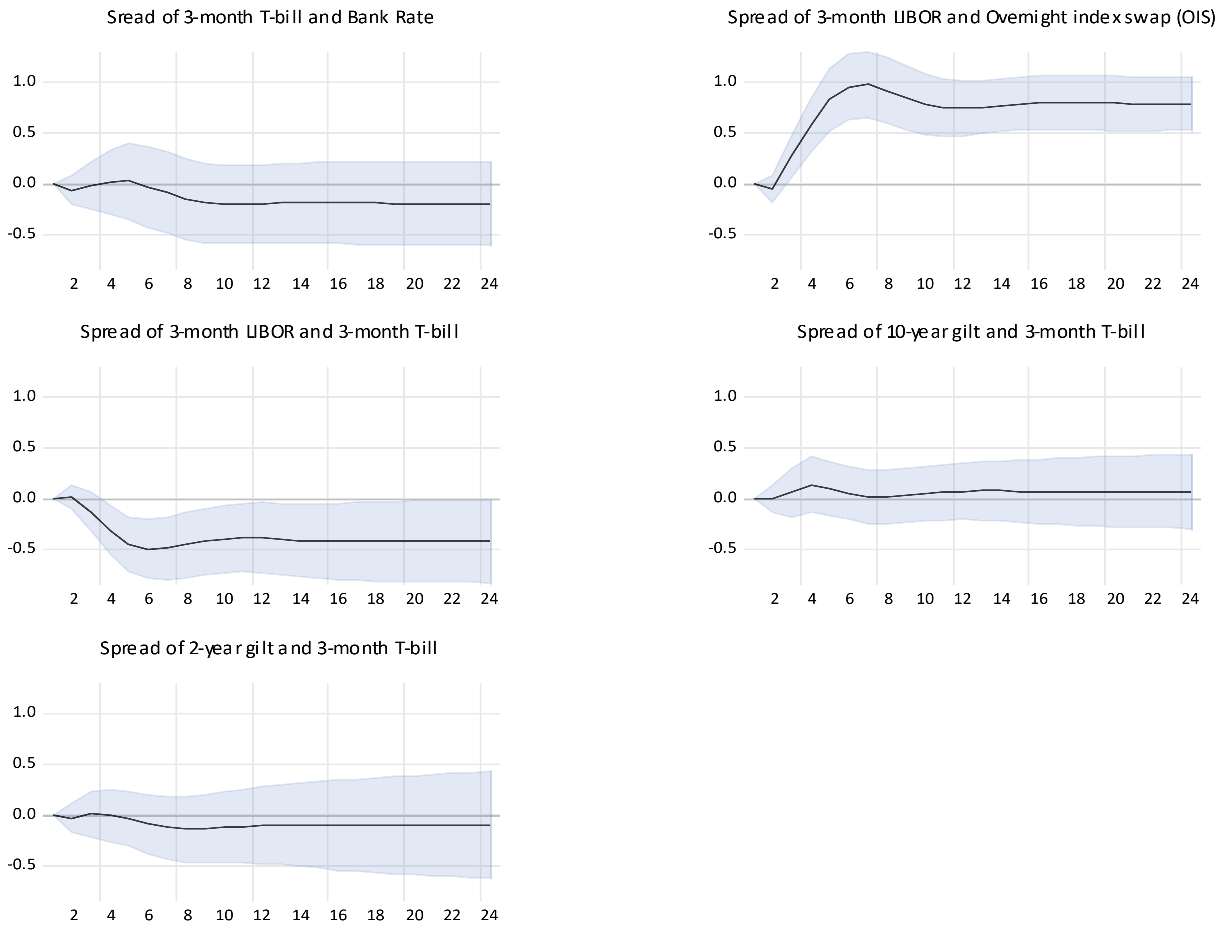
Table 39: Augmented Dickey-Fuller test for Default Free Spread Indicators

Variables	Level	1 lag	2 lags
spread of 3-month LIBOR and 3-month T-bill	*		
spread of 2-year gilt and 3-month T-bill	*		
spread of 10-year gilt and 3-month T-bill		*	
spread of 3-month T-bill and Bank Rate	*		
spread of 3-month LIBOR and Overnight index swap (OIS)	*		

After all variables transformed to stationarity, we construct impulse responses from two-variable VARS, and examines the cumulated impact on GDP growth. Figure 28 shows impulse responses following one standard deviation shock up to 24 months for all variables in the VARs, each estimated with two lags. The results show that the impact of the spread of 3-month LIBOR and OIS is stronger compared to other indicators, increasing the GDP growth one unit after 6 months. Therefore, this variable is selected as an indicator of default free spread section.

Figure 32: Impulse responses and 95% confidence bounds following Default Free Spread 1 SD shocks

This figure shows the impulse response functions of various interest rate spreads following a one standard deviation shock to the default-free spread, along with 95% confidence intervals. The responses are traced over a 24-month horizon. Each subplot represents a different spread: (1) the spread between the 3-month T-bill and the Bank Rate, (2) the spread between 3-month LIBOR and the overnight index swap (OIS), (3) the spread between 3-month LIBOR and the 3-month T-bill, (4) the spread between the 10-year gilt and the 3-month T-bill, and (5) the spread between the 2-year gilt and the 3-month T-bill. The solid lines represent the estimated response, while the shaded areas denote 95% confidence bands. The y-axis shows the response magnitude (in percentage points), and the x-axis shows months after the shock. This analysis captures the dynamic effects of funding and term premium conditions in response to credit risk-free spread shocks.



➢ Corporate Bonds Spread

In the research presented here, we create the subset of four spreads that we refer to as the "corporate bonds spread ", which is a reasonably pure set of financial indicators. This is driven by the findings of Gilchrist et al. (2009) and Gilchrist et al. (2012), who show that corporate bond spreads have a broad predictive capacity for a variety of business cycle activity indicators and account for a significant amount of the variance in economic activity. The variables considered in this section are spread of 75% LTV variable rate mortgage and Bank Rate, spread of £10k personal loan rate and 2-

year swap rate, spread of PNFC variable rate lending rate and 3-month LIBOR, and Investment grade corporate bond index. We gathered monthly information for every variable from December 1997 to December 2022 using the BOE website and Data-Stream since the data was not available before 1997. The number of lags required in each variable to reach stationarity is shown in the following table.

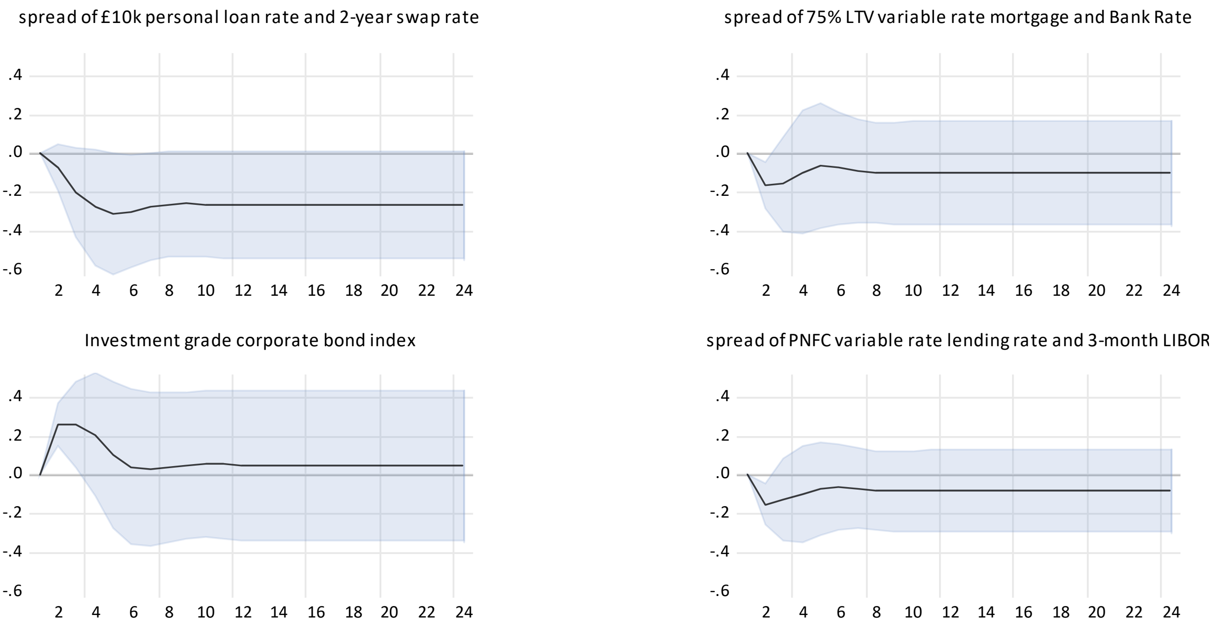
Table 40: Augmented Dickey-Fuller test for Corporate Bonds Spread Indicators

Variables	Level	1 lag	2 lags
spread of 75% LTV variable rate mortgage and Bank Rate		*	
spread of £10k personal loan rate and 2-year swap rate		*	
spread of PNFC variable rate lending rate and 3-month LIBOR		*	
Investment grade corporate bond index		*	

One SD shock to the variable Investment grade corporate bond index leads to more than 0.2 units increase in the GDP growth, reach the peak in the second period and the impact converges back to zero after period 8. This variable is considered as indicator of corporate bond spread section since it shows more significant impact on GDP growth which is shown in Figure 33.

Figure 33: Impulse responses and 95% confidence bounds following Corporate Bonds Spread Indicators 1 SD shocks

This figure presents the impulse responses of various lending and credit spreads to a one standard deviation shock in corporate bond spread indicators, with 95% confidence intervals over a 24-month horizon. The subplots display responses for: the spread between a £10k personal loan rate and the 2-year swap rate, the spread between a 75% loan-to-value (LTV) variable mortgage rate and the Bank Rate, the investment-grade corporate bond index spread, and the spread between non-financial corporate (NFC) variable rate lending and the 3-month LIBOR. The solid lines represent the estimated responses, while the shaded areas indicate 95% confidence bounds. The y-axis measures the response magnitude in percentage points, and the x-axis shows months after the shock. These results illustrate how credit conditions in retail and corporate lending channels adjust in response to shifts in corporate bond market spreads.



➢ Asset price

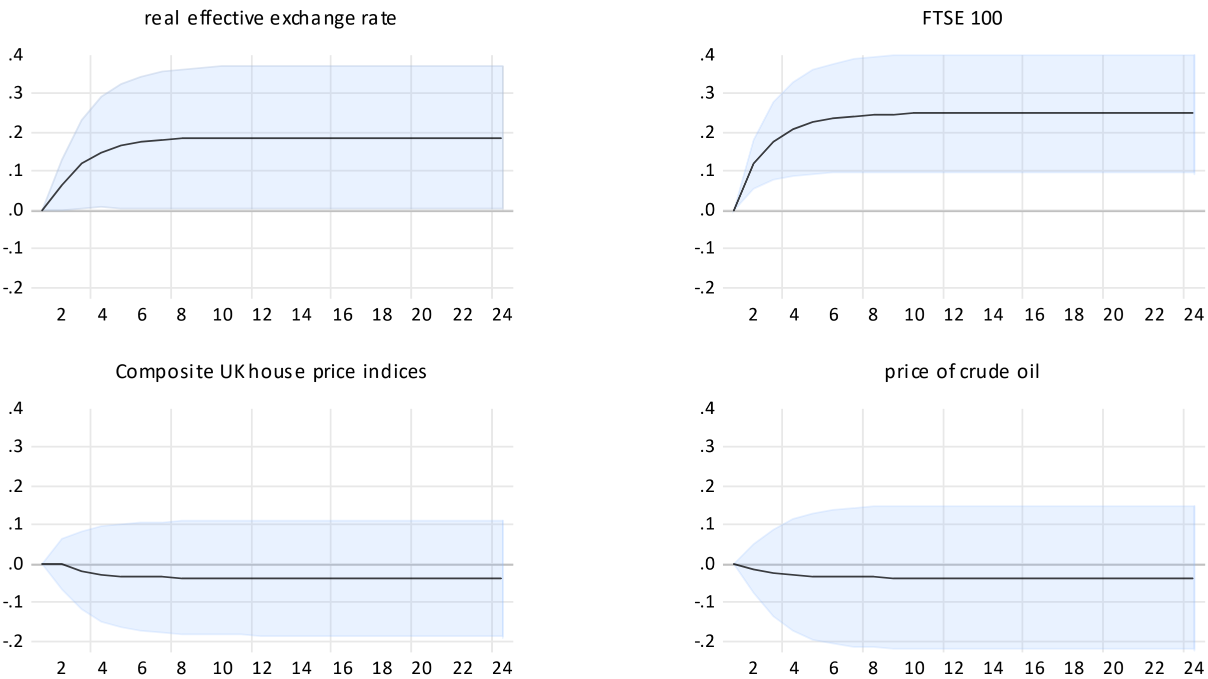
similar to Hatzius et al. (2010), we include variables perhaps better described as monetary rather than financial. This subsection compares four economic indicators: £real effective exchange rate, FTSE 100, Composite UK house price indices, and £price of crude oil, to identify the variable with the strongest explanatory power for GDP growth. To ensure a comprehensive analysis, we employed both the BOE website and Data-Stream, gathering monthly data for every variable from May 1987 to December 2022. The following table displays that the number of lags specified for all variable is one to reach stationarity. Based on the cumulative responses of GDP-growth to the indicators of asset price section, the variable real effective exchange rate is selected to construct the financial condition index.

Table 41: Augmented Dickey-Fuller test for Asset Price Indicators

Variables	Level	1 lag	2 lags
real effective exchange rate		*	
FTSE 100		*	
Composite UK house price indices		*	
price of crude oil relative to 2-year maturity		*	

Figure 34: Impulse responses and 95% confidence bounds following Asset Price Indicators 1 SD shocks

This figure shows the impulse responses of key asset price indicators to a one standard deviation shock in asset price variables, with 95% confidence bounds over a 24-month horizon. The panels display responses for the real effective exchange rate, FTSE 100 index, composite UK house price indices, and the price of crude oil. The solid lines represent the estimated responses, while the shaded blue areas indicate 95% confidence intervals. The y-axes show the response magnitude in percentage points, and the x-axis shows the time in months following the shock. These results capture the dynamic adjustment of major asset markets to systemic changes in asset price conditions.



➢ Lending

Financial market stress reduces economic activity and inflation by restricting the regular flow of loans to businesses and consumers through a variety of channels. Both wealth and intertemporal alternative effects exert pressure on consumption as financing expenses rise and asset prices decline. Capital costs are penalized by a greater external finance premium. Limitations in the availability of credit as well as shifts in risk tolerance and perceptions, which modify market risk premia, have an impact on consumption and investment (Paries et al., 2014). Therefore, based on data availability in this section, we considered four variables including bond issuance, stock of M0 (notes and coins and reserves), commercial paper Issuance, and stock of bank lending (M4L). For all variables we applied natural log. This table presents the number of lags used for each variable to achieve stationarity.

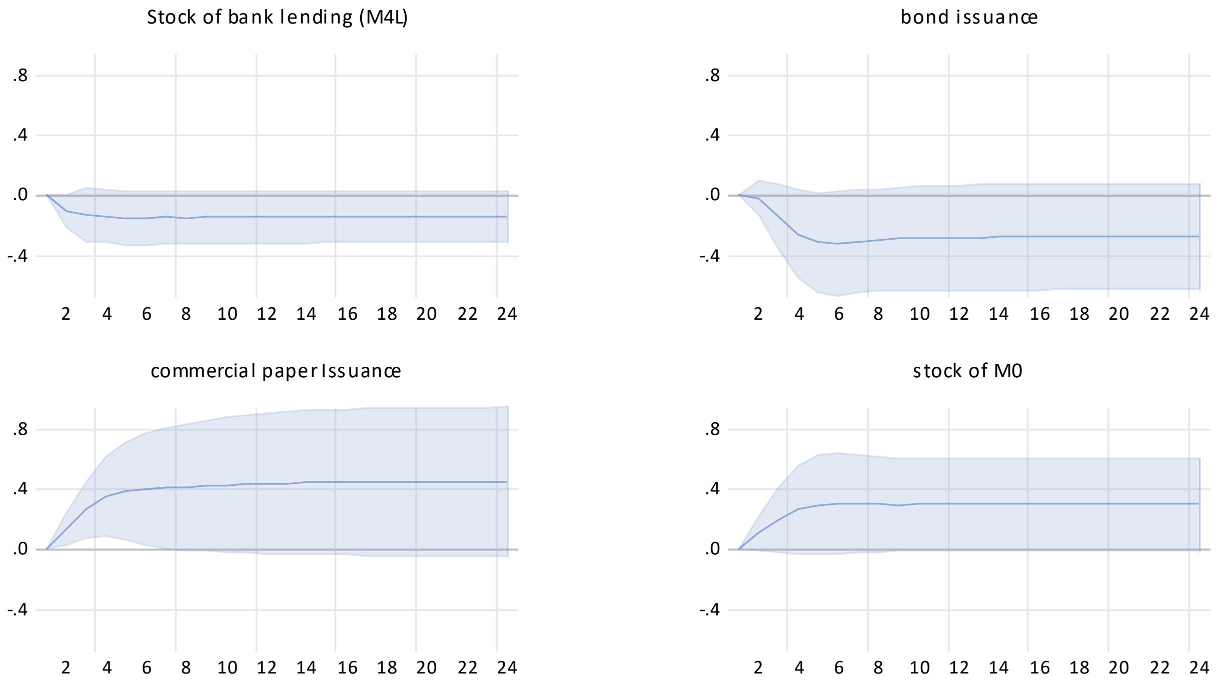
Table 42: Augmented Dickey-Fuller test for Lending Indicators

Variables	Level	1 lag	2 lags
bond Issuance	*		
Stock of M0		*	
commercial paper Issuance	*		
Stock of bank lending (M4L)			*

Again, we construct impulse responses to describe the dynamics of shocks on the variables of this section as they are transmitted through economy. Our research demonstrates that a one standard deviation shock to stock of M0 causes leads to significant increases in GDP-growth for approximately five months, with the impact remaining stable thereafter. However, other variables, like bond issuance and commercial paper Issuance, also exert significant influence on GDP-growth. We, therefore, investigate whether incorporating these variables could enhance the index's ability to identify periods of market stress. We found adding one of these variables improves the index's power due to their similar market trends.

Figure 35: Impulse responses and 95% confidence bounds following Lending Indicators 1 SD shocks

This figure displays the impulse responses of key lending indicators to a one standard deviation shock in lending conditions, with 95% confidence intervals plotted over a 24-month horizon. The panels illustrate responses in the stock of bank lending (M4L), bond issuance, commercial paper issuance, and the stock of M0 (narrow money). The solid lines represent the estimated responses, while the shaded bands reflect 95% confidence intervals around those estimates. The y-axes indicate the magnitude of responses (in percentage points), and the x-axis shows time in months after the shock. These results highlight the dynamic adjustment of credit and monetary aggregates to lending-related shocks.



➢ Broad money and debt level

The last section to cover the different aspects of economy is the level of debt which is measured by several indicators like Stock of broad money (M4-IOFC), PNFC Debt (SA), and Government bonds outstanding. All variables were natural log-transformed. This table summarizes the optimal lag lengths used for each variable to ensure stationarity in the analysis.

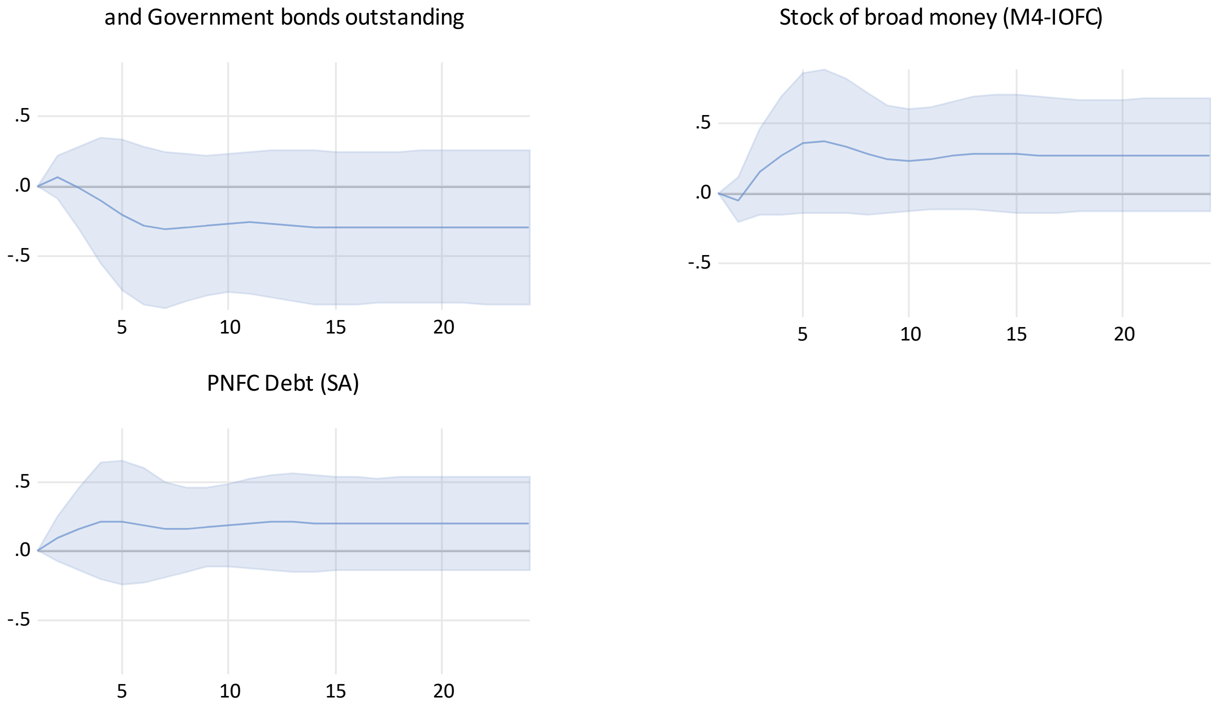
Table 43: Augmented Dickey-Fuller test for Broad money and debt level Indicators

Variables	Level	1 lag	2 lags
Stock of broad money		*	
PNFC Debt	*		
Government bonds outstanding		*	

Our analysis of the impulse responses and structural shocks revealed that both government bonds outstanding and the stock of broad money have a stronger impact on GDP-growth compared to PNFC. However, we opted to use government bonds outstanding because its data is available from April 2005, whereas the stock of broad money 's data is only available from July 2001. This earlier availability allows for a longer analysis period and potentially more robust results.

Figure 36: Impulse responses and 95% confidence bounds following Broad money and debt level Indicators 1 SD shocks

This figure illustrates the impulse responses of selected broad money and debt level indicators to a one standard deviation shock, with 95% confidence bounds shown over a 24-month horizon. The subplots present responses for government bonds outstanding, the stock of broad money (M4 excluding Other Financial Corporations), and Private Non-Financial Corporation (PNFC) debt (seasonally adjusted). The solid lines represent the estimated responses, while the shaded regions denote 95% confidence intervals. The y-axes reflect the magnitude of the response (in percentage points), and the x-axis represents the time in months after the shock. These results provide insights into how debt and liquidity conditions evolve following shocks to balance sheet aggregates.



The results of the analyse suggest that the Financial Condition Index (UKFCI) is best constructed by using the following six variables: TED Spread (3-month LIBOR –3-month Tbill), £commercial paper Issuance (Relative to 24-month MA), £real effective exchange rate, Government bonds outstanding value, Investment grade corporate bond index, Stock of M0 (notes and coins and reserves).

the UKFCI is calculated by applying the weighted average method, where the weights are taken from a VAR model:

$$y_t = B_0 + B_1 y_{t-i} + \varepsilon_t \tag{4}$$

Where y_t is a vector of endogenous variables including GDPGROWTH, TED Spread (3-month LIBOR –3-month Tbill), £Commercial paper issuance (Relative to 24-month MA), £Real effective exchange rate, Government bonds outstanding value, Investment grade corporate bond index, Stock of M0 (notes and coins and reserves) , B_0 and B_1 are matrices of the estimated coefficients, and i is the number of lag or the order of the VAR. The error term is a vector of innovations, which are I.I.D. Based on VAR Lag Order Selection Criteria test, shown in Table 44, we employed three lags in the model. Before estimating the VAR model, we apply VAR lag order selection criteria to determine the optimal number of lags in the model, reported in Table 44.

Table 44: VAR Lag Order Selection Criteria

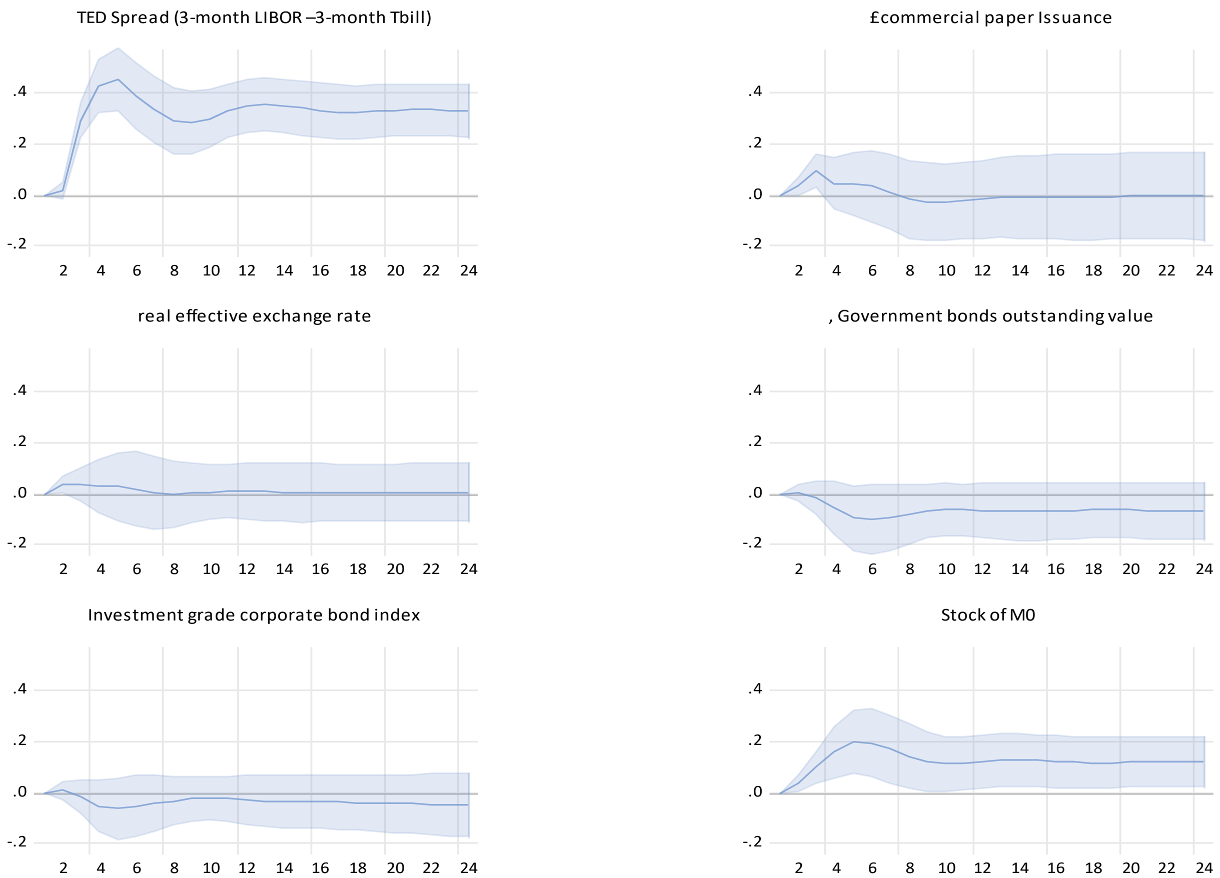
Endogenous variables: GDPGROWTH, TED Spread (3-month LIBOR –3-month Tbill), £commercial paper Issuance (Relative to 24-month MA), £real effective exchange rate, Government bonds outstanding value, Investment grade corporate bond index, Stock of M0 (notes and coins and reserves). Sample period is 1987 to 2022 with monthly observations. * indicates lag order selected by the criterion. LR: sequential modified LR test statistic (each test at 5% level). FPE: Final prediction error. AIC: Akaike information criterion. SC: Schwarz information criterion. HQ: Hannan-Quinn information criterion

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1432.075	NA	1.14e-18	-18.61536	-18.45690	-18.55099
1	1637.842	387.3260	1.78e-19	-20.46852	-19.04243*	-19.88922*
2	1719.328	144.8650	1.43e-19	-20.69710	-18.00338	-19.60287
3	1797.711	131.1494	1.20e-19*	-20.88511*	-16.92375	-19.27594
4	1858.103	94.73351	1.30e-19	-20.83795	-15.60896	-18.71385
5	1899.678	60.86711	1.84e-19	-20.54481	-14.04818	-17.90577
6	1987.716	119.6856*	1.45e-19	-20.85903	-13.09477	-17.70506
7	2045.847	72.94875	1.76e-19	-20.78231	-11.75042	-17.11341
8	2104.696	67.69598	2.21e-19	-20.71498	-10.41545	-16.53114

To extract the weights of indicators selected from each section, we calculate the cumulative responses of the growth of real GDP to one-unit shock from the financial indicator which is shown in the Figure 37.

Figure 37: Impulse responses and 95% confidence bounds following selected Indicators 1 SD shocks

This figure presents the impulse responses of a range of selected financial and macroeconomic indicators to a one standard deviation shock, with 95% confidence intervals plotted over a 24-month horizon. The indicators include the TED spread (3-month LIBOR minus 3-month T-bill), commercial paper issuance, the real effective exchange rate, government bonds outstanding, the investment-grade corporate bond index, and the stock of M0 (narrow money). Solid lines depict the estimated responses, while the shaded bands represent 95% confidence bounds. The y-axis shows the response magnitude (in percentage points), and the x-axis displays the number of months following the shock. These results provide a comparative view of how diverse financial and monetary indicators respond to systemic shocks.



The UKFCI is estimated by:

$$FCI_t = \sum_{i=1}^{n} w_i \left(\frac{z_{i,t} - \bar{z}_i}{\sigma_{z_{i,t}}} \right) \tag{5}$$

Where the weight w_i is extracted from the previous section from the VAR model by the cumulative responses of the growth of real GDP to one-unit shock from the financial indicator z_i including TED Spread (3-month LIBOR –3-month Tbill), £Commercial paper issuance (Relative to 24-month MA), £Real effective exchange rate, Government bonds outstanding value, Investment grade corporate bond index, and Stock of M0 (notes and coins and reserves) over 24 months, and where $\bar{z}_i$ and, $\mu_{z_{i,t}}$ denote the average value of $\bar{z}_i$ and standard deviation of z_i over the whole sample period, respectively. The episodes of systemic financial stress are identified by measuring the deviations of the UKFCI from its short-run trend. We determine a cut-off in terms of UKFCI percentiles (50% within 12 months) to identify the episodes of financial distress. We set the cut-off point in terms of the episodes of real financial stress in UK, following the works of Swiston (2008), Hatzius et al. (2010), and Wacker et al. (2014).

4. Determinants of the Bid-to-Cover Ratio in UK Government Debt

4.1. Introduction

The success of governments' debt sales becomes a big news story and a crucial gauge of market confidence when they confront financial challenges. Debt managers must balance the need to raise capital with the demand to prevent unsuccessful auctions, which could result in increased borrowing costs. This was especially true during the European financial crisis, when investors' concerns about government finances increased and the results of debt auctions were used as a key indicator of a country's creditworthiness.

The "bid-to-cover ratio," which is the entire amount bid during an auction divided by the total amount of new debt allotted, is a crucial indicator of the level of demand in an auction. To the best of our knowledge, this is the first study to link the factors that determine the bid-to-cover ratio for gilts. The reason of studying the bid-to-cover ratio is that this is an indirect measure of issuance cost for government since the more demand there is, the lower should be the issuance costs (concession). Therefore, we examine whether the factors impacting the issuance cost have an effect on the bid-to-cover ratio by employing the same theorical framework and data.

The objectives in this chapter are identifying the determinants of the bid-to-cover ratio, investigating the impact of Quantitative Easing on the bid-to-cover ratio from the first phase of QE in 2009 to 2022, differentiating between auctions for new bonds and secondary bonds, examining whether there are segmentation premia in different sectors of the conventional gilt market in regard to the bid-to-cover ratio, and investigating whether the results change if we re-define the explanatory variables based on maturity segmentation. The DMO might be interested in our results since they aid in determining the conditions necessary for successful auctions, i.e., the issuance of debt against the lowest costs feasible, considering the total funding requirements over time and potential maturity structure objectives that may arise from trade-offs involving default, roll-over, and other risks (e.g., see Beetsma et al., 2021; Broner et al., 2013). For example, the DMO may decide to postpone the volume of issuance until later while using the money market to temporarily fill any funding gaps in the event that the current situation is difficult and increases the likelihood of an undersubscribed auction.

A paper which is close to our research has been done by Beetsma et al. (2020), studying the factors influencing the bid-to-cover ratios of Eurozone public debt issues. Their findings imply that the bid-to-cover ratio is significantly impacted negatively by supply, market volatility, asset purchase facility program, and positively by the number of primary dealers, previous bid-to-cover ratio, and secondary market yield. However, our paper is different from this study in several ways. First, we apply more explanatory variables related to the gilt characteristics to find the impact of designing the auctions on demand, such as benchmark status, Post Auction Option Facility (PAOF), liquidity, and the frequency of issuance for all gilts and a specific gilt. Second, we explore the impact of different variables related to the prevailing market characteristics (FCI) and even different proxies for the same variables (volatility and primary dealer activity). Third, our sample covers the UK gilt market from 1987 to 2022, whereas their study only looks at the years 1999 to 2017, excluding the final stages of QE and QT as well as the most significant part of the COVID-19 crisis.

The theory in the papers cited above predicts that the bid-to-cover ratio is decreasing in the degree of auction size, time to maturity of gilt, and during the financial crisis. On the other hand, it anticipates that demand is increasing in response to rising liquidity of the outstanding issue, the bid-to-cover ratio of previous auction, turnover of primary dealers, and if the auction has PAOF service and benchmark status. The volatility of the stock market may change the bid-to-cover ratio through two channels. Because of risk and information dispersion, it might have a negative effect, but it might also have a positive effect because government bonds are considered safe havens. The impact of issuance frequency may be positive if gilt market liquidity increases, or negative if dealer inventories are impacted by substantial and frequent shocks. Additionally, the QE program may have a positive impact on the bid-to-cover ratio by decreasing the degree of "auction cycles" for sovereign debt in the secondary market, and a negative impact through a supply channel, in which the issuance of more gilts puts pressure on the GEMM inventories to absorb more issuance, which in turn causes a downward pressure on demand.

The rest of the chapter is organised as follows. The next part provides an explanation of the model's variables as well as a brief discussion of the theoretical perspectives presented in the earlier works. The summary statistics are discussed in Section 3 and the presentation of our model in Section 4 comes next. The estimated baseline regression framework's findings are shown in the next section, along with a brief discussion of the findings. In Section 6, we compare the outcomes with the preceding section by applying the baseline model to secondary issuance auctions. Section 7 gives the QE phase results for baseline estimation and introduces additional variables only available during this period. This section also gives the findings of the baseline regression model, which was estimated separately for secondary issuance. In the maturity segmentation analysis presented in Section 8, we apply the model to each maturity segment in order to determine whether or not there exist segmentation premia with respect to bid-to-cover ratio in any particular sector of the conventional gilt market. In addition, we conduct the same study again for secondary issuance in various maturity segments, and we compare the results with the general issuance outcomes. In section 9, the results of this chapter are compared with the outcomes of the previous chapter to see if the variables impacting the demand for gilt market have effect on the cost of issuance. The chapter's main conclusion comes to an end in Section 10. An appendix provides the investigation of whether the outcomes change if the explanatory variables are defined according to maturity segments. We then reassess the QE period in the context of a maturity segmented definition of the explanatory factors.

4.2. Data

In this chapter, we examine whether the variables explaining auction concession are also able to explain the bid to cover ratio. As the independent variables used in this chapter are identical to those in the previous chapter, we have omitted their detailed descriptions here to avoid repetition, but refer the reader back to Chapter 3, Section 2 for details. But here we will discuss the rationale behind our assumptions regarding each explanatory variable's possible influence on the bid-to-cover ratio.

Obtaining the data from the UK Debt Management Office (DMO) website, DataStream, and the Bank of England, our data covers all conventional auctions occurred between May 1987, the first auction, and December 31, 2022. A total of 779 conventional gilt auctions were held throughout the study period, accounting for 86% of the nominal value of conventional gilt gross issuance.

4.2.1. Bid-to-Cover Ratio

This is an indicator of auction demand and is measured as the entire amount of bid during an auction divided by the total amount of new debt allocated. Table 45 shows the average bid-to-cover ratio for all 779 conventional gilt auctions. During the financial crisis, the average bid-to-cover ratio dropped to 1.9 from a pre-crisis level of 2.01, which could be explained by limited risk-bearing capacity of primary dealers and liquidity effects during the crisis time period as clarified by Beetsma et al. (2016) With the introduction of QE, it returned almost to the pre-crisis level, at 1.97, but then exhibited a downward trend until the start of QE4. It is notable that the results of pairwise comparison of means over QE phases (Table 61) show that the drop and return from pre-crisis to crisis to QE1 are not statistically significant. The distribution of bid-to-cover ratio is shown in Figure 38, where it can be seen that during QE1, QE4, and QE5 the mean bid-to-cover ratio is above the median bid-to-cover ratio. Overall, average bid-to-cover ratio increased during all QE phases except QE2 and 3. This suggests a heightened demand for gilts in the market during QE periods. We compare the average bid-to-cover ratio over the eleven distinct time periods in our sample period using a between-subjects ANOVA, and the results show that the average bid-to-cover ratio varies between the sub-periods ($p < 0.01$, Table 60). We additionally perform pairwise comparison of means using the Tukey Honestly Significant Difference (HSD) tests. The results show the average of bid-to-cover ratio during QE5 and QT-P is significantly greater than all of the preceding sub-periods. In contrast, our analysis reveals that the demand for gilts during post-QE3 is statistically lower than during most sub-periods (see the results in Table 61 for more details).

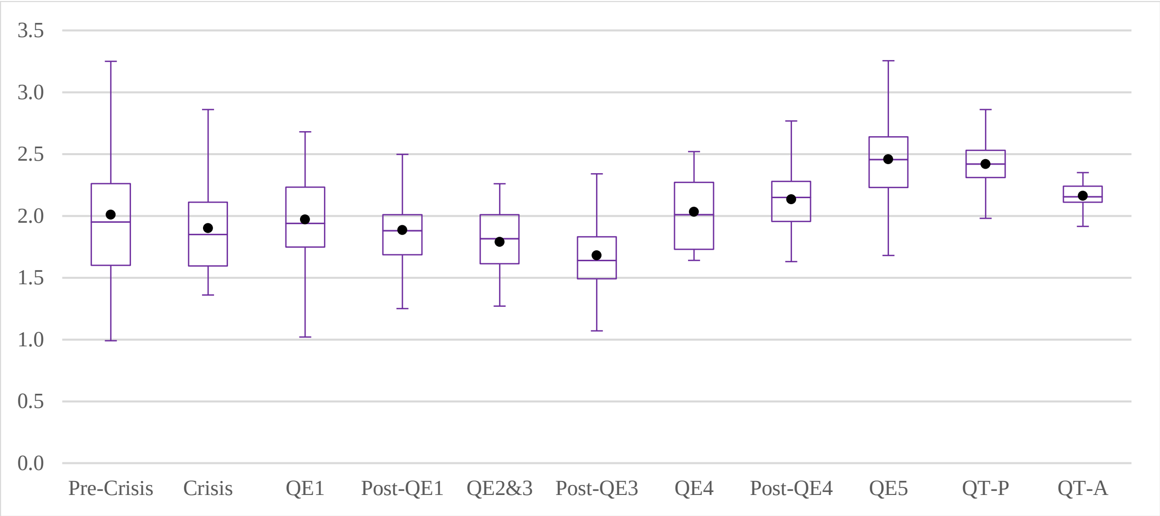
Table 45: Bid-to-Cover Ratio and Auction Size

This table contains the average auction size (£ million), the number of auctions, the average bid-to-cover ratio for the time-period 1987 to 2022. The bid-to-cover ratio is measured as entire amount of bid during that auction divided by the total amount of new debt allocated at that auction; a value of 1.0 means the value of bids equals the value of stock being auctioned. The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive period in the model.

Statistic	Average Auction Size (£m)	Average Bid-to-Cover ratio	Number of Auctions
Pre-crisis	2438	2.01	161
Crisis	2867	1.90	47
QE1	3767	1.97	40
Post-QE1	3375	1.89	59
QE2 and 3	3207	1.79	38
Post-QE3	3068	1.68	105
QE4	2574	2.03	17
Post-QE4	2708	2.13	95
QE5	2821	2.46	178
QT-P	2998	2.42	29
QT-A	3324	2.16	10
Full Sample	2881	2.07	779

Figure 38: Bid-to-Cover Ratio

This figure displays the distribution of the auction bid-to-cover ratio for all conventional gilt auctions conducted from May 1987 to December 2022, grouped by major policy-related sub-periods shown on the x-axis (e.g., Pre-Crisis, QE1, QT-A). The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive. The y-axis shows the bid-to-cover ratio, calculated as the total amount of bids received divided by the amount of debt allocated at auction. A higher ratio indicates stronger demand for government debt. The box plots represent the median and inter-quartile range (IQR) of bid-to-cover ratios within each sub-period, while the whiskers extend to the furthest values within 1.5 times the IQR. Data source: UK Debt Management Office (DMO).



4.2.2. Auction Size

The literature related to the impact of the size of an auction on the demand of auction predicts both positive and negative correlation. The negative impact could be generated through the auction cycle where secondary market yields increase ahead of auctions and decrease afterwards. Auction cycles have also been documented by Fleming and Rosenberg (2007) and Lou et al. (2013) for US

Treasuries, Beetsma et al. (2018) for the Eurozone, and Ahmad and Steeley (2008) for UK gilts. According to Lou et al. (2013) the V-shaped pattern becomes more pronounced when auction sizes are larger. Furthermore, recent papers illustrate the effects of auction size on the temporary price pressures around the auctions through dealers’ limited risk-bearing capacity (e.g., Fleming et al. (2024). The fact that dealers act as market intermediaries and are the primary players in government bond auctions explains why the size of the auction may matter. These dealers' ability to control their bond inventory frequently places restrictions on them. For instance, a dealer will probably incur higher expenses and bear greater risk for the same amount of a bond issued on a quarterly or annual basis if the bond is offered through a single, large auction as opposed to several smaller ones (Chang, 2023). The positive impact is predicted since bidders may raise their volume of bids in proportion to the volume offered to obtain a certain market share (Krawczyk, 2009) .Similarly, a positive impact of size has been shown by Shida (2023), implying that bidders do modify their offers to secure specific market shares, but demand does not nearly rise proportionally with the volume that is being offered. He explains that primary dealers might increase their demand in response to the increasing issuance volume to obtain a certain market share as a high market share may be considered necessary for obtaining a full perspective of market developments through order flow analysis. Furthermore, obtaining a specific position in the publicly available bidders rating may be noteworthy and incentivised by bank management. Given these mixed theoretical expectations, in this study we predict a predominantly negative relationship between auction size and the bid-to-cover ratio, due to the pressure large auction sizes place on dealers' risk-bearing capacities.

4.2.3. Benchmark Status

This variable is a measure of a measure of liquidity of the stock and motivated by Breedon and Ganley (2000) who discovered that bonds that were initially non-fungible with the parent issue had an under-pricing, and that this was largely related to the bond's benchmark (on-the-run) status. The price difference between the parent stock and the auction tranche decreased to nearly zero on the day of the auction for subsequent auctions when the bonds were fully fungible. Therefore, when it comes to bonds of the same maturity, the on-the-run bond is typically the most liquid, or traded; Krishnamurthy and Vissing-Jorgensen (2012) provide an explanation of this relationship. The on-the-run bonds are different from off-the-run bonds in a few ways: they have more liquidity and make better collateral for repos (Keane, 1996). Thus, the bond that is on the run might be more expensive Krishnamurthy and Vissing-Jorgensen (2012), whereas the bond that is no longer "on-the-run" is expected to have a lower price following the auction (Sundaresan, 1994). Another reason to examine if the issuance is of or into a 5,10- or 20-year benchmark issue is that demand and supply shocks have impacts that were not limited to the particular maturities of the shocks' location, as explained by Vayanos et al. (2009). For instance, even though the Treasury buybacks were limited to bonds with maturities of nine years or more, they nonetheless had an impact on rates on bonds with five-year maturities. In a similar vein, the yield differential between medium- and short-term bonds shrank even though the UK pension reform's effects were more noticeable for longer maturities. Bonds with neighbouring maturities are close substitutes, therefore arbitrageurs convey shocks local to one maturity to nearby maturities, which is why one would expect such impacts. This is also explained by Fuhrer and Giese (2021), indicating that demand shocks effect bonds throughout the yield curve, most affecting their neighbouring bonds first. As residual maturity varies, the impact of demand shocks on other bonds diminishes. Given this context, it is predicted that higher liquidity — as proxied by the bond's benchmark status or being 'on-the-run' — will lead to a higher bid-to-cover ratio, as more investors are likely to bid for more liquid and easily tradeable securities.

4.2.4. Liquidity of the gilt

This variable is intended to investigate whether an increase in the outstanding gilt size (including the amount up for auction) divided by the average outstanding size of all other (conventional) gilts on the day of the auction raises liquidity and, consequently, gilt demand. Greater outstanding size of securities are thought to have lower inventory holding costs, which makes them more liquid. Presumably, the holding period gets shorter for bigger issues due to more trading activity and/or lower costs for market makers to request offsetting trades from investors. Furthermore, the results of a study by Klingler and Sundaresan (2023) shows that dealers typically sell the Treasury bonds they have bought after the auction rather than being buy-and-hold investors. As a result, the bond's liquidity is probably going to have an impact on the results of auctions. Dick-Nielsen and Rossi (2019) and Bao et al. (2018) emphasise that liquidity is most important during certain market stress or liquidity shocks. Therefore, it is predicted that a higher value of this liquidity ratio — indicating a relatively larger outstanding gilt size (including the auction amount) compared to the average outstanding size of all other conventional gilts on the day of the auction — will increase the bid-to-cover ratio due to enhanced market liquidity and greater investor demand.

4.2.5. Volatility

Many papers investigate the debt market under the impact of volatility. Beetsma et al. (2020) find that market volatility lowers the slope of the demand curve and, consequently, lowers the difference between the quantity on auction and the quantity bid at the reservation price. They do this by using a five-day moving average of the implied volatilities of the call and put.

Shida (2023) indicates that excessive volatility for banks entails greater hedging costs and, if unhedged, a larger market risk of owning bonds. Another consideration may be particularly important due to the gap risk that bidders incur between the time they submit their bids and the publication of the allocation. There is no way to completely hedge this risk due to the uncertainty surrounding the exact allocation amount. According to Krawczyk (2009), brokers in charge of submitting demand functions are worried about potential overbidding (which is instantly viewed as a loss by bank management) rather than underbidding (which results in a less obvious loss due to missed opportunity). This suggests that bidders may be risk averse. Furthermore, high volatility may momentarily reduce end-investor demand. As implied volatility increases, demand should correspondingly decline. The impact of the other risk indicators is unknown.

Alvarez and Mazon (2019) investigate the implications of two multi-unit common value models with private information and an analytical characterisation of the equilibrium strategies using data for Spanish Treasury auctions performed between 2003 and 2007. In particular, they examine the ways in which bidding patterns and auction results are influenced by bond value uncertainty, as gauged by the volatility of government debt prices on the secondary market. They show that bid shading heterogeneity increases with volatility, as predicted by theoretical models, and that bidder profit and bid shading increase with volatility on average across auctions. They discover that bid shading, also known as the bid discount, rises in line with secondary market volatility. This is the difference between the price bids and the expected value of the bond at the time of bidding. Overbidding falls as bid shading rises, which implies that overpricing should likewise fall.

In contrast with previous studies, the variable volatility is designed to capture the safe haven impact indicating an increased general risk perception by market participants might even stimulate demand at the auctions, since the impact of financial crisis is captured by the variable *FCI*. The key idea is that investors take actions for the safety of the asset. Increased market size for Treasury bonds results in improved liquidity and depth, which attracts investors from all over the world. As a result, the Treasury has less rollover risk, improving the bonds' safety and encouraging investors to buy them. In poor economic times, when investors naturally fly for safety, the value of the safe asset increases.

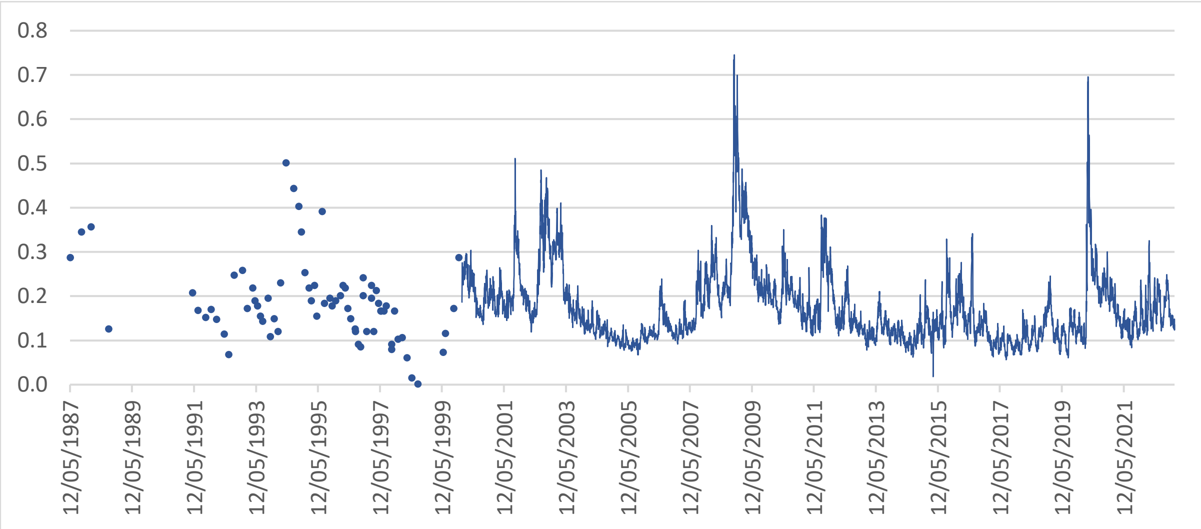
Based on the literature and the theoretical considerations outlined above, the predicted impact of volatility on the bid curve (BC) is twofold. could negatively affect the bid-to-cover ratio through information dispersion and increased risk, but might also have a positive effect by enhancing the safe-haven appeal of government bonds during periods of market stress.

Therefore, we apply a measure of equity market volatility, specifically, the implied volatility of at-the-money FTSE100 index call options instead of the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract which is used in the previous chapter. Since the data for the implied volatility of at-the-money FTSE100 index call options are only available from 2000, we spliced together the measure of volatility for gilt market, applied in previous chapter, and the FTSE100.

As shown in Table 59, there was not a significant difference in the gilt volatility between 1987 and 2000 in compared to the sample period of 2000 to 2022. The gilt volatility is normalised to have a zero mean and a unit standard deviation for the period between 1987 and 2000. This has been done by calculating the mean and standard deviation of the gilt volatility (for the period 1987 to 2000) and subtracting the mean from each gilt volatility observation and then dividing each by the standard deviation. Next, we unnormalize the gilt volatility by multiplying each normalized observation by the standard deviation of the FTSE100 volatility between 2000 and 2022 and then adding the mean FTSE volatility throughout that time period. The consistent volatility series is shown in Figure 39, where two episodes of stress can be seen in 2009 and 2020.

Figure 39:Volatility

This figure displays the time series of market volatility from 1987 to 2022. The x-axis represents time (in monthly intervals from May 1987 to December 2022), while the y-axis shows the level of volatility, expressed as an annualized standard deviation of returns; for example, a value of 0.1 corresponds to an annualized return volatility of 10%. From 1987 to 2000, volatility is derived from unnormalized gilt option data, calculated by rescaling the at-the-money implied volatility of the nearest maturity long gilt futures call option using the standard deviation and mean of FTSE100 volatility between 2000 and 2022. From 2000 onwards, the volatility series is based on the implied volatility of at-the-money FTSE100 index call options. This approach ensures comparability across the full sample.



4.2.6. Demand for Gilts

The variable bid-to-cover ratio of the previous auction is inspired by the paper of Beetsma et al. (2020), who explains that there are several ways in which a positive correlation between adjacent bid-to-cover ratios may be generated. First, over an extended period of time, a policy of modifying the amount of outstanding debt may be put into place. This would have an impact on reservation prices at following auctions and thus lead to a correlation in the bid-to-cover ratios. The DMO finds it easier to stay committed to this approach, in particular, because it can use the money market to temporarily keep extra funds or to bridge any unexpected funding needs. Second, it could be challenging to measure market volatility. In the event that this variable (volatility) is highly persistent, mismeasurement of it may lead to residuals that exhibit temporal correlation. A significant lagging bid-to-cover ratio might detect this. Lastly, the primary dealers may get serially correlated order flows that the DMO does not properly notice, resulting in a reserve price that is too high or too low in the future auction. In theory, the previous bid-to-cover ratio is unlikely to have an impact on the bid-to-cover ratio of the subsequent auction in a perfect market. But because only a small number of primary dealers are permitted to take on all the newly issued debt, the present situation creates an imperfect market. Additionally, due to different investment groups participating in various markets, markets are not totally integrated in reality. An overall rise in the prior bid-to-cover ratio for public debt may bring in capital from investors in other markets, such the equities market. It will be evident that the preceding bid-to-cover ratio has empirical significance.

In order to gauge gilt market activity and bond demand, we additionally create a second variable. It is the days since the latest conventional gilt issuance represented as the natural log of that number. Fleming et al. (2024) state that the frequency and magnitude of issuance are relevant to the Treasury market, exposing dealer inventories to significant and constantly repeated shocks. Since dealers are restricted in capital, how they manage to absorb supply shocks in addition to their usual secondary market generating activities is a matter of public interest and policy relevance. Therefore, the increase of issuance activity might impact the demand of primary dealers negatively.

4.2.7. Gilt Market Turnover

Market liquidity is measured by the Gilt-Edged Market Makers' (GEMMs) turnover, and Fleming et al. (2024) highlight that dealers also have the responsibility to make secondary markets by purchasing and selling securities for their own account in order to satisfy the transaction demands of clients and other dealers. The expectation is that primary dealers in particular will "showcase a substantial presence as a market maker for providing two-way liquidity." When they look at how non-issuance-driven inventory changes affect pricing, they find evidence to bolster the hypothesis that the order flow that dealers generate from their proprietary and secondary market trading is instructive for returns on Treasury securities.

The role of primary dealers in secondary market to provide liquidity is more important during the crisis time because unlike primary dealers who are required to bid competitively in every auction, alternative liquidity providers are not guaranteed to be present at all times to offer liquidity. The possibility that non-obligatory liquidity providers will cease to supply liquidity during times of crisis, just when it is most required, raises concerns about financial stability. The emergence of high-frequency trading firms boosts liquidity provision in normal times but may negatively influence liquidity stability in volatile times. This may have occurred in the secondary market for Treasury securities. The abrupt exit of liquidity providers from the primary market may have a negative impact on the US government's capacity to obtain cheap borrowing. Having said that, the primary market may be more resistant to unexpected liquidity withdrawals and more amenable to non-dealer intermediary roles than the secondary market due to its "one-to-all" market organisation and periodic and scheduled Treasury issuance. Auction records show that the main market operated nearly as usual, even at the height of the Covid-19 pandemic, when the secondary market had enormous disruptions owing to unprecedented selling pressure from clients (see Duffie, 2020).

While much of the evidence is based on the US Treasury market, the UK gilt market shares similar structural features, including a network of primary dealers (GEMMs) who are obligated to participate in auctions and provide two-way liquidity in the secondary market. Therefore, findings from the US market are considered relevant and applicable to the UK context.

Given that higher turnover generally signals greater market liquidity and lower dealer risk, we predict a positive relationship between gilt market turnover and the bid-to-cover ratio. Higher turnover is expected to support stronger demand at auctions by enhancing secondary market liquidity.

4.2.8. Post Auction Option Facility

Since June 1st, 2009, the DMO has provided all successful bidders with the opportunity, during a take-up window after the auction, to purchase an additional portion of the gilt allotted to each participant at that particular auction. This service is known as the Post Auction Option Facility (PAOF). Our method of capturing the PAOF presence at an auction involves the use of an indicator variable. This mechanism can increase demand for auctions by allowing successful bidders to purchase an additional percentage of their initial allocation at the same price. This is advantageous because if demand is high after the auction, the price will rise. Therefore, investors who win bids have the opportunity to purchase extra during the PAOF window at the favourable auction price. Accordingly, we predict a positive relationship between the presence of the PAOF and the bid-to-cover ratio, as the facility provides bidders with additional incentives to participate actively in the auction.

4.2.9. Time to Maturity

The remaining maturity of a gilt that is being offered at auction is indicated by this variable, which is motivated by Albuquerque et al. (2024), who study primary dealers’ bidding in auctions of sovereign bonds and the elasticity of demand thus revealed as a proxy for their risk-bearing capacity. They highlighted that longer-duration bonds are expected to exhibit a stronger marginal elasticity effect, calculating the price reduction that would have to be accepted in order to raise the bond's supply at the margin, due to their higher interest rate risk and consequent propensity to affect traders' profit volatility. In fact, the Portuguese Treasury and Debt Management Agency (IGCP) recognised dealers' reluctance to trade longer-term bonds by rewarding dealers who contribute more actively in these auctions. The economic and statistical significance of the marginal elasticity on predictive regressions of excess returns across all holding horizons increases when they include a short duration dummy and its interaction with the marginal elasticity in the predictive regression controls. This data indicates that, as would be predicted, the marginal elasticity's influence becomes stronger for longer-duration bonds. While still negative, the impact on short-duration securities is not statistically significant. They explain that bonds with longer maturities have a detrimental effect on dealers' ability to take on risk for four reasons. Firstly, they are more likely to affect traders' overall profitability due to their higher interest rate risk. Secondly, public debt securities are exposed to varying valuation haircuts that rise with the remaining bond maturity, even though they are all eligible to be used as collateral in the ECB's open-market operations. Third, the IGCP counters the dealers' apparent lack of motivation to trade longer-duration bonds by comparing the dealers' performance during the competitive auction phase to the bond's duration. Fourth, their result shows that the demand for shorter-duration bonds is generally more elastic. This implies that dealers have a higher average risk-bearing capacity for shorter-duration bonds. Therefore, we expect that the demand in auction decreases when the maturity of gilt raises.

4.2.10. Financial conditions

We construct this index to identify the episodes of systemic financial distress since the behaviour of dealers in the market is different during the market disruptions, as shown by Beetsma et al. (2016), offering a straightforward theoretical framework that outlines the primary dealers seeking compensation for the inventory risk incurred by holding the recently issued debt. When there is greater market uncertainty, as there is during a crisis, this compensation must be higher. There are several plausible forecasts in this theory. Primary dealers are expected to charge greater markups and anticipate a stronger auction cycle in the event of a riskier market. As a result, they anticipate that the auction cycle will be stronger during times of crisis and uncertainty. They discover that when the crises' intensity is higher as indicated by pertinent proxy factors, the yield movements associated with auctions are greater. Accordingly, when considering all of the findings collectively, it appears that financial and economic instability has a significant impact on how sovereign yields fluctuate around the dates of debt auctions by vulnerable economics. They can prove that there has been a significant increase in the issuance cost between the pre-crisis and crisis periods by taking advantage of the correlation between secondary-market yields and the yields at which new debt is auctioned. Therefore, more intense auction cycle around the gilt auctions and higher cost of issuance of debt for government during the crisis periods lead us to develop the hypothesis that the demand for bonds is less during the market turbulences.

4.2.11. Phases of QE

As explained before, this variable captures the impact of QE purchase, motivated by Spronsen and Beetsma (2022), providing the proof that the European System of Central Banks' (ESCB) purchases of sovereign debt really reduce the costs associated with issuance of new debt by lowering the so-called auction cycles in the secondary market for sovereign debt. According to Beetsma et al. (2020), the bid-to-cover ratios of government bond auctions in the euro area for the five and thirty-year segments were negatively impacted by Euro system asset purchases, but there were no significant effects for the two and ten-year segments. According to their logic, bond prices may rise as a result of central bank purchases, which would cause primary dealers to demand fewer bonds at auction and reduce bid-to-offer ratios. In contrast, Shida (2023) finds that the purchases have a strong positive impact in the demand in both the 2-year maturity and the pooled sample. He explains that the reason behind the absence of the favourable impact of net purchases in the official sector for the longer-term segments remains unknown, and he mentions that there's evidence that central banks favour holding short-term assets (Giese et al., 2021). Therefore, a structurally weaker demand by official sector entities may be the driving force behind the outcome for the longer-term segments. Plessen-Mátyás et al. (2023) investigate the impact of large-scale asset purchases on government debt management and find that the Public Sector Purchase Programme of the Euro system encouraged euro area debt management offices to extend the average maturity of debt issuance, both directly through a supportive demand effect and indirectly through lower yields.

Based on this evidence, we predict that QE phases are associated with a positive impact on the bid-to-cover ratio, particularly through improved secondary market conditions and stronger demand incentives during central bank purchase programmes.

4.3. Summary Statistics

In Table 46, we show the summary statistics of bid-to-cover ratio and volatility across 779 auctions from May 1987 to December 2022, and no outlier removal was performed for the summary statistics presented here. As the other independent variables in this model are identical to those in the previous chapter (Table 4), we only present the summary statistics for these two variables in Table 46. The correlation coefficients between the explanatory variables are in Appendix Table 58.

Table 46: Summary Statistics

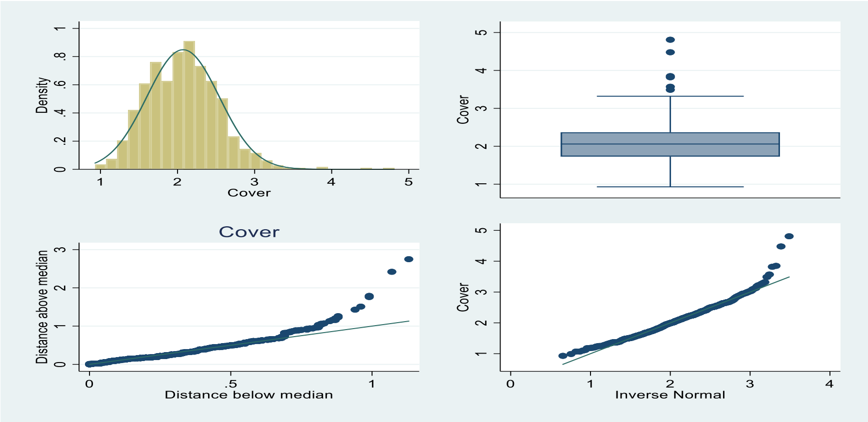
This table contains the summary statistics for the variable bid-to-cover ratio, hereafter abbreviated as BC, and volatility across 779 auctions from May 1987 to December 2022. The bid to cover ratio measures the extent to which the total amount bid at the auction exceeds the amount offered for sale at the auction; a value of 1.0 means the value of bids equals the value of stock being auctioned. From 1987 to 2000, the volatility is measured by unnormalizing the gilt volatility (the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract) by multiplying each normalized observation by the standard deviation of the FTSE100 volatility between 2000 and 2022 and then adding the mean FTSE volatility throughout that time period. From 2000 to 2022, the volatility measured by the implied volatility of at-the-money FTSE100 index call options, the implied volatility is expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. Mean is the sample mean of the variable, SD is the sample standard deviation, Min and Max are the minimum and maximum observations, and p25, p50, and p75 indicate the observation in percentile 25, 50, or 75, respectively. Skewness is a descriptive statistics measure that characterises the asymmetry of a data distribution. Kurtosis determines the heaviness of the distribution tails. P(S) shows the P-value for skewness, and P(K) shows the P-value for kurtosis. The last column shows the means are statistically significantly different from zero if the P-value is less than the significance level.

Variable	**Observation**	**Mean**	**SD**	**Min**	**P25**	**P50**	**P75**	**Max**	**Skewness**	**Kurtosis**	**Pr(S)**	**Pr(K)**	**Ha: mean=0 Pr (|T| > |t|)**
BC	779	2.07	0.47	0.93	1.73	2.06	2.37	4.81	0.7	5.10	0	0	0.00
Vol	779	0.19	0.09	0.002	0.13	0.16	0.22	0.7	1.91	8.35	0	0	0.00

Using the results of distribution analyse shown in Figure 40 for the variable BC across 779 auctions, we removed all auctions with a bid-to-cover ratio greater than 3.5, which is around 1.7 times the average value and 3 standard deviations from the mean. This reduces the sample size to 774 auctions.

Figure 40: Distribution Analyse for Bid-to-Cover

This figure presents a graphical analysis of the distributional properties of the bid-to-cover ratio based on 779 gilt auctions conducted between May 1987 and December 2022. The subplots include a histogram with a kernel density overlay (top left), a box plot (top right), a symmetry plot (bottom left), and a quantile–quantile (Q-Q) plot (bottom right). The x-axis in the histogram and box plot represents the bid-to-cover ratio (a measure of auction demand calculated as total bids divided by allocated amounts), while the y-axis in the histogram shows relative density (probability). The symmetry plot displays deviations from the median (in the original units), and the Q-Q plot compares the distribution of bid-to-cover ratios to a theoretical normal distribution (in the original units). These plots are used to visually assess the degree of normality and the presence of skewness or outliers in the bid-to-cover data.



The summary statistics for all variables, using the data without the observations on dates corresponding to the dates of the bid-to-cover ratio outliers are reported in Table 47.

Table 47: Summary Statistics of the Variables without Outliers

This table contains the summary statistics for eight variables across 774 auctions from May 1987 to December 2022, using data that excludes observations on dates corresponding to the bid-to-cover ratio outliers. The bid-to-cover ratio (BC) is measured as the entire amount of bid during an auction divided by the total amount of new debt allocated, where a value of 1.0 means bids equalled the amount offered. From 1987 to 2000, the volatility is measured by unnormalizing the gilt volatility (the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract) by multiplying each normalized observation by the standard deviation of the FTSE100 volatility between 2000 and 2022 and then adding the mean FTSE volatility throughout that time period. From 2000 to 2022, the volatility measured by the implied volatility of at-the-money FTSE100 index call options, the implied volatility is expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days. MAT is the time to maturity, calculated as the number of days from the auction to the gilt's maturity date divided by 365.25, and expressed in years. LIQ is the ratio of the size of the gilt being auctioned (including the auctioned amount) to the average outstanding size of all other conventional gilts on the auction day; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover ratio of the previous auction, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). Mean is the sample mean of the variable, SD is the sample standard deviation, Min and Max are the minimum and maximum observations, and p25, p50, and p75 indicate the observation in percentile 25, 50, or 75, respectively. Skewness essentially is a commonly used measure in descriptive statistics that characterizes the asymmetry of a data distribution, while kurtosis determines the heaviness of the distribution tails. Skewness is a descriptive statistics measure that characterises the asymmetry of a data distribution. Kurtosis determines the heaviness of the distribution tails. P(S) shows the P-value for skewness, and P(K) shows the P-value for kurtosis. The last column shows the means are significantly different from zero.

Variable	**Observation**	**Mean**	**SD**	**Min**	**P25**	**P50**	**P75**	**Max**	**Skewness**	**Kurtosis**	**Pr(S)**	**Pr(K)**	**H0: mean=0 Pr (|T| > |t|)**
BC	774	2.06	0.44	0.93	1.72	2.06	2.35	3.49	0.20	2.74	0.02	0.11	0
SIZE	774	7.92	0.3	6.62	7.72	7.92	8.14	8.66	-0.44	3.67	0	0	0
LIQ	774	0.87	0.48	0.08	0.51	0.82	1.15	2.98	0.85	4.06	0	0	0
ACT	774	1.77	0.96	0	1.1	1.61	2.4	4.37	0.10	2.79	0.90	0.22	0
VOL	774	0.19	0.09	0	0.13	0.16	0.22	0.7	1.92	8.39	0	0	0
DEM	774	2.08	0.48	0	1.72	2.06	2.38	4.81	0.57	5.10	0	0	0
TGEMMs	774	4.78	0.57	2.74	4.45	4.95	5.19	5.72	-1.07	3.70	0	0	0
MAT	774	15.36	11.94	2.12	5.51	10.17	23.25	53.37	1.05	3.11	0	0.46	0

4.4. Methodology

The bid to cover regressions are expected to respond to the same set of variables that can explain the concession cost, as both dependent variables reflect the competitive environment at the auction. Therefore, the explanatory variables are identical to those used in previous chapter.

$$BC_i = c + b_1 QEDUM_i + b_2 SIZE_i + b_3 LIQ_i + b_4 BENCH_i + b_5 VOL_i + b_6 ACT_i + b_7 MAT_i + b_8 DEM_i + b_9 TGMMs_i + b_{10} PAOF_i + b_{11} UKFCI_i + \varepsilon_i \quad (6)$$

The variable *BC* is the bid-to-cover ratio of the conventional gilt auctions measured as the entire amount of bid during an auction divided by the total amount of new debt allocated. The indicator known as *QEDUM* represents the impact of QE activity and takes value of unity during the sub sample corresponding to the asset purchase facility periods throughout QE. As we explained the independent variables previously, the variable *SIZE* is the natural log of auction size and indicates the auction's relative liquidity. *TGEMMs*, which reflects market liquidity, is calculated as the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers. From 1987 to 2000, the volatility is measured by unnormalizing the gilt volatility (the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract) by multiplying each normalized observation of the gilt volatility by the standard deviation of the FTSE100 volatility between 2000 and 2022 and then adding the mean FTSE volatility throughout that time period. From 2000 to 2022, the volatility measured by the implied volatility of at-the-money FTSE100 index call options. *BENCH* is an indicator that takes the value of a 5, 10, or 20-year benchmark issue and shows the stock's liquidity. *PAOF* is another variable used to assess liquidity, and it equals one if the issuance consists of a Post Auction Option Facility (PAOF). *ACT* is the natural log of the number of days from the last traditional gilt issue, and it reflects activity in the market and demand. *MAT*, a metric for assessing the impact of maturity, is calculated by dividing the difference between the maturity date and the auction date by 365.25. *LIQ*, which stands for liquidity of the outstanding issue, is calculated by dividing the size of the outstanding gilt (including the amount of gilt being auctioned) on the auction day by the average size of all other outstanding gilts (conventional). *DEM* is the bid-to-cover ratio of the previous auction. *FCI* is an indicator that values unity if it detects episodes of systemic financial crisis. [26]

A negative relationship is expected between the bid-to-cover ratio (BC) and the independent variables *SIZE, MAT*, and *FCI*, based on theoretical and empirical insights from the literature. For *SIZE*, larger auction volumes are expected to reduce demand due to the pressure large auction sizes place on dealers' risk-bearing capacities. For *MAT*, longer-maturity bonds are associated with higher interest rate risk and valuation uncertainty, which reduce primary dealers' willingness to participate actively in auctions. As demonstrated by Albuquerque et al. (2024), longer maturities lead to lower risk-bearing capacity and a less elastic demand, resulting in decreased auction participation. For *FCI*, tighter financial conditions represent heightened systemic stress and market volatility. As shown by Beetsma et al. (2016), during such periods, dealers demand greater compensation for inventory risk, which

[26] Episodes of systemic financial stress are identified by comparing the UKFCI to its short-run trend. A stress episode is defined as a period where the UKFCI falls to a level that is 50% or more below its average value over the preceding 12 months. This methodology follows the approach of Swiston (2008), Hatzius et al. (2010), and Wacker et al. (2014). See section 3.10.5 for more information.

translates into weaker auction participation and higher issuance costs for the government. Overall, these theoretical expectations support the prediction of a negative impact of *SIZE*, *MAT*, and *FCI* on auction demand, as measured by the bid-to-cover ratio. In contrast, positive correlations between BC and the variables *BENCH, DEM, TGEMMs, PAOF,* and *LIQ* are expected, as stronger benchmark status, higher market liquidity, and primary dealer activity typically support stronger auction demand. For some variables, the theoretical impact is ambiguous. For instance, *VOL* (volatility) could negatively affect the bid-to-cover ratio through information dispersion and increased risk, but might also have a positive effect by enhancing the safe-haven appeal of government bonds during periods of market stress. Similarly, *ACT* (issuance frequency) could lower auction demand by exposing dealer inventories to frequent shocks, but might also boost liquidity and support demand. Finally, the *QEDUM* variable (capturing phases of Quantitative Easing) is expected to influence BC positively by reducing auction cycle effects in the secondary market, and negatively through supply-side pressures increasing the burden on dealer inventories. While mechanisms such as a safe-haven effect and liquidity support could partly explain variations in the bid-to-cover ratio, the main channels through which the explanatory variables will affect the bid to cover ration are through the effects on auction cycles and signalling effects. Auction cycle effects, generated by inventory rebalancing that is more severe for larger auctions (measured by SIZE) and supply side pressures of increased issuance levels (captured by QEDum), and signalling effects, such as those of sustained low interest rates in QE that make longer term bonds (measured by MAT) less appealing, are expected to generate negative effects on bid to cover. By contrast, safe-haven and liquidity support effects are expected to have positive effects on bid to cover. We will see in the empirical results that the former effects dominate the latter effects.

There is a chance that there are cross-sectional and serial dependencies that are not explained by the explanatory variables because many bonds are submitted to multiple auctions throughout the years. Therefore, we use standard error adjustments to account for various types of error dependence. We use clustered standard errors, which are grouped according to the frequency of issue. We utilise the number of gilt issues prior to and including that auction as the clustering variable.

4.5. Empirical Results

All auctions with a bid-to-cover ratio higher than 3.5—roughly 1.7 times the mean and three standard deviations from the mean—are eliminated. As a result, 774 auctions make up the sample size. Table 48 displays the findings of the estimation of the coefficients in equation (6).

The results are shown in Table 48.[27] We observe that the gilts have been auctioned during the QE phases have higher bid-to-cover ratio, which is in line with some studies related to the impact of

[27] Insignificant variables are remaining in the results tables to provide a complete picture of the effects of variables whose potential explanatory power is motivated by theory, dropping some insignificant variables did not enhance the significance of others to any great degree, indicating that the reported results are stable to such modelling changes.

QE on the gilt market. As explained by Duffie and Keane (2023), investor demands to liquidate government securities can become quite intense in response to abrupt changes in the economy. Dealers may find their balance sheets overburdened by the ensuing requirement to warehouse substantial positions while seeking buyers. Dealers may be able to maintain some degree of market liquidity, but fire sales have the potential to impact prices and trigger other sales, increasing the risk of a downward spiral into financial instability. Central banks have periodically turned to buying government assets when lender-of-last-resort resources have proven insufficient to address market dysfunction. Reducing dealer inventories of government securities by central bank asset purchase program allows dealers to meet greater market requests for liquidity, which will improve the distribution of government securities, boost financial market liquidity, and improve financial stability. In support of this channel, Boneva, Kastl, et al. (2020) demonstrate that dealers sell gilts more aggressively in Bank of England reverse auctions when they have excess inventory, when they added to their gilt holdings shortly before the auctions, or when they are subject to greater constraints from the leverage-ratio rule. The authors also discover that the Bank of England's purchases gave dealers substantial liquidity advantages, noting that the BoE's QE purchases performed a contribution function in assisting to relieve market dysfunction and reduce price volatility by operating as a backstop in the secondary market for gilts. However, our finding is in contrast with Beetsma et al. (2020), discovering that the Euro system's asset purchases appear to reduce demand in particular term segments, which may be caused by the indirect impacts of the asset purchases on issuers' and bidders' behaviour.

We find a highly significant positive effect for the variables *TGEMMs*, *PAOF*, and *DEM*. In accordance with the DMO's assumption that the GEMM's activity enhances the liquidity in the gilt-edged market, we note that the GEMM market turnover is (highly) significant to the model and increases the bid-to-cover ratio. The findings support the claim made by Fleming et al. (2024) that primary dealers are crucial to the gilt market's ability to offer two-way liquidity. In line with the theoretical framework of section 4.2.8, we note that the bid-to-cover ratio is raised under the Post Auction Option Facility (PAOF). This might also be explained by increasing the gilt market's liquidity through selling an additional portion of the gilt allotted to each participant. Furthermore, investors are likely to bid more aggressively during the auction when they are aware of having the option to purchase an additional allotment at the same price. We find that the bid-to-cover ratio is positively correlated with the previous auction's bid-to-cover ratio, which is consistent with Beetsma et al. (2020) who find a positive correlation between the subsequent bid-to-cover ratios.

A highly significant negative impact has been discovered for the variables *SIZE*, *MAT*, and *FCI*. According to our findings, the bid-to-cover ratio increases as the auction size reduces. This is consistent with research by Nyborg et al. (2002), which shows that a larger auction size greatly lowers the auction discount and increases the bid dispersion. Our outcome agrees with Lou et al. (2013)'s findings which states that the V-shaped pattern intensifies with larger auction sizes, and Chang (2023) states that if a security is being offered through one large auction rather than multiple smaller ones, a dealer will likely pay more and take on more risk for the same amount of a bond issued on a quarterly or annual basis. Additionally, as time to maturity decreases, the bid-to-cover ratio rises. This is consistent with the findings of Albuquerque et al. (2024), who note that longer-duration bonds are anticipated to demonstrate a stronger marginal elasticity effect because of their greater risk of interest rates and ensuing propensity to impact traders' earnings risk. Finally, the coefficient on the FCI is negative and significant, indicating less demand for gilts during the crisis. M. J. Fleming and Ruela (2020) find that a decreasing order book depth and worsening bid-ask spreads were indicators of market illiquidity the government bond market. Furthermore, the government bond market has been subjected to stress due to COVID-19 shocks, as evidenced by three linked works:(Duffie, 2020; Schrimpf et al., 2020; Vissing-Jorgensen, 2021). The initial two research papers highlight policy proposals that could strengthen the Treasury market's resilience to disruptions, whereas the final article contends that subsequent Fed purchases were the reason behind the yields' decline following a spike in the market during the week of March 9–15, 2021. In their summary of these publications, He and Krishnamurthy (2020) highlight that the collapse of the Treasury market in March 2020 happened only on the long end of the maturity duration.

We do not find evidence of a statistically significant impact for the variables *ACT*, *LIQ*, *VOL*, and *BENCH*. We expect that gilts having benchmark maturities have higher bid-to-cover ratio, indicating that these gilts are generally more expensive (for primary dealers, and cheaper for government to finance) and liquid than other gilts. This is in line with evidence provided by Pasquariello and Vega (2009), suggesting that even after accounting for a number of fundamental bond features, including as duration, convexity, repo rates, and term premiums, their data indicates that off-the-run liquidity differentials are statistically as well as economically significant. However, a gilt's benchmark status is insignificant in the model, which may be explained by the sharp rise in gilt issuance activity in recent years, which has lessened the significance of the benchmark status of issuance. The results of other papers, discussed in section 1.5, show that market volatility decreases the slope of the demand curve, which in turn lowers the difference between the quantity bid at the reservation price and the quantity on auction. However, their measure of volatility reflects the gilt market volatility rather than economics and stock market. The variable *VOL* is designed to capture the safe haven impact which is not significant in our estimation. This might happen since the effect of these variable are captured by the constant in the model.

In terms of economic significance, QE phases (*QEDUM*) are associated with a 36% standard deviation increase in bid to cover ratio, highlighting the supportive effect of asset purchase programs. The results indicate that auction size (*SIZE*) has a substantial negative effect on auction demand, with a one-unit increase reducing the bid-to-cover ratio by 0.47 units — approximately 107% of the standard deviation of bid to cover ratio. GEMM turnover (*TGEMMs*) positively impacts auction demand, with a one-unit increase raising bid to cover ratio by about 30% of a standard deviation. The presence of *PAOF* increases bid to cover ratio by about 25% of a standard deviation. Previous auction demand (*DEM*) exhibits a strong persistence effect, with a one-unit increase boosting bid to cover ratio by about 66% of a standard deviation Conversely, financial crises (*FCI*) are associated with a 25% standard deviation reduction in bid to cover ratio, reflecting weaker demand under stress conditions. Overall, the statistically significant variables have economically meaningful impacts on auction outcomes, consistent with the theoretical framework outlined earlier.

Table 48: Determinants of Bid-to-Cover Ratio

This table has the estimated coefficients of equation (6) being used to identify the determinants of the bid-to-cover ratio for gilt auctions between May 1987 and December 2022 inclusive. Regression results for all issuance are displayed in the first column, while secondary issuance results are displayed in the second column. The bid-to-cover ratio is measured as the entire amount of bid during an auction divided by the total amount of new debt allocated. QEDUM is a dummy equal to 1 during the Bank of England's Asset Purchase Facility (QE) periods, and 0 otherwise (indicator variable). SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. From 1987 to 2000, the volatility is measured by unnormalizing the gilt volatility (the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract) by multiplying each normalized observation by the standard deviation of the FTSE100 volatility between 2000 and 2022 and then adding the mean FTSE volatility throughout that time period. From 2000 to 2022, the volatility measured by the implied volatility of at-the-money FTSE100 index call options, the implied volatility is expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. BENCH is a dummy variable equal to 1 if the issuance is into a 5-, 10-, or 20-year benchmark line, and 0 otherwise (indicator variable). PAOF equals 1 if the Post Auction Option Facility was available, and 0 otherwise (indicator variable). ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days. MAT is the time to maturity, calculated as the number of days from the auction to the gilt's maturity date divided by 365.25, and expressed in years. LIQ is the ratio of the size of the gilt being auctioned (including the auctioned amount) to the average outstanding size of all other conventional gilts on the auction day; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover ratio of the previous auction, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). FCI equals 1 when the Financial Conditions Index identifies systemic financial stress, and 0 otherwise (indicator variable). For the regression of secondary issuances, the variable LIQ is redefined to exclude the auctioned amount, and represents liquidity on the day before auction. Also, the variable ACT is changed to the log of the number of days since the last conventional gilt issuance for that specific gilt instead of any gilt. Other variables are exactly the same for modelling secondary issuance as those used for the baseline regression model. We applied clustered standard errors, and the clusters are defined by the gilt issuance's frequency. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels.

$$Y_i = c + b_1 QEDUM_i + b_2 SIZE_i + b_3 LIQ_i + b_4 BENCH_i + b_5 VOL_i + b_6 ACT_i + b_7 MAT_i + b_8 DEM_i + b_9 TGEMMs_i + b_{10} PAOF_i + b_{11} UKFCI_i + \varepsilon_i$$

	Baseline	Secondary
QEDUM	0.16***	0.14***
	(6.3)	(4.53)
SIZE	-0.47***	-0.48***
	(-7.75)	(-7.18)
TGEMMs	0.13***	0.11**
	(3.99)	(2.74)
VOL	0.19	0.23
	(1.05)	(1.15)
BENCH	0.04	0.02
	(1.44)	(0.88)
PAOF	0.11***	0.11***
	(7.16)	(6.19)
ACT	0.00	-0.05*
	(0.11)	(-2.07)
MAT	-0.01***	-0.01***
	(-9.17)	(-8.06)
LIQ	0.07	0.12*
	(1.69)	(2.04)
DEM	0.29***	0.30***
	(6.41)	(6.41)
FCI	-0.11***	-0.09***
	(-3.9)	(-3.22)
Constant	4.55***	4.87***
	(8.35)	(7.25)
No. Observations	774	689
R-squared	0.35	0.37

4.6. An Analysis of Secondary Issuance

In this section, we apply equation (6)'s model to secondary issuance auctions. It is reasonable to differentiate between auctions for new bonds and those for existing bonds. There are two main factors to separate secondary issuances according to Scalia (1998b) findings. First, the goal of reopening is to improve each security's liquidity and accessibility by creating immediate data aggregation on the secondary market following the first auction, which will benefit all later auctions of the same security. Frequent reopening also reduces the possibility of short squeezes in post-issue auctions by raising the total amount of outstanding assets. Reopening has been associated to increased borrowing costs when compared to a security's initial issue, according to M. J. Fleming (2002). Reopening is observed to have a more noticeable impact on trade activity and liquidity when bills are off-the-run, and to have less effect when bills are on-the-run. If a significant portion of an issue is owned by investors who want to hang onto their securities and are hesitant to sell or lend them, the effective (tradable) supply of the existing issue may already be fairly little when it is reopened. In this scenario, the quantity released at the most recent auction may be more significant than the quantity issued at previous auctions in terms of the relationship between issue size and liquidity. Reopened securities should, however, be more liquid as long as the effective supply from prior auctions is greater than zero, since effective supply influences liquidity. Re-openings may also have an impact on bond valuation due to an indirect liquidity effect as well as a direct supply effect. The liquidity effect refers to the theory that, in the absence of any other factors, more liquid securities will have higher prices and lower yield from investors' demand. Furthermore, Cafiso (2019) discovers that the market yield of a bond that has already been traded is more significantly impacted by new bond auctions than by subsequent bond auctions.

Additionally, certain data for the primary issuance is only obtainable on the day of the auction, meaning it could be contaminated by the auction itself. On the day before to the auction, however, we are able to measure the explanatory variables for secondary issuance. The size of the outstanding gilt that is being auctioned (including the amount of the gilt being auctioned) divided by the average size outstanding of all other (conventional) gilts is how the baseline model calculates the variable *LIQ*, which represents the liquidity of the existing gilt. This variable has been modified to reflect liquidity on the day before the auction, excluding the amount of auction for secondary issuance. likewise, the variable *ACT* is modified to the log of the number of days from the previous conventional gilt issuance for the particular gilt, rather than any gilt, because the first one cannot be utilised for primary issuance. The other variables employed in the modelling of secondary issuance are identical to those employed in the baseline regression model presented in previous section.

The summary statistics of the bid-to-cover ratio for 694 auctions that were secondary issuance are shown in Table 49, and the results are presented prior to the removal of outliers. We do not report the summary statistics of the independent variables in this model except volatility which is different from the previous chapter and similar to table 4, as they are the same as those in Table 6 of the previous chapter. However, the summary statistics of the explanatory variables without the observations that correspond to the outlier dates for the bid-to-cover ratio are reported in Table 49 below. In line with our theorical literature mentioned above, the auctions that were secondary issuance have higher bid-to-cover ratio compared to those that were initial issuance. This finding is further supported by the t-test comparison of means (table 51). The difference of the means of the bid-to-cover ratio between primary and secondary issuance is -0.171, and the t-statistic is 3.19 with 777 degrees of freedom. This is a big difference and is sufficient ex-post to justify looking at secondary issuance separately.

Table 49: Summary Statistics of Bid-to-Cover Ratio

This table contains the summary statistics for the variable bid-to-cover ratio, hereafter abbreviated as BC, across 694 that were secondary issuance auctions from May 1987 to December 2022. The bid to cover ratio measures the extent to which the total amount bid at the auction exceeds the amount offered for sale at the auction; a value of 1.0 means the value of bids equals the value of stock being auctioned. From 1987 to 2000, the volatility is measured by unnormalizing the gilt volatility (the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract) by multiplying each normalized observation by the standard deviation of the FTSE100 volatility between 2000 and 2022 and then adding the mean FTSE volatility throughout that time period. From 2000 to 2022, the volatility measured by the implied volatility of at-the-money FTSE100 index call options, the implied volatility is expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. Mean is the sample mean of the variable, SD is the sample standard deviation, Min and Max are the minimum and maximum observations, and p25, p50, and p75 indicate the observation in percentile 25, 50, or 75, respectively. Skewness is a descriptive statistics measure that characterises the asymmetry of a data distribution. Kurtosis determines the heaviness of the distribution tails. P(S) shows the P-value for skewness, and P(K) shows the P-value for kurtosis. The last column shows the means are statistically significantly different from zero if the P-value is less than the significance level.

Variable	Observation	Mean	SD	Min	P25	P50	P75	Max	Skewness	Kurtosis	Pr(S)	Pr(K)	Ha: mean=0 Pr (|T| > |t|)
BC	694	2.09	0.47	0.93	1.74	2.08	2.38	4.81	0.73	5.29	0	0	0.00
VOL	694	0.19	0.09	0.02	0.13	0.16	0.22	0.7	2.03	9.12	0	0	0.00

Table 50: Summary statistics of main variables for auctions that were secondary issuance

This table contains the summary statistics for eight variables across 689 auctions that were secondary issuance from May 1987 to December 2022 using data that excludes observations on dates corresponding to the bid-to-cover ratio outliers. The bid to cover ratio, hereafter abbreviated as BC, measures the extent to which the total amount bid at the auction exceeds the amount offered for sale at the auction; a value of 1.0 means the value of bids equals the value of stock being auctioned. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. From 1987 to 2000, the volatility is measured by unnormalizing the gilt volatility (the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract) by multiplying each normalized observation by the standard deviation of the FTSE100 volatility between 2000 and 2022 and then adding the mean FTSE volatility throughout that time period. From 2000 to 2022, the volatility measured by the implied volatility of at-the-money FTSE100 index call options, the implied volatility is expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. ACT is the log of the number of days since the last conventional gilt issuance for that specific gilt instead of any gilt, measured in days. MAT is the time to maturity, calculated as the number of days from the auction to the gilt's maturity date divided by 365.25, and expressed in years. LIQ is the ratio of the size of the gilt being auctioned (excluding the auctioned amount) to the average outstanding size of all other conventional gilts and represents liquidity on the day before auction; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover ratio of the previous auction, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). Mean is the sample mean of the variable, SD is the sample standard deviation, Min and Max are the minimum and maximum observations, and p25, p50, and p75 indicate the observation in percentile 25, 50, or 75, respectively. Skewness essentially is a commonly used measure in descriptive statistics that characterizes the asymmetry of a data distribution, while kurtosis determines the heaviness of the distribution tails. Skewness is a descriptive statistics measure that characterises the asymmetry of a data distribution. Kurtosis determines the heaviness of the distribution tails. P(S) shows the P-value for skewness, and P(K) shows the P-value for kurtosis. The last column shows the means are significantly different from zero. Mean is the sample mean of the variable, SD is the sample standard deviation, Min and Max are the minimum and maximum observations, and p25, p50, and p75 indicate the observation in percentile 25, 50, or 75, respectively.

Variable	Observation	Mean	SD	Min	P25	P50	P75	Max
BC	689	2.08	0.44	0.93	1.74	2.08	2.38	3.49
SIZE	689	7.92	0.31	6.62	7.72	7.92	8.14	8.66
LIQ	689	0.76	0.4	0.08	0.46	0.73	1.02	2.73
ACT	689	3.89	1.05	1.79	3.14	3.66	4.25	8.36
VOL	689	0.19	0.09	0.02	0.13	0.16	0.22	0.7
DEM	689	2.09	0.48	0.93	1.74	2.08	2.39	4.81
TGEMMs	689	4.83	0.54	2.74	4.5	4.97	5.21	5.72
MAT	689	15.64	12.09	2.12	5.49	10.13	24.08	53.37

Table 51: t-test Comparison of Means of Bid-to-Cover Ratio

This table contains the results of t-test comparison of means of bid-to-cover ratio between secondary and primary issuance. The bid to cover ratio measures the extent to which the total amount bid at the auction exceeds the amount offered for sale at the auction; a value of 1.0 means the value of bids equals the value of stock being auctioned. Mean is the sample mean of the variable.

Group	Observation	Mean	Std. errs.	Std. dev.	[95% conf.	interval]
Primary	85	1.919	0.048	0.443	1.824	2.015
Secondary	694	2.090	0.018	0.470	2.055	2.125
Combined	779	2.072	0.017	0.470	2.039	2.105
diff		-0.171	0.054		-0.276	-0.066
Diff = mean (Primary) - mean (Secondary)					T = 3.19	
H0: Diff = 0					Degree of freedom = 777	

Before estimating the coefficient of the regression model, equation (6), the sample has been reduced from 694 auctions to 689 to eliminate outliers, and it is notable that all of the outliers in our sample are the re-opening securities. The outcomes of the secondary issuance modelling are shown in Table 48. The results of the secondary issuance model closely match those of the combined sample of primary and secondary auctions, indicating the robustness of the findings. The variables *SIZE*, *PAOF*, *MAT*, *DEM*, *QEDUM*, and *FCI* are highly significant in the estimation of secondary issuance, which is in line with the estimation findings across all issuance. Therefore, the results of the estimations for the secondary issuance show that the bid-to-cover ratio rises, as the auction size is smaller, time to maturity is shorter, the bid-to-cover ratio of the previous auction is higher, the gilt has post auction option facility, the auction of gilt occurred during the QE phases, and if the gilt has not been auctioned during the crisis. Consistent with the baseline estimation results, the variable volatility and *BENCH* are not significant. The role of primary dealer's turnover weakens in the estimation of secondary issuance implying the importance of primary dealers' activity in primary issuance. Interestingly, the alternative measure for market activity and demand (*ACT*, now measured on a bond specific basis) is significant at 10% level in the secondary issuance model, implying that measuring the issuance activity based on the specific gilt captures the impact better than all gilts. However, the impact of *ACT* on demand is not statistically strong. Similarly, the variable *LIQ* is significant in 10% level and increase the demand for the gilt, which is in line with the results of study by Klingler and Sundaresan (2023), explaining that dealers do not usually buy and hold their Treasury bonds; instead, they usually sell them after the auction. Therefore, the outcome of auctions is most likely to be influenced by the bond's liquidity.

4.7. Quantitative Easing and the Gilts Market

Intrigued by the strong evidence of QE's impact on the bid-to-cover ratio in the previous section, we have designed two variables to gain a deeper understanding of this relationship. There has been a significant increase in research on QE channels since Krishnamurthy and Vissing-Jorgensen (2012). Nonetheless, there is still a lack of precise terminology and channel differentiation. A crucial differentiation exists between channels that have a direct effect on household and corporate borrowing rates, which is QE programmes' ultimate goal, and those that are intermediate or indirect channels.

The communication channel and the portfolio rebalancing channel are two of the former. The actual communication route is made up of two different networks. First, according to Bauer and Rudebusch (2014), pronouncements from central banks can affect market interest rates through a process known as the "announcement channel" by influencing predictions of upcoming monetary policy. Furthermore, according to Clouse et al. (2003), this mechanism acts as a "signalling channel," apparently committing central banks to keeping interest rates low.

On the other hand, a large amount of the literature has been allocated to intermediate channels. These channels mostly function by pushing down the yields on securities that central banks actively target for purchasing. When investors move their investments away from the targeted assets in search of higher returns, this in turn causes a rebalancing of the portfolio. The two most commonly mentioned examples of intermediate channels are the local supply/scarcity channel and the duration risk channel.

The supply and demand consequences of central banks purchasing assets are among the indirect transmission channels of quantitative easing (QE). Both of these factors originate endogenously from the micro-structure of debt markets and are comparable to the "stock effect" and "flow effect" as outlined in D'Amico and King (2013). A local supply or scarcity channel causes the stock impact, which lowers asset free float and raises yields as a result of central bank purchases. On the contrary side, the central bank's role as an important purchaser in the asset market is what causes the flow effect. The stock effect lasts as long as the central bank retains the acquired assets on its balance sheet, whereas the flow effect only lasts during the QE purchase period.

According to Ferdinandusse et al. (2020), in nations where there are fewer preferred habitat investors, the supply or scarcity effects become more prominent and likely to overwhelm the demand impacts. Corresponding to this, the majority of empirical research indicates that stock effects should be greater than flow effects (Arrata and Nguyen, 2017; De Santis and Holm-Hadulla, 2020).

Empirical research has also considered the effects of quantitative easing (QE) on market liquidity. While some studies (Beirne et al., 2011; Coroneo, 2015; Eser and Schwaab, 2016; Steeley, 2015) show that central bank asset purchases have a positive impact on liquidity, others (D'Amico and King, 2013; Kandrac, 2013) show evidence of a negative impact. Examples of these studies include improved liquidity of Treasury Inflation-Protected Securities (TIPS) in the US (Christensen and Gillan, 2022) and enhanced corporate bond liquidity in the UK (Boneva, Elliott, et al., 2020). Kandrac (2018) findings, which show that market liquidity was negatively impacted by Federal Reserve purchases of mortgage-backed securities, provide as an example of this.

Ferdinandusse et al. (2020) distinguish between scarcity and demand effects to offer a possible explanation for these obviously contradictory results. According to their proposal, asset acquisitions should first create liquidity by driving up demand for the desired assets (Pelizzon et al., 2018). But when central banks retain onto these assets, the supply may become less available, which could affect liquidity (Corradin and Maddaloni, 2020; Schlepper et al., 2017). The euro region has observed this phenomenon; Corradin and Maddaloni (2020) document the incorporation of a "scarcity premium" into the price of acquired government bonds. Similar to this, Schlepper et al. (2017) show that asset purchases by the European Central Bank have gradually increased scarcity over time by using high-frequency German bond data.

The purpose of this section is to test the robustness of our previous findings on the impact of QE by using two alternative measures of QE intensity. We are not attempting to separately test all the theoretical channels through which QE may operate, such as the communication or portfolio rebalancing channels. Rather, the discussion of transmission mechanisms provides theoretical background to understand the potential pathways through which QE, and specifically the Bank of England's Asset Purchase Facility (APF), could influence the gilt market. Our empirical focus remains on evaluating whether the effects of QE on auction demand, as captured by the bid-to-cover ratio, are consistent across different measures of QE activity.

In the following section, two variables are introduced related to the QE activity:

4.7.1. BOE debt holding ratio

The portion of gilts held by the Bank of England at the time of the auction that was acquired through the Asset Purchase Scheme is known as the variable *BOE* debt holding ratio. A theoretical model presented by Ferdinandusse et al. (2020) illustrates how a central bank's acquisitions of assets impact the assets' price and liquidity. They clarify that there are two ways in which central bank intervention in the bond market affects prices and liquidity. First, when the central bank begins purchasing bonds, demand rises (demand effect). Second, when it has bonds on its balance sheets, it decreases the number of sellers in the market (supply effect). The supply and demand impact of quantitative easing have adverse effects on liquidity, even though both of them raise the price of the bonds purchased. Market liquidity first rises as a result of the central bank's initial increase in asset demand, which facilitates sellers' ability to find a buyer. Nevertheless, as the central bank retains the bonds on its balance sheet, the buyback plan gradually decreases the number of possible suppliers and causes liquidity to drop. It is likely that market liquidity drops below what it was before the asset purchase programme started. The QE's negative impact on yields could discourage new purchasers from entering the gilt market. QE involves a price-liquidity trade-off due to these conflicting effects. Therefore, we design the share of Bank of England for a gilt being auctioned to capture the scarcity impact caused by QE program. As can be seen in Figure 13 of the previous chapter, the BOE owns 70% of some gilts, which may severely restrict the gilt's market liquidity. Conversely, for certain gilts, the BOE share is zero, indicating that there is a greater supply available in the market.

The purpose of using the BOE debt holding ratio is to capture the 'scarcity effect' of QE on auction demand. A higher BOE holding share for a specific gilt is expected to reduce the available supply in the market, potentially affecting investor behaviour at auction. We predict that higher BOE holdings may reduce demand at auction if liquidity deteriorates, but may also stimulate demand if scarcity raises the value of the remaining supply.

4.7.2. Asset Purchase Activity

The impact of QE activity on the bid-to-cover ratio is gauged by a variable named *APF*, which is determined by taking the natural log of the number of (working) days since the Bank of England last purchased APF. Unexpected changes in the economy may lead to huge requests from investors to sell sovereign debt. As a result, dealers can discover that they have excessively large positions on their balance sheets to warehouse while they seek for purchasers. The demand provided by the BOE in the gilt market rises with increased QE activity frequency. Thus, central bank bond purchases during a period of financial instability may enhance market tightness, or the ease with which buyers and sellers match, which in turn restore the functionality of the market.

Both the amount and type of assets to be purchased are essential components of each QE operation. The frequency of purchasing is another design decision that has gained prominence with the 2020 QE episodes. Generally, the MPC declares a target for the quantity of purchasing as well as the time frame of the program's completion. These two elements collaborate in order to set the pace at which the Bank makes purchases. For example, the MPC stated in March 2009 that the Bank would finish the £75 billion acquisition strategy in three months, which suggests an average weekly pace of about £6 billion. Before QE5, subsequent QE phases were typically performed at a speed that was around half of that.

In normal market conditions, the effectiveness of QE is mostly decided by its size and crystallises during the announcement of the plan rather than during actual purchases. Nonetheless, during periods of market pressure, actual purchases may also help in enhancing market function, and thereby emphasising the significance of purchase pace (Bailey et al., 2020). The March 2020 QE program differed significantly in its pace of implementation. From March to June 2020, purchases proceeded at a considerably faster rate of £13.5 billion per week. This accelerated pace aligned with the Monetary Policy Committee's (MPC) objective of executing the plan as immediately as is operationally achievable, consistent with improved market functioning. Following the announcement of an additional £100 billion asset purchase program in June 2020, the MPC indicated that the pace could potentially slow down with stable liquidity conditions. However, they also emphasized the possibility of a renewed acceleration if situations deteriorated considerably again.

Predictions regarding the future stock of purchased securities may also be influenced by the pace at which assets are purchased. Froemel et al. (2022) deduce, based on survey data on expectations among investors, that the response of the yield curve to the 2020 QE announcements was consistent with medium-term expectations of the purchasing stock responding to news regarding the pace of purchases. As such, a slower-than-expected declared pace is probably linked to a lower expected buy stock over the medium run, which could increase the yields, and vice versa.

The purpose of using the APF variable is to capture the flow effect of QE by measuring the frequency of the Bank of England’s asset purchases. A shorter time since the last APF purchase (i.e., more frequent purchases) is expected to support market liquidity and raise the bid-to-cover ratio by enhancing investor confidence and market functioning. Therefore, we predict a negative relationship between the APF variable (log of days since last purchase) and the bid-to-cover ratio.

4.7.3. Number of Gilt-Edged Market Makers

The demand for the gilt up for auction may rise if more primary dealers take part in the auction. Evidence of a major role for primary dealers in intertemporal intermediation is presented by Fleming et al. (2024). To be more precise, dealers take up a significant portion of the new Treasury supply that contributes to increase dealer positions during auction weeks. Because of this, more market makers may lessen the burden on primary dealers to absorb the shock to supply, particularly in light of the limited risk-bearing capacity of primary dealers as highlighted by Albuquerque et al. (2024).

However, there could be a negative relationship between the number of market makers and the bid-to-cover ratio. Because they have more market power when fewer market makers engage in the auction, they might bid more aggressively. A higher bid-to-cover ratio could result from this aggressive bidding. Using data from September 1994 to February 1996, Drudi and Massa (2005) analyse jointly dealers' bids in the primary market and their secondary market trades for government securities for the Italian market. They offer proof that prices in the secondary market are manipulated by primary dealers who take advantage of the more transparent secondary market to influence prices in the auction (less transparent market). In parallel, they actively bid in the auction and, once it ends, they buy back shares in the secondary market. During the time the primary market is open, this technique results in losses in the secondary market; but, as it ends, profits are generated.

The purpose of using the Number of GEMMs variable is to capture the potential effect of market participation intensity on auction demand. A higher number of primary dealers is expected to improve the distribution of supply and enhance market liquidity, leading to a positive impact on the bid-to-cover ratio. However, we acknowledge that the relationship could also be ambiguous, as a smaller number of aggressive bidders could temporarily raise the bid-to-cover ratio. It is possible that a smaller number of market makers could collude to offset government attempts to exploit the announcement or signalling channels. So, more dealers could be better. In this study, we predict that a higher number of GEMMs will generally have a positive effect on auction demand.

4.7.4. Summary Statistics

Excluding the observations on dates that correspond to the bid-to-cover ratio outliers, Table 52 presents summary statistics for the explanatory variables included in the estimation designed to assess the effect of QE on the gilt market. The summary statistics of the variables before outlier removal is presented in Table 10 of previous chapter and Table 62 of this chapter for two variables bid-to-cover ratio and volatility. Table 53 shows that there was a statistically significant increase in the mean bid-to-cover ratio from 1.98 to 2.10 when comparing sample periods before and after QE. It is notable that the results of t-test comparison of means for concession cost between these two sample periods show that the gilt issuance was more expensive for government prior to 2009, the start of QE program, which is consistent with the comparison of means for the bid-to-cover ratio. The results of the t-test comparisons of means for other explanatory variables are reported in Table 63, which illustrate that the means of variables are statistically different over these two sub-periods.

Table 52: Summary statistics of main variables from 2009 to 2022

This table contains the summary statistics for eleven variables across 570 auctions from March 2009 to December 2022, using data that excludes observations on dates corresponding to the bid-to-cover ratio outliers. The bid to cover ratio, hereafter abbreviated as BC, measures the extent to which the total amount bid at the auction exceeds the amount offered for sale at the auction; a value of 1.0 means the value of bids equals the value of stock being auctioned. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. From 1987 to 2000, the volatility is measured by unnormalizing the gilt volatility (the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract) by multiplying each normalized observation by the standard deviation of the FTSE100 volatility between 2000 and 2022 and then adding the mean FTSE volatility throughout that time period. From 2000 to 2022, the volatility measured by the implied volatility of at-the-money FTSE100 index call option; the implied volatility is expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days. MAT is the time to maturity, calculated as the number of days from the auction to the gilt's maturity date divided by 365.25, and expressed in years. LIQ is the ratio of the size of the gilt being auctioned (including the auctioned amount) to the average outstanding size of all other conventional gilts on the auction day; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover ratio of the previous auction, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). BOE is the share of the gilt owned by the Bank of England under the Asset Purchase Scheme at the time of the auction, expressed as a percentage. APF is the natural log of the number of working days since the previous APF. Mean is the sample mean of the variable, SD is the sample standard deviation, Min and Max are the minimum and maximum observations, and p25, p50, and p75 indicate the observation in percentile 25, 50, or 75, respectively.

Variable	Observation	Mean	SD	Min	P25	P50	P75	Max
BC	570	2.1	0.42	0.93	1.79	2.11	2.39	3.32
SIZE	570	7.96	0.31	6.91	7.74	8.01	8.18	8.66
LIQ	570	0.77	0.38	0.08	0.47	0.76	1.04	1.81
ACT	570	1.48	0.79	0	1.1	1.61	2.08	3.09
VOL	570	0.18	0.07	0.06	0.13	0.16	0.21	0.7
DEM	570	2.11	0.43	0.93	1.79	2.11	2.41	3.85
TGEMMs	570	5.06	0.29	4.14	4.88	5.09	5.28	5.72
MAT	570	14.8	11.71	2.12	5.43	9.97	22.31	53.37
BOE	570	0.17	0.18	0	0	0.1	0.28	0.75
APF	570	2.09	2.15	0	0	1.1	4.26	6.05
NGEMMs	570	18.61	1.63	15	18	18	20	22

Table 53: t-test Comparison of Means of Bid-to-Cover Ratio

This table contains the results of t-test comparison of means of bid-to-cover ratio between two sample periods. The bid to cover ratio, hereafter abbreviated as BC, measures the extent to which the total amount bid at the auction exceeds the amount offered for sale at the auction; a value of 1.0 means the value of bids equals the value of stock being auctioned. The first sample period starts from the first auction occurred in 1987 to the start of QE program in 2009, and the second group starts from the beginning of QE to the end of year 2022. The bid to cover ratio measures the extent to which the total amount bid at the auction exceeds the amount offered for sale at the auction. Mean is the sample mean of the variable.

Group	Observation	Mean	Std. errs.	Std. dev.	[95% conf.	interval]
1987-2009	208	1.98	0.04	0.57	1.91	2.06
2009-2022	571	2.10	0.02	0.42	2.07	2.14
Combined	779	2.07	0.02	0.47	2.04	2.10
diff		-0.12	0.04		-0.19	-0.05
Diff = mean (group1) - mean (group2)					T = -3.15	
H0: Diff = 0					Degree of freedom = 777	

4.7.5. Empirical Results for Alternative Measures of QE Activity

This subsection adds the BOE share, APF, and the number of GEMMs to the baseline regression found in equation (6). Considering that *BOE* and *APF*, two other variables associated with the *QE* activity, the variable *QEDUM* is removed from the model. This results in the regression equation that follows:

$$Y_i = c + b_1BOE_i + b_2APF_i + b_3SIZE_i + b_4LIQ_i + b_5BENCH_i + b_6VOL_i + b_7ACT_i \quad (6)$$
$$+b_8MAT_i + b_9DEM_i + b_{10}TGMMs_i + b_{11}PAOF_i + b_{12}NGEMMs_i + b_{13}UKFCI_i + \varepsilon_i$$

The results of equation (7) are reported in Table 54 and show almost same results to the baseline outcomes for the sample period from 1987 to 2022, implying the robustness of the findings. The variable *APF* is designed to capture the impact of the purchase frequency and show the importance of timing design. We find evidence of positive impact of purchase frequency on the bid-to-cover ratio, and this could be explained by both the demand and supply impact. According to Ferdinandusse et al. (2020), asset purchase programmes reduce supply by lowering the number of sellers and raise demand in the gilt market through the central bank's demand. Nonetheless, they show how the liquidity effect of the QE programme can negatively impact market functionality. Regarding this channel, our findings suggest that raising the frequency of purchasing assets boosts the demand for a gilt established for auction; however, this influence may be temporary and the pace at which the bank accomplishes the purchases has an adverse long-term impact on the gilt market's demand. Furthermore, we observe that the BOE share has negative impact on demand at 10% level of significance. This finding can provide further evidence for the statement that central bank asset purchases lower bond prices and decrease liquidity over time. As we explained previously, the effects of QE on supply and demand have opposing effects on liquidity. The central bank's initial rise in asset demand facilitates the process of finding a buyer for sellers, hence increasing market liquidity. Liquidity, however, decreases over time as central bank asset purchases lower the free-float of bonds. A price-liquidity trade-off of QE is thus created. It also offers a rationale for the contradictory empirical results regarding the impact of asset purchases on liquidity. At first, liquidity increases, but as central bank holdings increase, liquidity decreases.

We observe that the primary dealers bid more aggressively in auctions with smaller gilt size and shorter maturity. Consistent with the baseline results and our theorical prediction, the demand for a gilt being auctioned increases with higher turnover of market makers, and if the auction has PAOF. As in the full-sample, the demand is found to be positively correlated with the bid-to-cover ratio from the previous auction. The variables volatility, *BENCH*, and *ACT* are not significant, in line with the results of the full-sample estimation.

From a statistical perspective, the variable liquidity is stronger than it was throughout the 1987–2022 study period. This could occur because liquidity showed large levels of dispersion during the pre-crisis and crisis sub-periods (figure 5 of previous chapter), and we omit these two sub-periods from the QE estimation. Moreover, the variable *FCI* does not show a significant impact on demand when we examine the determinants of bid-to-cover ratio under the impact of QE. This could be explained by the fact that the use of QE program could diminish the severity of crisis's impact on demand in gilt market by improving the price stability and liquidity.

Finally, the number of market makers is highly significant with negative impact, and this could be explained by the fact that they bid more aggressively in auction when fewer of them participate in auctions to obtain a higher profit by biding strategy. As previously discussed, both negative and positive impact could be created by the number of primary dealers, however, we find the negative correlation. It is noteworthy that the number of primary dealers increase the cost of issuance for government in previous chapter. However, again this result should not be over-interpreted due to the limitation of variation in the number of primary dealers over the sample period. (shown in Figure 15 of previous chapter).

The second column of Table 54 displays the findings on QE's effect on the bid-to-cover ratio exclusively for auctions that were secondary issuance. The results are almost same to the baseline findings. An increase in the natural log of the number of days since the previous auction for that specific gilt expand the demand for the gilt. Furthermore, the share of BOE loses the significance when the primary issuance excluded from the estimation. Interestingly, the alternative measure for market activity and demand (ACT, now measured on a bond specific basis) is significant at 10% level in the secondary issuance model.

This section evaluates the robustness of our baseline results by examining the impact of alternative QE measures — the APF variable capturing the frequency of asset purchases, and the BOE debt holding ratio capturing the scarcity effect from accumulated holdings. Based on the theoretical background discussed earlier in Section 4.7, we expect that higher purchase frequency (lower APF) should enhance demand, while higher BOE holdings could have mixed effects depending on whether liquidity improvements dominate or scarcity effects prevail. The concept of a price-liquidity trade-off, introduced when discussing QE channels, is used here only to help interpret the results — not to introduce new mechanisms beyond those already outlined.

Table 54: Determinants of Bid-to-Cover Ratio under the Impact of QE

This table has the estimated coefficients of equation (7) being used to identify the determinants of the bid-to-cover ratio for gilt auctions between March 2009 and December 2022 inclusive. Regression results for all issuance are displayed in the first column, while secondary issuance results are displayed in the second column. The bid-to-cover ratio is measured as the entire amount of bid during an auction divided by the total amount of new debt allocated; a value of 1.0 means the value of bids equals the value of stock being auctioned. BOE is the share of the gilt owned by the Bank of England, purchased under the Asset Purchase Scheme, at the point of the auction, expressed as a percentage. APF is the natural log of the number of (working) days since a previous APF purchase by the BOE, measured in days. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. From 1987 to 2000, the volatility is measured by unnormalizing the gilt volatility (the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract) by multiplying each normalized observation of the gilt volatility by the standard deviation of the FTSE100 volatility between 2000 and 2022 and then adding the mean FTSE volatility throughout that time period. From 2000 to 2022, the volatility is measured by the implied volatility of at-the-money FTSE100 index call options, expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. BENCH is an indicator that takes the value unity if the issuance is of or into a 5,10 or 20-year benchmark issue. PAOF is an indicator that takes the value unity if the issuance has the Post Auction Option Facility (PAOF). ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days. MAT is the difference between maturity date and auction date divided by 365.25, expressed in years. LIQ is the ratio of the size of the gilt being auctioned (including the auctioned amount) to the average outstanding size of all other conventional gilts on the auction day; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover ratio of the previous auction, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). NGEMMs is the number of Gilt-Edged Market Makers on the auction day, measured as a count. FCI is an indicator that takes value unity if the FCI identifies the episodes of systemic financial distress. For the regression of secondary issuances, the variable LIQ is redefined to exclude the auctioned amount, and represents liquidity on the day before auction. Also, the variable ACT is changed to the log of the number of days since the last conventional gilt issuance for that specific gilt instead of any gilt. Other variables are exactly the same for modelling secondary issuance as those used for the baseline regression model. We applied clustered standard errors, and the clusters are defined by the gilt issuance's frequency. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels.

$$Y_i = c + b_1 SIZE_i + b_2 LIQ_i + b_3 BENCH_i + b_4 VOL_i + b_5 ACT_i + b_6 MAT_i + b_7 DEM_i + b_8 TGMMs_i + b_9 PAOF_i + b_{10} BOE_i + b_{11} APF_i + b_{12} NGEMMs_i + b_{13} UKFCI_i + \varepsilon_i$$

	Baseline	Secondary
BOE	-0.13^{*}	-0.05
	(-1.89)	(-0.61)
APF	-0.02^{***}	-0.02^{**}
	(-4.03)	(-2.71)
SIZE	-0.48^{***}	-0.47^{***}
	(-5.5)	(-5.2)
TGEMMs	0.36^{***}	0.33^{***}
	(6.36)	(5.86)
VOL	-0.18	-0.10
	(-1.02)	(-0.54)
BENCH	0.03	0.03
	(0.86)	(0.66)
PAOF	0.19^{***}	0.19^{***}
	(6.33)	(5.78)
ACT	-0.02	-0.04^{*}
	(-0.97)	(-1.92)
MAT	-0.01^{***}	-0.01^{***}
	(-6.62)	(-6.43)
LIQ	0.08^{**}	0.09^{*}
	(2.25)	(2)
DEM	0.30^{***}	0.30^{***}
	(10.77)	(10.85)
NGEMMs	-0.07^{***}	-0.07^{***}
	(-7.97)	(-7.05)
FCI	-0.03	-0.02
	(-1.08)	(-0.63)
Constant	4.95^{***}	5.04^{***}
	(5.7)	(5.58)
No. Observations	570	532
R-squared	0.55	0.56

4.8. An Analysis of Maturity Segmentation

In order to determine whether there exist segmentation premia in various segments of the conventional gilt market with respect to the bid-to-cover ratio, we apply the model in equations (6) across the various maturity segments in this section. This suggests that there may be imperfect substitutability within the bond market itself and is motivated by the preferred habitat and segmentation theories of Culbertson et al. (1957), Modigliani and Sutch (1966), Vayanos et al. (2009), and Greenwood and Vayanos (2010), where investors have a preference for a specific range of maturities along the yield curve. Additionally, J. Allen et al. (2020) discover evidence that the demand for shorter bonds is generally less price-sensitive than the demand for longer bonds.

The main argument is that investors have preferences for specific asset classes or, in the case of bonds, maturities, and they value certain assets for reasons other than expected return or risk. This implies generally that, as investors need compensation for adjusting their asset holdings in reaction to shocks, local supply and demand conditions may become significant in determining price. The story of how QE policies spread via the so-called portfolio balance channel and the theory that it primarily operates by lowering term premia has revolved around this theoretical outcome in recent years. Preferred habitat behaviour, in general, has significant impacts for several other works where the investor structure is significant, such as debt management (Andritzky, 2012), the way in which various investors absorb or magnify price shocks (Timmer, 2018), and the way in which prices are formed (Koijen and Yogo, 2020).

Using their demand estimates, J. Allen et al. (2020) investigate if and how a government might lower funding costs by strategically rearranging its debt across maturities in order to raise total auction proceeds. They concentrate on the distribution of debt across various maturities. By incorporating roll-over costs of debt that absorb the (mechanical) price difference of bonds with different maturities, they leave aside the dynamic features of the debt allocation problem. They then draw attention to how a government can lower its financing costs by taking advantage of the fact that demand for shorter bonds is typically less price-sensitive than demand for longer bonds.

4.8.1. Summary Statistics

The average bid-to-cover ratio and average auction size for conventional gilt auctions with three maturity segments are displayed in Table 55, which also features eleven divisions for the sample period. The market standard for the maturity categories is Short (less than 7 years), Medium (7 to 15 years), and Long (more than 15 years). As shown in Table 55, the average of the bid-to-cover ratio for medium term gilts is almost close to it for short term segmentation; however, it is significantly lower for longer maturity gilts. The results of Table 55 demonstrate that the average bid-to-cover ratio for medium-term gilts is about identical to that for short-term segmentation; however, it is significantly lower for gilts with longer maturities. As shown in figure 41, the fluctuation of the bid-to-cover ratio is higher for short-term gilts in comparison with other maturities.

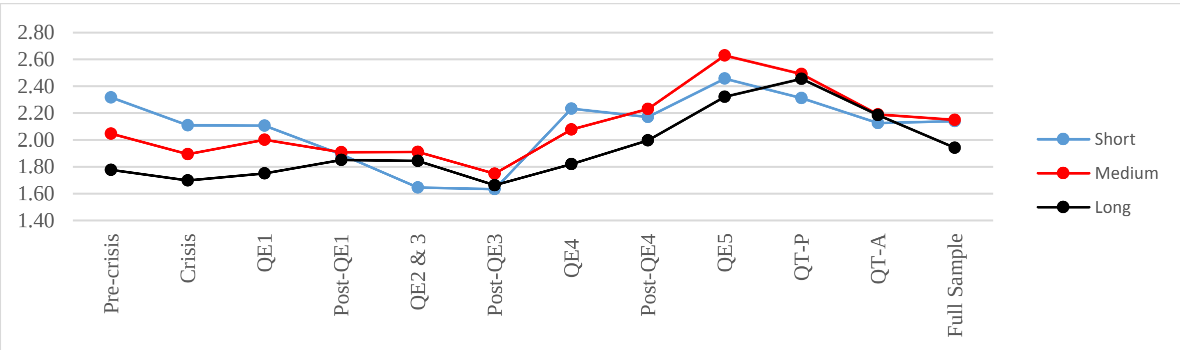
Table 55: Bid-to-cover ratio and Auction Size for Different Maturity Segments

This table contains the average auction size (£ million), the number of auctions, the average bid-to-cover ratio for the time-period 1987 to 2022 throughout three maturity segments. The bid-to-cover ratio is measured as the entire amount of bid during an auction divided by the total amount of new debt allocated; a value of 1.0 means the value of bids equals the value of stock being auctioned. The maturity buckets use the standard market convention of Short (< 7 years), Medium (7 to 15 years), and Long (>15 years). The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive.

Maturity	Statistic	Pre-crisis	Crisis	QE1	Post-QE1	QE2 and 3	Post-QE3	QE4	Post-QE4	QE5	QT-P	QT-A	Full Sample
Short	Average Auction Size (£m)	2540	3559	4896	4421	4297	4073	2945	3035	3509	3429	3904	3538
	Average Bid-to-Cover Ratio	2.32	2.11	2.11	1.89	1.65	1.63	2.23	2.17	2.46	2.31	2.13	2.14
	Number of Auctions	44	17	14	20	14	34	5	35	60	10	4	257
Medium	Average Auction Size (£m)	2504	2865	3785	3376	3361	3270	2602	2758	3061	3133	3250	3006
	Average Bid-to-Cover Ratio	2.05	1.89	2.00	1.91	1.91	1.75	2.08	2.23	2.63	2.49	2.19	2.15
	Number of Auctions	50	13	15	21	11	32	6	30	53	10	3	244
Long	Average Auction Size (£m)	2322	2176	2306	2213	1904	2026	2236	2276	1989	2370	2625	2164
	Average Bid-to-Cover Ratio	1.78	1.70	1.75	1.85	1.84	1.66	1.82	2.00	2.32	2.46	2.19	1.94
	Number of Auctions	67	17	11	18	13	39	6	30	65	9	3	278

Figure 41: Average of the Bid-to-Cover Ratio for Three Maturity Segments

This figure illustrates the average bid-to-cover ratio for gilt auctions from 1987 to 2022, segmented by three maturity categories—Short (< 7 years), Medium (7 to 15 years), and Long (>15 years)—and grouped across major monetary policy sub-periods indicated on the x-axis (e.g., QE1, QT-P, etc). The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive. The y-axis shows the bid-to-cover ratio, a metric calculated as the total value of bids received divided by the value of debt allocated; a value of 1.0 means the value of bids equals the value of stock being auctioned. A higher ratio indicates stronger investor demand for a given maturity segment during that period. This visual comparison highlights variations in auction demand across time and maturity classifications.



The summary statistics for the main variables are presented separately for each maturity bucket in Table 56. By using a pairwise comparison of means across several maturity segments, we find that gilts with long-term maturity have a statistically lower bid-to-cover ratio than gilts with short- and medium-term maturities (Table 65). Moreover, the findings indicate that gilts with short-term maturity have a significantly bigger auction size than gilts with medium- and long-term maturities. The variable time to maturity differs greatly across different maturity buckets, as predicted. It is noteworthy that there is a highly significant difference between the variable benchmark for long-term gilts and the other maturities. However, we cannot find a significant difference for other variables across maturity segments.

Notably, all of the outliers in the bid-to-cover ratio fall inside the short-term maturity range. As a result, Table 64 only reports the summary statistics for short-term maturity using data that removes observations on days that match to the bid-to-cover ratio outliers. The appendix contains the correlation coefficients with significance levels between the explanatory variables across maturity segments. The results of pairwise correlation show that a higher bid-to-cover ratio from prior auction and QE program result in a higher bid-to-cover ratio for the gilt being auctioned across all maturities. The outcome of this pairwise correlation test for gilts with short-term maturity reveals that for gilts with shorter maturities, smaller auction sizes have higher bid-to-cover ratios, and this impact is highly significant. At the 10% level, the variables *FCI*, *TGEMMs*, and *ACT* have an effect on bid-to-cover ratio. For gilts with medium maturity, the results of pairwise correlation indicate that a higher bid-to-cover ratio could be due to the increase of issuance activity in the gilt market and higher turnover of primary dealers. However, at 10% level, the bid-to-cover ratio is affected positively by *PAOF* and negatively by *FCI*. Finally, the bid-to-cover ratio of gilts, considered long-term, increases significantly as a result of higher turnover of primer dealers, and high frequency of gilt issuance, and *PAOF*. The impact of size of auction is significant at 10% level.

Table 56: Summary Statistics of Main Variables Over Maturity Segments

This table contains the summary statistics for seven variables across 779 auctions from May 1987 to December 2022 over different maturity segments. The bid-to-cover ratio is measured as the entire amount of bid during an auction divided by the total amount of new debt allocated; a value of 1.0 means the value of bids equals the value of stock being auction. SIZE is the natural log of auction size, measured in £ million. LIQ is the size of the outstanding gilt that is being auctioned (including the auctioned amount) divided by the average size outstanding of all other (conventional) gilts on the auction day; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days. From 1987 to 2000, the volatility is measured by unnormalizing the gilt volatility (the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract) by multiplying each normalized observation by the standard deviation of the FTSE100 volatility between 2000 and 2022 and then adding the mean FTSE volatility throughout that time period. From 2000 to 2022, the volatility is measured by the implied volatility of at-the-money FTSE100 index call options, expressed as an annualized standard deviation of returns. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. MAT is the difference between maturity date and auction date divided by 365.25, expressed in years. Mean is the sample mean of the variable, SD is the sample standard deviation, Min and Max are the minimum and maximum observations, and p25, p50, and p75 indicate the observation in percentile 25, 50, or 75, respectively. The maturity buckets use the standard market convention of Short (< 7 years), Medium (7 to 15 years), and Long (>15 years).

Variable	Maturity	n	Mean	S.D.	Min	0.25	Mdn	0.75	Max
	Short	257	8.14	0.27	6.62	8.01	8.16	8.31	8.66
SIZE	Medium	244	7.99	0.2	6.91	7.84	8.01	8.14	8.39
	Long	278	7.66	0.21	6.68	7.56	7.72	7.81	8.05
	Short	257	0.9	0.49	0.09	0.51	0.88	1.24	2.53
LIQ	Medium	244	0.87	0.51	0.08	0.47	0.84	1.18	2.5
	Long	278	0.85	0.46	0.1	0.54	0.8	1.03	2.98
	Short	257	1.76	0.87	0	1.39	1.61	2.48	3.76
ACT	Medium	244	1.74	1.04	0	1.1	1.61	2.4	4.34
	Long	278	1.81	0.97	0	1.39	1.61	2.48	4.37
	Short	257	0.19	0.1	0.07	0.13	0.17	0.24	0.68
VOL	Medium	244	0.19	0.09	0	0.13	0.17	0.22	0.63
	Long	278	0.18	0.08	0.02	0.12	0.16	0.22	0.7
	Short	257	2.07	0.47	0	1.72	2.09	2.38	3.49
DEM	Medium	244	2.03	0.46	1.1	1.68	2.01	2.33	4.48
	Long	278	2.13	0.52	0.99	1.77	2.1	2.44	4.81
	Short	257	4.83	0.54	2.97	4.5	4.98	5.23	5.71
TGEMMs	Medium	244	4.75	0.61	2.74	4.44	4.93	5.17	5.72
	Long	278	4.76	0.57	2.92	4.42	4.92	5.19	5.64
	Short	257	4.78	1.11	2.12	4.38	5.1	5.49	6.98
MAT	Medium	244	10.31	1.53	7.04	9.72	10.09	10.57	14.95
	Long	278	29.4	8.5	15.55	21.75	29.6	34.33	53.37

4.8.2. Results

To assess the gilts within each maturity segment, we apply equation (6) separately for three distinct maturities, covering the period May 1987 to December 2022. We employ the same set of explanatory variables as used earlier in this chapter in three estimations, in appendix, we apply a set of explanatory variables where some of them are re-defined based on maturity segmentation. For example, the variable *ACT*, which is the number of days since the previous issuance in any gilt, is redefined to be since the previous issuance in any gilt in the same maturity segment as the auction being considered. According to the results of the estimation 1 of the coefficients given in Table 57, there is higher demand for gilts during the phases of QE program; however, the impact is stronger for short- and medium-term gilts. The size of auction reduces the bid-to-cover ratio of gilts with short- and medium-term gilts which is in line with the theory that the size of auction increase the bid dispersion. The impact is statistically stronger for short-term maturity bucket. This might be due to larger average of auction size for gilts with short-maturity.

The positive correlation between turnover of primary dealers and the bid-to-cover is highly significant for long-term maturity bucket. This could be the result of smaller average size of issuance for gilts with longer maturity which causes the bid-to-cover ratio to be more sensitive to the demand provided by primary dealers in the market. In contrast, the average size of issuance is larger for gilts with shorter maturity, and an increase of demand by primary dealers does not make a significant change in the bid-to-cover ratio. In medium-term maturity bucket, the impact of *TGEMMs* is significant at 10% level of significance, and the average issuance size is between two other maturity buckets; however, the turnover of primary dealers is higher in compared to other maturity segments which is shown in figure 19 of previous chapter. Therefore, the increase of market maker's turnover shows a weaker significance.

It is interesting to note that, at the 10% significance level, the variable volatility positively influences the demand for short-term gilts. This is consistent with the theoretical assumption that investors favour short-term government bonds under financial market stress because longer-term bonds have a higher interest rate risk. The results indicate that investors bid more for short- and long-term gilts with PAOF. Furthermore, we find that consistent with the impact of benchmark status on the cost of issuance, gilts with 20 years benchmark status have higher demand in the market, and this might be due to the ranges that each maturity covers could make their correlations with the benchmark state weaker. In accordance with the definition of maturity segments, gilts with a maturity of less than seven years are included in the short-term bucket; gilts with a maturity of seven to fifteen years are classified as medium-term; and gilts with a maturity of fifteen years or more are all regarded long-term gilts. Since the long-term bucket has an average maturity of about 30 years and a maximum maturity of 53 years, it covers a larger variety of maturities. Long term gilts are therefore less resistant to changes in the benchmark status.

As we expect that the demand increases when the maturity is shorter, our findings indicate that investors with preference of short-term assets are more sensitive to the maturity of gilts. However, we do not find significant impact of maturity on the demand of investors within medium- and long-term segments. Moreover, Increasing the frequency of issuance for long-term gilts is likely to raise demand in this maturity segment, with a statistically significant effect at the 10% level. This effect could result from the smaller average issuance size within the long-term maturity segment, which might not be sufficiently satisfying current market demand. The estimation result reveals that, at a 10% significance level, enhancing the medium-term gilts' liquidity condition increases demand. This suggests that medium-term gilts are more susceptible to changes in liquidity condition.

Interestingly, the positive correlation between demand and the bid-to-cover ratio of previous auction is highly significant across three maturities, implying the power of this ratio in the market to attract investments from the other markets. Additionally, during a crisis, the demand for short- and medium-term gilts is significantly lower.

Figure 42 illustrates that, although it declined in the short and medium segments during the financial crisis, the average bid-to-cover ratio of long-term gilts grew during the crisis episodes. This could be explained by the investors' expectation during the crisis. Except the first phase of QE, investors might predict a quantitative easing strategy to cope with the financial instability. Therefore, they increase their demand for long-term gilts as they are aware of the concentration of QE activities in the long-term segmentation.

The results for secondary issuance are almost same to the baseline results. The bid-to-cover ratio for medium-term gilts is significantly impacted when the variable *ACT* is redefined to reflect the number of days since the previous issuance for that particular gilt rather than for any gilt. In a similar vein, changing the variable liquidity for secondary issuances to the day before the auction raises the impact's significance level for medium-term segmentation.

Table 57: Determinants of the Bid-to-Cover Ratio for Maturity Segments

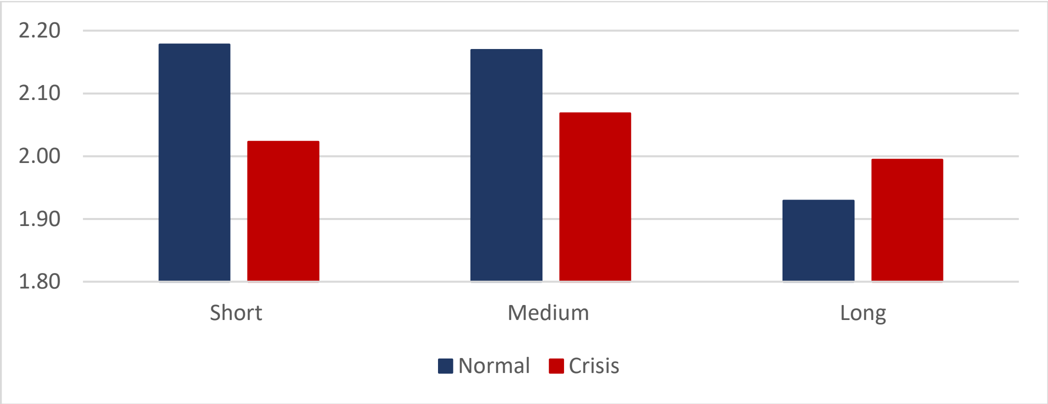
This table has the estimated coefficients of equation (6) being used to identify the determinants of the bid-to-cover ratio for gilt auctions between May 1987 and December 2022 across three maturity segments. Regression results for all issuance are displayed in the first column, while secondary issuance results are displayed in the second column. The bid-to-cover ratio is measured as the entire amount of bid during an auction divided by the total amount of new debt allocated; a value of 1.0 means the value of bids equals the value of stock being auctioned. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. From 1987 to 2000, the volatility is measured by unnormalizing the gilt volatility (the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract) by multiplying each normalized observation of the gilt volatility by the standard deviation of the FTSE100 volatility between 2000 and 2022 and then adding the mean FTSE volatility throughout that time period. From 2000 to 2022, the volatility is measured by the implied volatility of at-the-money FTSE100 index call options, expressed as an annualized standard deviation of returns. BENCH is an indicator that takes the value unity if the issuance is of or into a 5,10 or 20-year benchmark issue. PAOF is an indicator that takes the value unity if the issuance has the Post Auction Option Facility (PAOF). ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days. MAT is the difference between maturity date and auction date divided by 365.25, expressed in years. LIQ is the size of the outstanding gilt that is being auctioned (including the auctioned amount) divided by the average size outstanding of all other (conventional) gilts, on the auction day; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover of the previous auction, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). $QEDUM$ is an indicator that takes value unity during the sub sample corresponding to the periods of asset purchase facility throughout QE. FCI is an indicator that takes value unity if the FCI identifies the episodes of systemic financial distress. For the regression of secondary issuances, the variable LIQ is redefined to exclude the auctioned amount, and represents liquidity on the day before auction. Also, the variable ACT is changed to the log of the number of days since the last conventional gilt issuance for that specific gilt instead of any gilt. Other variables are exactly the same for modelling secondary issuance as those used for the baseline regression model. The maturity buckets use the standard market convention of Short (< 7 years), Medium (7 to 15 years), and Long (>15 years). We applied clustered standard errors, and the clusters are defined by the gilt issuance's frequency. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels.

$$Y_i = c + b_1 QEDUM_i + b_2 SIZE_i + b_3 LIQ_i + b_4 BENCH_i + b_5 VOL_i + b_6 ACT_i + b_7 MAT_i + b_8 DEM_i + b_9 TGMMs_i + b_{10} PAOF_i + b_{11} UKFCI_i + \varepsilon_i$$

	Baseline	Secondary	Baseline	Secondary	Baseline	Secondary
	Short	Short	Medium	Medium	Long	Long
QEDUM	0.19***	0.21***	0.17***	0.16**	0.12**	0.09*
	(4.96)	(5.3)	(4.46)	(2.94)	(2.63)	(1.91)
SIZE	-0.86***	-0.82***	-0.51*	-0.62**	-0.08	-0.13
	(-12.82)	(-9.39)	(-1.91)	(-2.53)	(-0.98)	(-1.26)
TGEMMs	0.04	-0.07	0.19*	0.25***	0.24***	0.19***
	(0.38)	(-1.35)	(2.01)	(4.07)	(5.3)	(3.73)
VOL	0.66*	1.93	-0.38	1.42	0.21	0.87
	(2.1)	(1.39)	(-1.42)	(1.55)	(1.09)	(0.68)
BENCH	-0.01	0.00	0.05	0.07	0.18**	0.17
	(-0.17)	(-0.01)	(1.04)	(1.53)	(2.19)	(1.78)
PAOF	0.19***	0.16***	0.02	0.03	0.13***	0.14***
	(5.76)	(3.83)	(0.39)	(0.51)	(3.38)	(3.81)
ACT	0.02	0.01	-0.05	-0.11***	0.06*	-0.05
	(0.57)	(0.2)	(-1.18)	(-3.6)	(2.14)	(-1.62)
MAT	-0.08***	-0.08***	-0.01	0.002	-0.002	0.00
	(-4.84)	(-4.57)	(-0.6)	(0.2)	(-1.13)	(-1.54)
LIQ	0.07	0.05	0.16*	0.33***	0.05	0.06
	(1.41)	(0.7)	(2.08)	(4.17)	(0.93)	(0.71)
DEM	0.30***	0.35***	0.32***	0.32***	0.32***	0.31***
	(5.51)	(7.94)	(7.18)	(6.83)	(6.3)	(4.87)
FCI	-0.11***	-0.06	-0.15***	-0.16***	-0.01	0.02
	(-4.48)	(-1.78)	(-4.16)	(-3.99)	(-0.13)	(0.33)
Constant	8.31***	8.43	4.74*	5.23**	0.49	1.46
	(14.44)	(10.95)	(1.79)	(2.32)	(0.64)	(1.58)
No. Observations	253	220	243	212	278	257
R-squared	0.43	0.46	0.39	0.46	0.42	0.43

Figure 42: Comparison of Average Bid-to-Cover Ratio across Maturity Buckets between Crisis and Normal Condition

This figure compares the average bid-to-cover ratio across three maturity segments—Short (< 7 years), Medium (7 to 15 years), and Long (>15 years)—during periods classified as crisis and normal conditions. The x-axis represents the maturity buckets, while the y-axis shows the bid-to-cover ratio, an indicator of auction demand calculated as the total amount of bids received divided by the amount of new debt allocated; a value of 1.0 means the value of bids equals the value of stock being auctioned. Higher values reflect stronger market demand. The bars illustrate how investor participation varied between periods of market stress and stability for different bond maturities.



4.9. A Comparison of Results with the Concession Cost

A comparison of the outcomes between two chapters may be instructive since the bid-to-cover ratio is an indirect indicator of issuance cost and may represent the level of competition at the auction. remarkably, the outcomes align with the concession cost. On the other hand, we find evidence that the bid-to-cover ratio has a higher capacity to reflect the auction characteristics and market condition when comparing the adjusted R-squared of both estimations (0.12 for concession cost and 0.35 for bid-to-cover ratio). This could allow auction design to better manage issuance costs.

According to both estimates, the variable size has a negative relationship with a highly significant impact, meaning that the larger the auction, the higher the bid dispersion and, consequently, the issuance cost. The activity of the primary dealers is determined to have a positive coefficient in both estimations. As a result, the activities of the market makers raise the issuance premium and demand. In addition, PAOF lowers the cost of issuance for the government and raises demand for gilts up for auction; the effect is statistically stronger on the bid-to-cover ratio estimate. We note that the issuing cost rises with the time to maturity, which is consistent with the negative coefficient in the bid-to-cover ratio estimate. As before, the demand-based regression shows a statistically significant impact from the variable *MAT*. Lastly, neither estimation finds evidence of the influence of the variables *BENCH*, *ACT*, and *LIQ*.

The variable *VOL* in the issuance cost estimate aims to replicate the bond market volatility by applying data from gilt future contracts; however, we use the stock market volatility to reflect the safe heaven influence in the demand-based regression. As a result, we discover that gilt market volatility has a negative effect on government issuing costs. However, in the demand-based regression, the variable *VOL* does not show statistical significance. As a result, we find no proof of the safe heaven influence. besides, the variable *FCI* is designed to identify times of financial strain; the effect on the cost of issuance is not statistically significant, but it is statistically significant and negative when estimating the bid-to-cover ratio. This could be explained by the fact that when estimating concession costs, the variable *VOL* captures the effect of *FCI*.

The demand for the subsequent auction is positively and statistically significantly impacted by the bid-to-cover ratio of the previous auction; however, the analysis of concession cost does not find it to be statistically significant. We only find evidence for gilts with long-term maturity that the issuance cost was impacted by the prior bid-to-cover ratio.

Another intriguing discovery is that QE activities raise the demand for gilt auctions, but surprisingly raise the government's cost of issuance. This could be explained by the fact that the government must pay more for the issuance even when the demand from the BOE increases the bid-to-cover ratio. As can be shown, the variable *QE* has a positive and very significant impact on the demand-based regression but a negative and highly significant impact on the concession cost estimation. By adding more variables to the asset purchase facility and investigating the impact of the QE program in section 5, we find evidence that increased activity related to the program raises demand and the issuance cost for the government (the coefficient of *APF* is positive in the estimation of concession cost and negative in the estimation of bid-to-cover ratio). The perverse results for concession was explained away by *APF* being a "noisy" version of *QEDUM*. Concession itself is not without measurement issues and this makes it more difficult to establish the role of various factors. This perverse result is an artefact of including both QE and non-QE phases. In a QE phase, APF takes small values. In a non-QE phase, it generally takes higher values. Thus, it is like a "noisy" version of *QEDUM*. Hence it mirrors the *QEDUM* result. Additionally, that if this analysis is repeated for only periods of QE, the sign of the *APF* variable flips showing that more APF activity is helpful (reduces concession) all other things equal, and then in the long run, the reduction in liquidity measured by *BOEShare* dominates, to produce the overall negative effect seen when using only *QEDUM*. The share of *BOE* has a negative coefficient in both estimates, suggesting that if the BOE owns a larger share of gilt, that the government must pay a higher issuance cost, and that there would be less demand for the gilts at auction.

4.10. Conclusion

The determinants of the bid-to-cover ratio of UK debt issues—the most widely used indicator of demand in these kinds of auctions—have been examined in this chapter covering the period from the first auction in 1987 through the financial crisis, QE phases, and the period of policy responses to SARS-CoV-2. The results of pairwise comparison of means show that the average of bid-to-cover ratio during the phases of QE5 and QT-passive is significantly higher than the other sub-periods. Furthermore, the sub-period QE4 has greater average of the bid-to-cover ratio compared to the previous sub-period, implying a positive impact of QE program on the demand of gilt market.

To identify the determinants, we apply the same set of variables that can explain the concession, as both dependent variables reflect the competitive environment at the auction, and so the explanatory variables are exactly the same for the bid to cover regressions as those used for auction concession. Our theory suggests that the bid-to-cover ratio should be decreasing in the degree of market instability, the size of auction, and the time to maturity. The empirical results confirm our predictions. The size of issuance for gilts has a negative coefficient, which is consistent with the impact of auction size on the issuance cost for government. This suggests that the DMO can take this into account when designing the issuance procedures, possibly by reducing the auction size. Furthermore, we note that the longer the maturity, the lower the demand is for an auction, supporting the effect of maturity on the issuing cost (from previous chapter). The demand is lower during the financial crisis, as we would expect.

Furthermore, our theory also predicts that the demand should rise in response to factors such as increased outstanding issue liquidity, the preceding auction's bid-to-cover ratio, primary dealer turnover, and if the auction has benchmark (on-the-run) status, and PAOF service. In line with our findings in the previous chapter, the positive correlation between GEMMs' turnover and the bid-to-cover ratio is confirmed through various estimations. This statistically significant impact underscores the importance of enhancing the activity of primary dealers in the gilt market. As predicted, the Post Auction Option Facility (PAOF) has a highly significant positive impact on demand by increasing the liquidity of the gilt being auctioned. There is a positive association between demand and the bid-to-cover ratio from the previous auction. However, this impact is statistically more significant than that found in the previous chapter. In accordance with the preceding chapter, the model determines that the benchmark status of a gilt is not significant. This could be ascribed to the notable increase in gilt issuance activity in the recent past, which reduces the importance of the issuance benchmark status.

Lastly, our hypothesis suggests that there may be both positive and negative interactions between the bid-to-cover ratio and the independent variables, which are the frequency of issuance activity, the QE program, and the stock market volatility. There is no statistically significant evidence that the frequency of issuance and stock market volatility have an impact. In the previous chapter, we find evidence of a greater cost of issuance of government debt during the QE program; however, during the QE phases, we discover a higher level of demand. To gain a deeper understanding of the impact of QE on gilt market, we introduce two more variables related to the asset purchase program, the portion of gilt held by the Bank of England at the time of the auction and the pace at which the Bank makes purchases. The results indicate that asset purchase programs increase demand in the gilt market by driving down the number of sellers and increasing supply due to central bank demand. However, the QE program's liquidity effect may have a detrimental influence on market functioning. In relation to this channel, our results indicate that increasing the frequency of asset purchases increases the demand for a gilt being auctioned; this effect, however, might only last temporarily, and the speed at which the bank completes the purchases has a negative long-term effect on the demand for gilts. The contrasting findings for volatility and the safe haven impact motivate us to investigate more the relationship between gilt volatility and the stock market volatility in the next chapter.

To determine whether the gilt market is segmented, we apply the model to all maturity categories. The DMO can consider the following recommendations based on our results to boost demand in the gilt market:

- Reduce the size of auction for short- and medium-term gilts;
- Increase the turnover of primary dealer in the medium and long maturity segments;
- Increase the proportion of short-term gilts within the structure of government debt portfolios during periods of stock market volatility;
- Issue long-term gilts which have benchmark status;
- Provide PAOF service for gilts with short- and long-term maturity;
- Decrease the frequency of issuance for long-term gilts;
- The investors with short-term habitats are more sensitive to the increase of time to maturity;
- Raise the bid-to-cover ratio from the previous auction across all maturity segments;
- Raise in the percentage of long-term gilts in government debt portfolios during periods of financial crisis;[28]
- Short-term debt should be issued at the start of phases of QE (when volatility has yet to decrease), but when QE begins to reduce volatility, then longer term gilts (which are more sensitive to volatility and so more costly and more costly to issue) should take over to lock in the stability.

[28] The recommendation to increase the proportion of short-term gilts during periods of stock market volatility and the recommendation to increase the proportion of long-term gilts during periods of financial crisis are not contradictory. Stock market volatility episodes, often temporary and affecting liquidity preferences, justify a tactical shift toward short-term issuance. In contrast, financial crises typically involve deeper and more prolonged systemic risks, making the issuance of long-term gilts more appropriate to lock in low borrowing costs and stabilize financing conditions.

4.11. Appendix

4.11.1. Correlations

Table 58: Correlations

The table reports the Pearson correlations among the main variables across 774 auctions from 1987 to 2022. The bid-to-cover ratio is measured as the entire Amount of bid during an auction divided by the total amount of new debt allocated; a value of 1.0 means the value of bids equals the value of stock being auctioned. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. From 1987 to 2000, the volatility is measured by unnormalizing the gilt volatility (the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract) by multiplying each normalized observation of the gilt volatility by the standard deviation of the FTSE100 volatility between 2000 and 2022 and then adding the mean FTSE volatility throughout that time period. From 2000 to 2022, the volatility is measured by the implied volatility of at-the-money FTSE100 index call options, expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. BENCH is an indicator that takes the value unity if the issuance is of or into a 5,10 or 20-year benchmark issue. PAOF is an indicator that takes the value unity if the issuance has the Post Auction Option Facility (PAOF). ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days. MAT is the difference between maturity date and auction date divided by 365.25, expressed in years. LIQ is the size of the outstanding gilt that is being auctioned (including the auctioned amount) divided by the average size outstanding of all other (conventional) gilts, on the auction day; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover of the previous auction, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). $QEDUM$ is an indicator that takes value unity during the sub sample corresponding to the periods of asset purchase facility throughout QE. FCI is an indicator that takes value unity if the FCI identifies the episodes of systemic financial distress. *, **, *** correspond to significance levels of 10%, 5%, and 1%, respectively.

	BC	VOL	BENCH	SIZE	TGEMMs	PAOF	MAT	LIQ	ACT	DEM	QEDUM	FCI
BC	1											
VOL	0.01	1										
BENCH	0.05	-0.06*	1									
SIZE	-0.01	0.08**	0.30***	1								
TGEMMs	0.29***	-0.07**	-0.03	0.17***	1							
PAOF	0.17***	-0.13***	-0.01	0.23***	0.45***	1						
MAT	-0.19***	-0.07	-0.42	-0.67***	-0.02	0.00	1					
LIQ	0.03	0.10***	0.05	-0.05	-0.42***	-0.16***	-0.09**	1				
ACT	-0.23***	-0.21***	0.05	-0.14***	-0.59***	-0.27***	0.02	0.17	1			
DEM	0.43***	0.02	-0.14***	-0.07**	0.25***	0.07*	0.06	0.00	-0.26***	1		
QEDUM	0.34***	0.15***	-0.08**	0.07*	0.44***	0.23***	0.00	-0.08**	-0.45***	0.33***	1	
FCI	-0.05	0.40***	0.01	0.09***	0.17***	0.03	-0.06*	-0.02	-0.19***	-0.04	0.11***	1

4.11.2. Some Detailed Results

Table 59: One-Way ANOVA for Gilt Volatility

This tables contains the results for the one-way ANOVA, indicating whether there is a statistically significant difference in the gilt volatility between 1987 and 2000 in compared to the sample period of 2000 to 2022. The variable gilt volatility is the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract.

Sub-periods					
Source	SS	df	MS	F	Prob >F
Between groups	0.001	1	0.001	2.61	0.106
Within groups	0.405	777	0.001		
Total	0.406	778	0.001		

Table 60: One-Way ANOVA for Bid-to-Cover Ratio

This tables contains the results for the one-way ANOVA, indicating whether there is a statistically significant difference throughout three maturity segments, short, medium, and long-term gilts (in the left side), and also eleven sub-periods (in the right side). The variable is the bid-to-cover ratio measured as the entire amount bid divided by the total amount of new debt allocated. The dataset contains 779 auctions from 1987 to 2022. The maturity buckets use the standard market convention of Short (< 7 years), Medium (7 to 15 years), and Long (>15 years).

Maturity Segmentation						**Sub-periods**					
Source	SS	df	MS	F	Prob >F	Source	SS	df	MS	F	Prob >F
Between groups	7.38	2	3.69	17.41	0	Between groups	54.24	10	5.42	35.42	0
Within groups	164.48	776	0.21			Within groups	117.62	768	0.15		
Total	171.86	778	0.22			**Total**	171.86	778	0.22		

Table 61: Pairwise Comparisons of Means over QE Phases

This table reports the comparisons as contrasts (differences) of margins along with significance tests or confidence intervals for the contrasts as output of Tukey's honestly significant difference test. The bid-to-cover ratio is measured as the entire amount of bid during an auction divided by the total amount of new debt allocated; a value of 1.0 means the value of bids equals the value of stock being auctioned. dataset contains 779 auctions from 1987 to 2022. *, **, *** correspond to significance levels of 10%, 5%, and1%, respectively. The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive.

	Pre-crisis	**Crisis**	**QE1**	**Post-QE1**	**QE2 and 3**	**Post-QE3**	**QE4**	**Post-QE4**	**QE5**	**QT-P**
Crisis	-0.11									
QE1	-0.04	0.07								
Post-QE1	-0.12	-0.02	-0.08							
QE2 and 3	-0.22**	-0.11	-0.18	-0.09						
Post-QE3	-0.33***	-0.22**	-0.29***	-0.21**	-0.11					
QE4	0.02	0.13	0.06	0.15	0.24	0.35**				
Post-QE4	0.13	0.23*	0.16	0.25***	0.34***	0.46***	0.10			
QE5	0.45***	0.56***	0.49***	0.57***	0.67***	0.78***	0.43***	0.32***		
QT-P	0.41***	0.52***	0.45***	0.53***	0.63***	0.74***	0.39**	0.28*	-0.04	
QT-A	0.15	0.26	0.19	0.28	0.37	0.48***	0.13	0.03	-0.30	-0.26

Table 62: Summary Statistics from 2009 to 2022 without Outlier Removal

This table contains the summary statistics for the variable bid-to-cover ratio (BC) and volatility across 571 auctions from 2009 to December 2022. The bid-to-cover ratio (BC) measures the extent to which the total amount bid at the auction exceeds the amount offered for sale at the auction; a value of 1.0 means the value of bids equals the value of stock being auctioned. From 1987 to 2000, the volatility (VOL) is measured by unnormalizing the gilt volatility (the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract) by multiplying each normalized observation by the standard deviation of the FTSE100 volatility between 2000 and 2022 and then adding the mean FTSE volatility throughout that time period. From 2000 to 2022, the volatility is measured by the implied volatility of at-the-money FTSE100 index call options, expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. Mean is the sample mean of the variable, SD is the sample standard deviation, Min and Max are the minimum and maximum observations, and p25, p50, and p75 indicate the observation in percentile 25, 50, or 75, respectively. Skewness is a descriptive statistics measure that characterises the asymmetry of a data distribution. Kurtosis determines the heaviness of the distribution tails. P(S) shows the P-value for skewness, and P(K) shows the P-value for kurtosis. The last column shows the means are statistically significantly different from zero if the P-value is less than the significance level.

Variable	**Observation**	**Mean**	**SD**	**Min**	**P25**	**P50**	**P75**	**Max**	**Skewness**	**Kurtosis**	**Pr(S)**	**Pr(K)**	**Ha: mean=0 Pr (|T| > |t|)**
BC	571	2.1	0.42	0.93	1.79	2.11	2.39	3.85	0.21	3.04	0.04	0.73	0.11
VOL	571	0.18	0.07	0.06	0.13	0.16	0.21	0.7	1.89	11.01	0	0	0

Table 63: t-test Comparison of Means of Main Variables

This table presents the results of t-test comparison of means of main variables before and after the use of QE program. The first sample period starts from 1987 to the first phase of QE in 2009, and the second sample period covers 2009 to 2022. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. From 1987 to 2000, the volatility is measured by unnormalizing the gilt volatility (the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract) by multiplying each normalized observation of the gilt volatility by the standard deviation of the FTSE100 volatility between 2000 and 2022 and then adding the mean FTSE volatility throughout that time period. From 2000 to 2022, the volatility is measured by the implied volatility of at-the-money FTSE100 index call options, expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days. MAT is the difference between maturity date and auction date divided by 365.25, expressed in years. LIQ is the size of the outstanding gilt that is being auctioned (including the auctioned amount) divided by the average size outstanding of all other (conventional) gilts, on the auction day; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover of the previous auction, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio).

between Groups	SS	df	MS	F	Prob>F
SIZE	3.7	1	3.7	40.9	0.00
LIQ	20.8	1	20.8	98.7	0.00
ACT	187.7	1	187.7	272.9	0.00
VOL	0.2	1	0.2	25.4	0.00
DEM	3.1	1	3.1	13.3	0.00
TGEMMs	168.3	1	168.3	1474.9	0.00
MAT	546.4	1	546.4	3.9	0.05

Table 64: Summary Statistics of the Main Variables for short-term gilts without outliers

This table contains the summary statistics for eight variables across 253 auctions with short-term maturity from May 1987 to December 2022, using data that excludes observations on dates corresponding to the bid-to-cover ratio outliers. The bid-to-cover ratio (BC) measures the extent to which the total amount bid at the auction exceeds the amount offered for sale at the auction; a value of 1.0 means the value of bids equals the value of stock being auctioned. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. From 1987 to 2000, the volatility is measured by unnormalizing the gilt volatility (the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract) by multiplying each normalized observation of the gilt volatility by the standard deviation of the FTSE100 volatility between 2000 and 2022 and then adding the mean FTSE volatility throughout that time period. From 2000 to 2022, the volatility is measured by the implied volatility of at-the-money FTSE100 index call options, expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days. MAT is the difference between maturity date and auction date divided by 365.25, expressed in years. LIQ is the size of the outstanding gilt that is being auctioned (including the auctioned amount) divided by the average size outstanding of all other (conventional) gilts, on the auction day; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover of the previous auction, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). Mean is the sample mean of the variable, SD is the sample standard deviation, Min and Max are the minimum and maximum observations, and p25, p50, and p75 indicate the observation in percentile 25, 50, or 75, respectively.

Variable	**Observation**	**Mean**	**SD**	**Min**	**P25**	**P50**	**P75**	**Max**
BC	253	2.11	0.45	1.07	1.78	2.11	2.44	3.49
SIZE	253	8.15	0.26	6.62	8.01	8.16	8.31	8.66
LIQ	253	0.89	0.48	0.09	0.5	0.87	1.22	2.42
ACT	253	1.75	0.86	0	1.39	1.61	2.48	3.76
VOL	253	0.19	0.1	0.07	0.13	0.17	0.24	0.68
DEM	253	2.06	0.47	0	1.72	2.09	2.38	3.49
TGEMMs	253	4.85	0.52	3	4.52	4.99	5.24	5.71
MAT	253	4.77	1.12	2.12	4.36	5.1	5.49	6.98

Table 65: Pairwise Comparisons of Means over Maturity Segments

This table reports the comparisons as contrasts (differences) of margins along with significance tests or confidence intervals for the contrasts as output of Tukey's honestly significant difference test. The dataset contains 779 auctions from 1987 to 2022. The bid-to-cover ratio (BC) is measured as the entire Amount of bid during an auction divided by the total amount of new debt allocated; a value of 1.0 means the value of bids equals the value of stock being auctioned. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. From 1987 to 2000, the volatility is measured by unnormalizing the gilt volatility (the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract) by multiplying each normalized observation of the gilt volatility by the standard deviation of the FTSE100 volatility between 2000 and 2022 and then adding the mean FTSE volatility throughout that time period. From 2000 to 2022, the volatility is measured by the implied volatility of at-the-money FTSE100 index call options, expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. BENCH is an indicator that takes the value unity if the issuance is of or into a 5,10 or 20-year benchmark issue. PAOF is an indicator that takes the value unity if the issuance has the Post Auction Option Facility (PAOF). ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days. MAT is the difference between maturity date and auction date divided by 365.25, expressed in years. LIQ is the size of the outstanding gilt that is being auctioned (including the auctioned amount) divided by the average size outstanding of all other (conventional) gilts, on the auction day; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover of the previous auction, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). $QEDUM$ is an indicator that takes value unity during the sub sample corresponding to the periods of asset purchase facility throughout QE. FCI is an indicator that takes value unity if the FCI identifies the episodes of systemic financial distress. The maturity buckets use the standard market convention of Short (< 7 years), Medium (7 to 15 years), and Long (>15 years). *, **, *** correspond to significance levels of 10%, 5%, and1%, respectively.

variable	Maturity	Short	Medium	variable	Maturity	Short	Medium
BC	Medium	0.01		TGEMMs	Medium	-0.08	
	Long	-0.20***	-0.21***		Long	-0.07	0.01
MAT	Medium	5.54***		PAOF	Medium	0.05	
	Long	24.62***	19.08***		Long	0.02	-0.03
SIZE	Medium	-0.15***		LIQ	Medium	-0.03	
	Long	-0.48***	-0.33***		Long	-0.05	-0.02
ACT	Medium	-0.02		DEM	Medium	-0.03	
	Long	0.05	0.07		Long	0.07	0.10**
VOL	Medium	-0.01		FCI	Medium	-0.04	
	Long	-0.01	-0.01		Long	-0.06	-0.02
BENCH	Medium	0.06		QEDUM	Medium	-0.01	
	Long	-0.42***	-0.47***		Long	-0.02	-0.01

Table 66: Correlations for Short-Term Gilts

The table reports the Pearson correlations among the main variables across 253 short-term auctions from 1987 to 2022. The bid-to-cover ratio (BC) is measured as the entire Amount of bid during an auction divided by the total amount of new debt allocated; a value of 1.0 means the value of bids equals the value of stock being auctioned. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. From 1987 to 2000, the volatility is measured by unnormalizing the gilt volatility (the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract) by multiplying each normalized observation of the gilt volatility by the standard deviation of the FTSE100 volatility between 2000 and 2022 and then adding the mean FTSE volatility throughout that time period. From 2000 to 2022, the volatility is measured by the implied volatility of at-the-money FTSE100 index call options, expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. BENCH is an indicator that takes the value unity if the issuance is of or into a 5,10 or 20-year benchmark issue. PAOF is an indicator that takes the value unity if the issuance has the Post Auction Option Facility (PAOF). ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days. MAT is the difference between maturity date and auction date divided by 365.25, expressed in years. LIQ is the size of the outstanding gilt that is being auctioned (including the auctioned amount) divided by the average size outstanding of all other (conventional) gilts, on the auction day; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover of the previous auction, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). $QEDUM$ is an indicator that takes value unity during the sub sample corresponding to the periods of asset purchase facility throughout QE. FCI is an indicator that takes value unity if the FCI identifies the episodes of systemic financial distress. *, **, *** correspond to significance levels of 10%, 5%, and1%, respectively.

	BC	MAT	SIZE	ACT	VOL	BENCH	TGEMMs	PAOF	LIQ	DEM	FCI	QEDUM
BC	1											
MAT	-0.23***	1										
SIZE	-0.30***	-0.16***	1									
ACT	-0.12*	0.22***	-0.32***	1								
VOL	0.06	-0.20***	0.11*	-0.29***	1							
BENCH	-0.10	0.23***	-0.05	0.17***	-0.09	1						
TGEMMs	0.12*	-0.06	0.35***	-0.49***	-0.12*	-0.13**	1					
PAOF	0.06	0.01	0.44***	-0.18***	-0.17***	-0.07	0.34***	1				
LIQ	0.08	-0.15**	0.00	0.00	0.20***	0.16***	-0.30***	-0.05	1			
DEM	0.44***	-0.15***	0.01	-0.30***	-0.04	-0.11*	0.45***	0.13**	-0.08	1		
FCI	-0.11*	0.02	0.12*	-0.19***	0.43***	-0.04	0.10	-0.06	-0.02	-0.01	1	
QEDUM	0.28***	-0.07	0.23***	-0.46***	0.13**	-0.12*	0.41***	0.21***	-0.03	0.37***	0.09	1

Table 67: Correlations for Medium-Term Gilts

The table reports the Pearson correlations among the main variables across 243 medium-term auctions from 1987 to 2022. The bid-to-cover ratio (BC) is measured as the entire Amount of bid during an auction divided by the total amount of new debt allocated; a value of 1.0 means the value of bids equals the value of stock being auctioned. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. From 1987 to 2000, the volatility is measured by unnormalizing the gilt volatility (the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract) by multiplying each normalized observation of the gilt volatility by the standard deviation of the FTSE100 volatility between 2000 and 2022 and then adding the mean FTSE volatility throughout that time period. From 2000 to 2022, the volatility is measured by the implied volatility of at-the-money FTSE100 index call options, expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. BENCH is an indicator that takes the value unity if the issuance is of or into a 5,10 or 20-year benchmark issue. PAOF is an indicator that takes the value unity if the issuance has the Post Auction Option Facility (PAOF). ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days. MAT is the difference between maturity date and auction date divided by 365.25, expressed in years. LIQ is the size of the outstanding gilt that is being auctioned (including the auctioned amount) divided by the average size outstanding of all other (conventional) gilts, on the auction day; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover of the previous auction, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). $QEDUM$ is an indicator that takes value unity during the sub sample corresponding to the periods of asset purchase facility throughout QE. FCI is an indicator that takes value unity if the FCI identifies the episodes of systemic financial distress. *, **, *** correspond to significance levels of 10%, 5%, and1%, respectively.

	BC	MAT	SIZE	ACT	VOL	BENCH	TGEMMs	PAOF	LIQ	DEM	FCI	QEDUM
BC	1											
MAT	-0.08	1										
SIZE	-0.10	-0.19***	1									
ACT	-0.31***	0.12*	-0.38***	1								
VOL	-0.11	-0.05	0.05	-0.12*	1							
BENCH	-0.02	-0.15**	0.11*	-0.02	-0.08	1						
TGEMMs	0.33***	-0.21***	0.37***	-0.66***	-0.09	0.08	1					
PAOF	0.15*	-0.17***	0.47***	-0.36***	-0.17***	0.08	0.49***	1				
LIQ	0.08	0.00	-0.30***	0.22***	0.14**	-0.15**	-0.45***	-0.15**	1			
DEM	0.48***	-0.03	-0.06	-0.31***	0.05	-0.11*	0.27***	0.14**	0.03	1		
FCI	-0.12*	-0.03	0.10	-0.14**	0.38***	0.05	0.16**	0.06	0.05	-0.02	1	
QEDUM	0.36***	-0.03	0.24***	-0.48***	0.13*	-0.10	0.43***	0.25***	0.00	0.34***	0.11	1

Table 68: Correlations for Long-Term Gilts

The table reports the Pearson correlations among the main variables across 278 long-term auctions from 1987 to 2022. The bid-to-cover ratio (BC) is measured as the entire Amount of bid during an auction divided by the total amount of new debt allocated; a value of 1.0 means the value of bids equals the value of stock being auctioned. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. From 1987 to 2000, the volatility is measured by unnormalizing the gilt volatility (the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract) by multiplying each normalized observation of the gilt volatility by the standard deviation of the FTSE100 volatility between 2000 and 2022 and then adding the mean FTSE volatility throughout that time period. From 2000 to 2022, the volatility is measured by the implied volatility of at-the-money FTSE100 index call options, expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. BENCH is an indicator that takes the value unity if the issuance is of or into a 5,10 or 20-year benchmark issue. PAOF is an indicator that takes the value unity if the issuance has the Post Auction Option Facility (PAOF). ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days. MAT is the difference between maturity date and auction date divided by 365.25, expressed in years. LIQ is the size of the outstanding gilt that is being auctioned (including the auctioned amount) divided by the average size outstanding of all other (conventional) gilts, on the auction day; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover of the previous auction, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). $QEDUM$ is an indicator that takes value unity during the sub sample corresponding to the periods of asset purchase facility throughout QE. FCI is an indicator that takes value unity if the FCI identifies the episodes of systemic financial distress. *, **, *** correspond to significance levels of 10%, 5%, and1%, respectively.

	BC	MAT	SIZE	ACT	VOL	BENCH	TGEMMs	PAOF	LIQ	DEM	FCI	QEDUM
BC	1											
MAT	-0.03	1										
SIZE	-0.11*	-0.30***	1									
ACT	-0.26***	-0.05	0.20***	1								
VOL	0.05	-0.03	-0.05	-0.24***	1							
BENCH	-0.02	-0.25***	0.07	0.13**	-0.11*	1						
TGEMMs	0.41***	0.12**	-0.15**	-0.61***	-0.02	-0.19***	1					
PAOF	0.30***	0.03	0.05	-0.28***	-0.03	-0.09	0.52***	1				
LIQ	-0.09	-0.21***	-0.06	0.26***	-0.05	0.20***	-0.49***	-0.26***	1			
DEM	0.47***	-0.03	-0.06	-0.21***	0.08	-0.15**	0.10	-0.03	0.06	1		
FCI	0.07	-0.05	-0.02	-0.25***	0.37***	-0.02	0.23***	0.10*	-0.10*	-0.05	1	
QEDUM	0.41***	0.10	-0.24***	-0.43***	0.19***	-0.06	0.47***	0.23***	-0.20***	0.29***	0.15**	1

4.11.3. Baseline Results with Maturity Based Explanatory Variables

As an additional robustness check, we examine whether the outcomes of our model for baseline regression and under the impact of QE change if we redefine two explanatory variables in the baseline estimation and three in the QE impact estimation based on maturity. The variable *ACT* is changed to the natural log of the number of days since the last issuance of a gilt within the same maturity segment instead of any gilts. Moreover, *LIQ* is re-calculated by dividing the outstanding gilt's size (including the amount up for auction) by the average outstanding gilt's size of other gilts (conventional) in the same maturity segment. *APF* is the natural logarithm of the number of (working) days since the BOE last purchased a gilt in the same maturity segment through an APF operation.

The summary statistics of variables which are redefined based on maturity are shown in Table 69. Applying the t-test comparison of means for the redefined variables (Table 70, Table 71, Table 72), we find that the differences of means of the variables *ACT* and *APF* between maturity base and non-maturity base are significantly different from zero. However, the difference of means of variable *LIQ* is not statistically different from zero. Furthermore, the correlations between the variables are reported in Table 73.

It is interesting to note that the results presented in Table 74 align with the baseline findings from Section 5 (Empirical Results). This study demonstrates that it is not necessary to use maturity-segmented variables. The findings demonstrate that the estimation's output is unaffected by assessing demand, frequency of issuance, and liquidity according to maturity segments.

Table 69: Summary statistics of the variables based on maturity segmentation

This table contains the summary statistics for three variables constructed based on the maturity segmentation. The variable ACT is the natural log of the number of days since the last public issuance in a gilt in the same maturity segment, measured in days. LIQ is measured as the size of the outstanding gilt that is being auctioned (including the auctioned amount) divided by the average size outstanding of other (conventional) gilts in the same maturity segment; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). APF is the natural logarithm of the number of (working) days since the BOE last purchased a gilt in the same maturity segment through an APF operation, measured in days. Mean is the sample mean of the variable, SD is the sample standard deviation, Min and Max are the minimum and maximum observations, and p25, p50, and p75 indicate the observation in percentile 25, 50, or 75, respectively. Skewness essentially is a commonly used measure in descriptive statistics that characterizes the asymmetry of a data distribution, while kurtosis determines the heaviness of the distribution tails. Skewness is a descriptive statistics measure that characterises the asymmetry of a data distribution. Kurtosis determines the heaviness of the distribution tails. P(S) shows the P-value for skewness, and P(K) shows the P-value for kurtosis. The last column shows the means are statistically significantly different from zero.

Variable	**Observation**	**Mean**	**SD**	**Min**	**P25**	**P50**	**P75**	**Max**	**Skewness**	**Kurtosis**	**Pr(S)**	**Pr(K)**	**Ha: mean=0 Pr (|T| > |t|)**
LIQ	774	0.83	0.46	0.08	0.51	0.8	1.1	2.9	0.90	4.59	0	0	0
ACT	774	1.24	0.41	0	1	1.3	1.49	2.83	-0.14	3.87	0.10	0	0
APF	566	1.09	0.83	0	0.48	0.85	1.88	2.63	0.15	1.62	0.11	0	0

Table 70: t-test Comparison of Means of Issuance Activity

This table presents the results of a t-test comparing the means of issuance activity for two definitions: maturity and non-maturity. The variable ACTMAT is the natural log of the number of days since the last public issuance in a gilt in the same maturity segment, measured in days. ACT is the natural log of the number of days since the last conventional gilt issuance, measured in days.

Group	Observation	Mean	Std. errs.	Std. dev.	[95% conf.	interval]
ACT	774	1.77	0.03	0.96	1.71	1.84
ACTMAT	774	1.24	0.01	0.41	1.22	1.27
Combined	1,548	1.51	0.02	0.78	1.47	1.55
diff		0.53	0.04		0.46	0.60
Diff = mean (Primary) - mean (Secondary)					T = 14.09	
H0: Diff = 0					Degree of freedom = 1546	

Table 71: t-test Comparison of Means of Liquidity

This table presents the results of a t-test comparing the means of liquidity for two definitions: maturity and non-maturity. LIQMAT is measured as the size of the outstanding gilt that is being auctioned (including the auctioned amount) divided by the average size outstanding of other (conventional) gilts in the same maturity segment. LIQ is the size of the outstanding gilt that is being auctioned (including the auctioned amount) divided by the average size outstanding of all other (conventional) gilts, on the auction day; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio).

Group	Observation	Mean	Std. errs.	Std. dev.	[95% conf.	interval]
LIQ	774	0.868	0.017	0.481	0.834	0.902
LIQMAT	774	0.834	0.016	0.458	0.802	0.866
Combined	1,548	0.851	0.012	0.470	0.827	0.874
diff		0.034	0.024		-0.013	0.080
Diff = mean (Primary) - mean (Secondary)					T = 1.4	
H0: Diff = 0					Degree of freedom = 1546	

Table 72: t-test Comparison of Means of Purchase Activity

This table presents the results of a t-test comparing the means of purchase activity for two definitions: maturity and non-maturity. APFMAT is the natural logarithm of the number of (working) days since the BOE last purchased a gilt in the same maturity segment through an APF operation. APF is the natural logarithm of the number of (working) days since the BOE last purchased through an APF operation. Both are measured in days.

Group	Observation	Mean	Std. errs.	Std. dev.	[95% conf.	interval]
APF	570	0.909	0.039	0.935	0.832	0.986
APFMAT	566	1.088	0.035	0.828	1.020	1.156
Combined	1,136	0.998	0.026	0.888	0.946	1.050
diff		-0.179	0.052		-0.282	-0.076
Diff = mean (Primary) - mean (Secondary)					T = -3.42	
H0: Diff = 0					Degree of freedom = 1134	

Table 73: Correlation with maturity-based variables

The table reports the Pearson correlations among maturity-based variables and other variables from 1987 to 2022. The bid-to-cover ratio is measured as the entire amount of bid during an auction divided by the total amount of new debt allocated; a value of 1.0 means the value of bids equals the value of stock being auctioned. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. From 1987 to 2000, the volatility is measured by unnormalizing the gilt volatility (the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract) by multiplying each normalized observation of the gilt volatility by the standard deviation of the FTSE100 volatility between 2000 and 2022 and then adding the mean FTSE volatility throughout that time period. From 2000 to 2022, the volatility is measured by the implied volatility of at-the-money FTSE100 index call options, expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. The variable ACT is the natural log of the number of days since the last public issuance in a gilt in the same maturity segment, measured in days. LIQ is measured as the size of the outstanding gilt that is being auctioned (including the auctioned amount) divided by the average size outstanding of other (conventional) gilts in the same maturity segment; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover of the previous auction in the same maturity segment, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). BENCH is an indicator that takes the value unity if the issuance is of or into a 5,10 or 20-year benchmark issue. PAOF is an indicator that takes the value unity if the issuance has the Post Auction Option Facility (PAOF). MAT is the difference between maturity date and auction date divided by 365.25, expressed in years. $QEDUM$ is an indicator that takes value unity during the sub sample corresponding to the periods of asset purchase facility throughout QE. FCI is an indicator that takes value unity if the FCI identifies the episodes of systemic financial distress. *, **, *** correspond to significance levels of 10%, 5%, and 1%, respectively.

	BC	VOL	BENCH	SIZE	TGEMMs	PAOF	MAT	LIQ	ACT	DEM	QEDUM	FCI
BC	1											
VOL	0.01	1										
BENCH	0.05	-0.06*	1									
SIZE	-0.01	0.08**	0.30***	1								
TGEMMs	0.29***	-0.07**	-0.03	0.17***	1							
PAOF	0.17***	-0.13***	-0.01	0.23***	0.45***	1						
MAT	-0.19***	-0.07*	-0.42***	-0.67***	-0.02	0.00	1					
LIQ	0.06	0.13***	0.05	-0.09**	-0.36***	-0.11***	-0.10***	1				
ACT	-0.28***	-0.26***	0.17***	-0.09**	-0.63***	-0.29***	-0.06*	0.07*	1			
DEM	0.44***	0.03	-0.13***	-0.09***	0.24***	0.06*	0.05	-0.05	-0.32***	1		
QEDUM	0.34***	0.15***	-0.08**	0.07*	0.44***	0.23***	0.00	-0.05	-0.60***	0.33***	1	
FCI	-0.05	0.40***	0.01	0.09***	0.17***	0.03	-0.06*	0.00	-0.17***	-0.04	0.11***	1

Table 74: Baseline and QE Period Results with Maturity Based Explanatory Variables

This table has the estimated coefficients of equation (6) being used to identify the determinants of the bid-to-cover ratio with some variable re-defined based on maturity. The second column presents re-estimated coefficients of equation (7) with three variables defined based on maturity. The bid-to-cover ratio is measured as the entire amount of bid during an auction divided by the total amount of new debt allocated; a value of 1.0 means the value of bids equals the value of stock being auctioned. SIZE is the natural log of auction size, measured in £ million. TGEMMs is the natural log of the weekly aggregate turnover of Gilt-Edged Market Makers, measured in £ billion. From 1987 to 2000, the volatility is measured by unnormalizing the gilt volatility (the at-the-money implied volatility of the nearest maturity call option on the nearest maturity long gilt futures contract) by multiplying each normalized observation of the gilt volatility by the standard deviation of the FTSE100 volatility between 2000 and 2022 and then adding the mean FTSE volatility throughout that time period. From 2000 to 2022, the volatility is measured by the implied volatility of at-the-money FTSE100 index call options, expressed as an annualized standard deviation of returns, where a value of 0.1 corresponds to an annualized return volatility of 10%. The variable ACT is the natural log of the number of days since the last public issuance in a gilt in the same maturity segment, measured in days. LIQ is measured as the size of the outstanding gilt that is being auctioned (including the auctioned amount) divided by the average size outstanding of other (conventional) gilts in the same maturity segment; a value above 1.0 indicates that the gilt is larger than the average and likely more liquid (liquidity ratio). DEM is the bid-to-cover of the previous auction in the same maturity segment, where a value of 1.0 means bids equalled the amount offered, and 2.0 means bids were double the offer (demand ratio). BENCH is an indicator that takes the value unity if the issuance is of or into a 5,10 or 20-year benchmark issue. PAOF is an indicator that takes the value unity if the issuance has the Post Auction Option Facility (PAOF). MAT is the difference between maturity date and auction date divided by 365.25, expressed in years. FCI is an indicator that takes value unity if the FCI identifies the episodes of systemic financial distress. BOE is the share of the gilt owned by the Bank of England, purchased under the Asset Purchase Scheme, at the point of the auction, expressed as a percentage. APF is the natural log of the number of (working) days since a previous APF purchase of a gilt in the same maturity segment by the BOE, measured in days. NGEMMs is the number of Gilt-Edged Market Makers on the auction day, measured as a count. We applied clustered standard errors, and the clusters are defined by the gilt issuance's frequency. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels.

	Baseline	QE
APF		-0.04**
		(-2.23)
BOE		-0.14**
		(-2.2)
SIZE	-0.43***	-0.48***
	(-7.09)	(-5.46)
TGEMMs	0.13***	0.33***
	(4.51)	(5.27)
VOL	0.13	-0.18
	(0.77)	(-0.97)
BENCH	0.04	0.04
	(1.48)	(1.12)
PAOF	0.10***	0.18***
	(6.38)	(6.35)
ACT	-0.01	-0.11
	(-0.24)	(-1.63)
MAT	-0.01***	-0.01***
	(-8.27)	(-6.17)
LIQ	0.09	0.05
	(1.69)	(1.51)
DEM	0.30***	0.29***
	(6.66)	(10.12)
QEDUM	0.15***	
	(5.48)	
NGEMMs		-0.08***
		(-8.52)
FCI	-0.10***	-0.02
	(-4.05)	(-0.66)
Constant	4.26***	5.33***
	(6.78)	(5.88)
No. Observations	774	566
R-squared	0.36	0.55

5. The Effects of QE and QT on the Integration of UK Capital Markets

5.1. Introduction

Monetary policy interventions, particularly quantitative easing (QE) and quantitative tightening (QT), play a critical role in shaping financial markets. The interplay between these policies and market volatility is a cornerstone of understanding their broader economic impacts. While previous studies have focused on the effects of QE on asset returns and market correlations, their implications for volatility remain less explored, especially when considering distinct phases of monetary policy and different measures of volatility.

In previous chapters, we examined the relationship between QE and market volatility using various definitions, including volatility in bond and stock markets. These analyses revealed differences in the volatility dynamics across asset classes, emphasizing the importance of measurement choice in understanding the transmission of monetary policy effects. This chapter extends this inquiry by directly analyzing the impact of QE and QT on market volatility through a univariate and multivariate GARCH framework.

Our study builds on existing literature, particularly close to the paper by Steeley (2015) and its extensions, which investigated the effects of QE on UK market volatility and correlations. However, our research goes further by incorporating additional phases of QE and explicitly distinguishing between active and passive phases of QT. This allows us to examine the differential impacts of these monetary policy interventions on short-term bonds (FTSG), long-term bonds (FTLG), and equities (FTSE) with greater granularity.

By employing a detailed GARCH modelling approach, we aim to provide a deeper understanding of the stabilizing or disruptive roles of QE and QT in financial markets. Through this analysis, we explore not only the persistence and dynamics of volatility but also the broader implications of these unconventional monetary policies for financial stability and market behaviour. This chapter contributes to the literature by offering new insights into the time-varying impacts of QE and QT, highlighting their significance in shaping the evolution of market volatility.

The chapter is structured as follows: the next section discusses the data and methodology used in our analysis, followed by the modelling framework. The results are then presented, highlighting the key findings of the study. Finally, the chapter concludes with a summary of the implications of our results for monetary policy and financial markets.

5.2. Data

The data and methods used to create the dependent and independent variables are described in this section. Data is obtained for the period January, 4 2000 – June, 30 2024, providing some 6190 trading day observations for each series from the UK Debt Management Office (DMO) website, DataStream, and the Bank of England.

5.2.1. Financial Markets' Return

The daily closing data for the FTSE-100 share price index (FT100) represents stock returns, the price index of long-term government stocks (FTLG) represents bond returns with maturity over 15 years, the price index of short-term government stocks (FTSG) represents yields under 5 years. Log differences in the corresponding price index are used to compute return series.[29]

Summary statistics for the returns of the FTSE 100 share index (FTSE), the FTA Government Stocks (<5 years, FTSG), and the FTA Government Stocks (>15 years, FTLG) for the sample period are shown in Table 75 and the series are plotted in Figure 43.

The average daily returns in each market are shown by the mean numbers. The average for the long-term gilt market (FTLG) was -0.00215 percent. These negative averages show a pattern of declining performance over time, especially as a result of recent changes in the economy and in policy as will be explained below. Prior to 2019, the long-term gilt market (FTLG) showed positive average returns, as seen in Figure 44. The 2020 COVID-19 pandemic caused a precipitous drop in FTSE equities market returns. This decline reflects a flight to safety, as investors reallocated capital away from riskier equities into safer assets such as bonds, often perceived as a safe haven during periods of heightened uncertainty. Furthermore, central banks' asset purchase raised demand for bonds and helped to boost bond market returns throughout that time frame.

However, the debt market saw a sharp drop in returns in 2022, which is consistent with the reversal of monetary policies intended to control inflation. Bond demand declined and prices fell as a result of central banks starting quantitative tightening (QT) and ceasing to reinvest the proceeds from maturing bonds bought under previous QE programs. The bond market's dynamics were greatly affected by these policy changes, particularly for long-term gilts (FTLG), underscoring how susceptible these markets are to adjustments in central bank policies and general economic conditions.

An average return of -0.00529 percent was achieved by the short-term gilt market (FTSG). The distortions associated with index changes are primarily responsible for the short-term gilt market's negative average return. When these skewed observations are removed from the analysis, the average return is positive at 0.00654 percent and the kurtosis is lower (8.93 against 34.36 in the original data). This modification emphasises how important it is to take structural shifts in the index composition into consideration when analysing the short-term gilt market's performance.

[29] The data are obtained from Datastream, codes FTSE100, FTBGSHT, FTBGLNG.

The variance in daily returns is emphasised by the standard deviation (SD). In contrast to bond markets, the FTSE had the highest volatility (1.15 percent), highlighting its riskier character. The long-term gilts (FTLG) showed a higher price variability (SD of 0.84 percent) among the bond indices than the short-term gilts (FTSG), which had a significantly lower SD of 0.16 percent. This difference is consistent with long-term bonds' higher duration risk and interest rate sensitivity.

With low coefficients that vary in sign, the autocorrelation analysis for returns shows no indication of persistence in the short-term gilt series (FTSG). However, there is observable autocorrelation at smaller lags for the FTSE and the long-term gilt series (FTLG), particularly within the first five periods. These autocorrelation coefficients are quite tiny, yet being statistically significant. With consistently positive and sizable autocorrelation coefficients over several lags, autocorrelation of squared returns shows notable variance clustering in both the equities and long-term gilt markets. Interactions between the returns of several markets are indicated by cross-serial correlations. According to the updated data, there is a positive and comparatively large temporal correlation (0.580) between historical returns in the short-term gilt market (FTSG) and the long-term gilt market (FTLG). This shows how closely these two bond segments are related, possibly as a result of similar economic conditions or the impact of monetary policy.

Table 75: Summary statistics of returns

Returns are calculated from daily observations on the FTA Government Stocks (<5 years) index (FTSG), the FTA Government Stocks (>15 years) index (FTLG) and the FTSE 100 share index (FTSE), between January 4th, 2000 and June 30th, 2024. Returns are daily returns, so that e.g., the daily return on the FTSE (of 0.00265) corresponds to an annualized return of 252 * 0.00265 = 0.67% pa. Mean, Std. Dev., Skew., and Kurt., are the sample mean $\times 10^2$, standard deviation $\times 10^2$, skewness and kurtosis of the return's series. Min., Max., and Med., are the two extreme and central values of the return's distribution, and Q1 and Q3 are the lower and upper quartile values. The cross autocorrelation at lag τ is the correlation coefficient between the returns of the first named series in period t with the return on the second named series in period t-τ.

	Observation	Mean	SD	Min	P25	P50	P75	Max	Skewness	Kurtosis
FTSG	6190	-0.529	0.16	-2.03	-0.05	0.01	0.07	0.78	-3.77	34.36
FTLG	6190	-0.215	0.84	-6.92	-0.43	0.01	0.44	15.43	1.11	28.38
FTSE	6190	0.265	1.15	-11.51	-0.51	0.04	0.57	9.38	-0.34	11.07
	Summary statistics of short-term index without index change distortions									
	Observation	Mean	SD	Min	P25	P50	P75	Max	Skewness	Kurtosis
FTSG	6105	0.654	0.12	-1.08	-0.05	0.01	0.07	0.78	-0.31	8.93
	Autocorrelations of returns at lag									
	1	2	3	4	5	6	7	8	9	10
FTSG	0.032	-0.018	-0.021	0.002	-0.016	-0.028	0.015	-0.010	0.024	0.017
FTLG	0.029	-0.030	-0.045	-0.002	-0.015	-0.023	-0.022	-0.054	0.026	0.023
FTSE	-0.037	-0.036	-0.049	0.040	-0.026	-0.045	0.035	0.014	0.000	-0.012
	Autocorrelations of squared returns at lag									
	1	2	3	4	5	6	7	8	9	10
FTSG	0.012	0.000	-0.002	-0.006	0.002	-0.001	0.004	-0.004	0.001	0.006
FTLG	0.220	0.240	0.105	0.078	0.103	0.065	0.058	0.120	0.049	0.063
FTSE	0.215	0.245	0.339	0.261	0.269	0.205	0.198	0.247	0.232	0.229
			Cross serial correlations of returns at lag							
			-1			0			1	
FTSG	FTLG		-0.0195			0.580			0.014	
FTSG	FTSE		0.003			-0.158			0.023	
FTLG	FTSE		-0.007			-0.239			0.026	

Figure 43: Returns (daily log price difference)

This figure presents the daily log returns for three indices—FTSG, FTLG, and FTSE—over their respective sample periods. Returns are calculated as the difference in the natural logarithm of daily closing prices. The y-axis shows the return measured by percentage. This format captures both the direction and magnitude of daily price movements, facilitating comparison across assets.

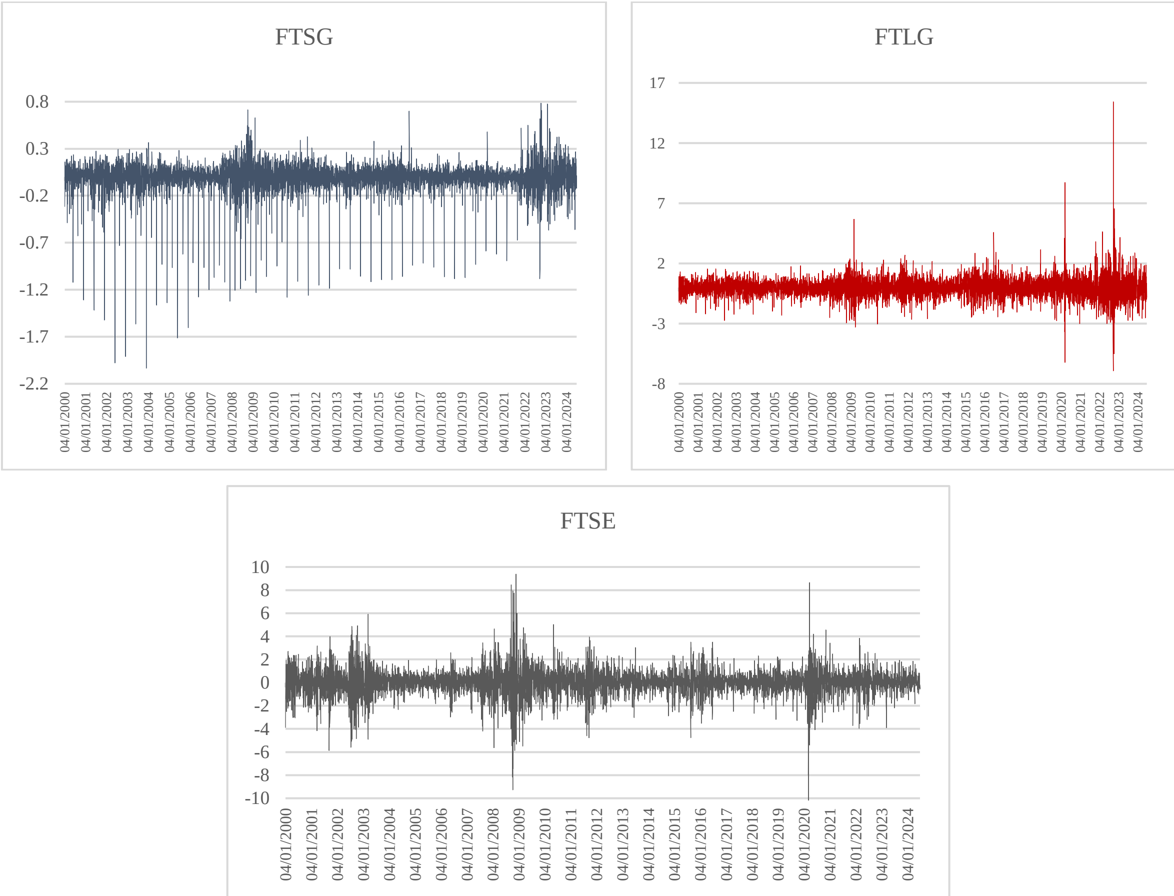
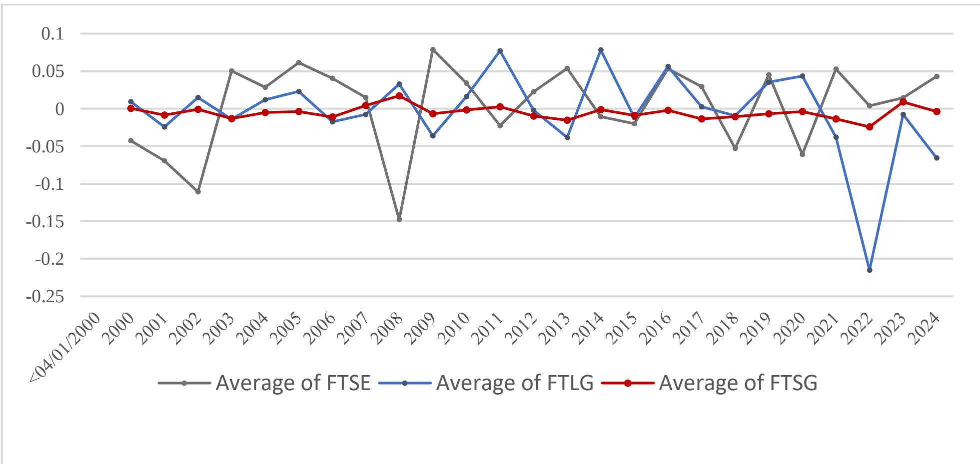


Figure 44: Annual Average of percentage daily returns ($x10^2$)

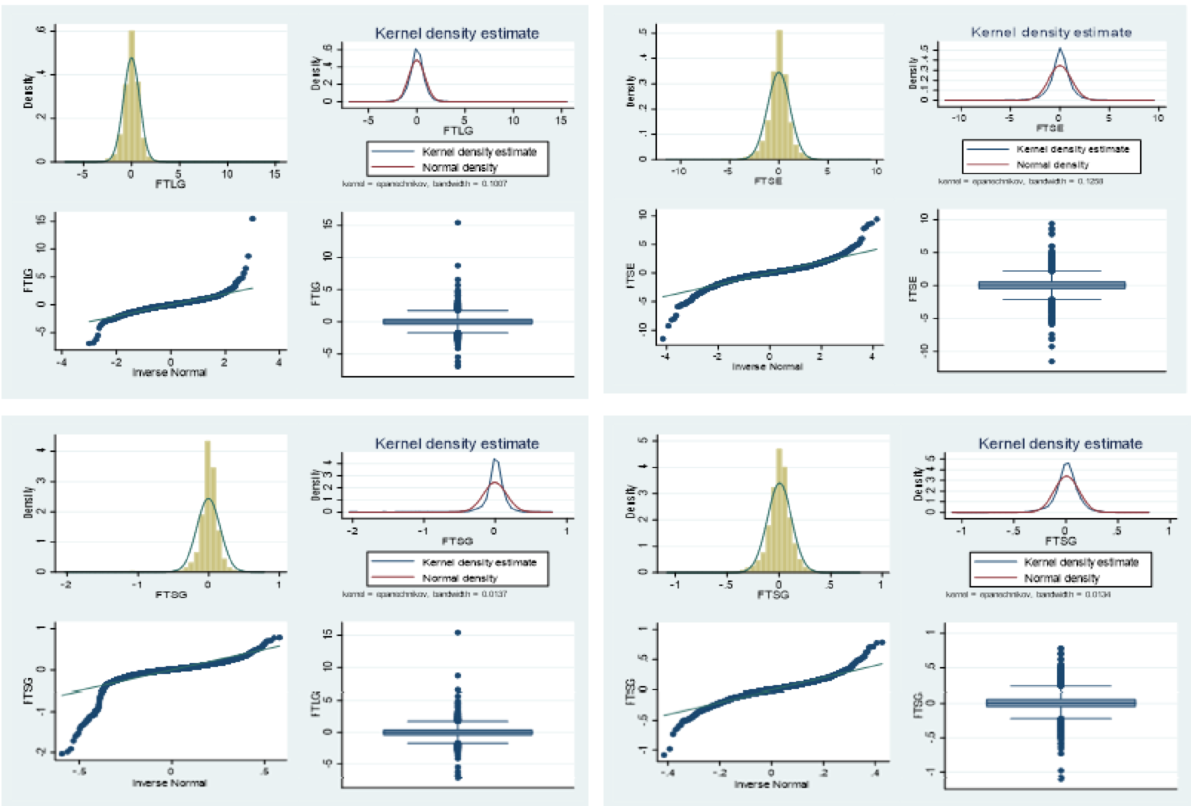
This figure illustrates the annual average of daily returns for FTSE, FTLG, and FTSG from 2000 to 2024. The returns are expressed as percentages and scaled by 100 (i.e., multiplied by 10^2) to improve visual clarity. The y-axis reflects the average percentage daily return for each year, allowing comparison across the three indices.



All three markets' return distributions—equities (FTSE), long-term gilts (FTLG), and short-term gilts (FTSG)—show notable deviations from normality. The return distribution for FTSG shows severe kurtosis, with heavy tails and a clustering of returns close to the mean. In line with its excess kurtosis (28.38) and positive skewness, the kernel density map of the FTLG market shows a strong peak and heavy tails, indicating significant positive outliers. The FTSE's return distribution shows larger tails and a higher peak than the normal distribution, indicating variance clustering and possible market volatility, even if it has lower kurtosis than the bond markets. These conclusions are supported by the Q-Q plots and kernel density estimates for each of the three markets. The normality of FTSG returns is greatly enhanced by eliminating index change's distortions.[30] When distortions are present, the market shows heavy tails and strong kurtosis (34.36), but when they are absent, the distribution becomes more symmetrical and the kurtosis drops to 8.93 (comparing the figures in the second row). However, even without distortions, the returns still deviate from normality, retaining some heavy tails and variance clustering.

Figure 45: Normality tests

This figure presents normality assessments for the return distributions of FTLG, FTSE, and FTSG. The second row focuses on FTSG returns, with the left-hand side including all data and the right-hand side excluding index change distortions. For each variable, the subplots include a histogram with a kernel density overlay (top left of each panel), a kernel density estimate with a normal distribution overlay (top right), a quantile–quantile (Q–Q) plot (bottom left), and a box plot (bottom right). The histograms and kernel density estimates show the distribution of each variable, allowing visual comparison with a theoretical normal distribution. The Q–Q plots compare the empirical quantiles of each variable against the quantiles of a standard normal distribution to evaluate normality; systematic deviations from the 45-degree line suggest skewness or kurtosis. The x-axis in the histogram represents daily returns, calculated from the respective index, while the y-axis in the histogram shows relative density (probability). The Q–Q plot compares the empirical distribution of returns to a theoretical normal distribution (in the original units), and the box plot shows the dispersion and presence of outliers in each return series. Returns are calculated from daily observations on the FTSE 100 share index (FTSE), the FTA Government Stocks (>15 years) index (FTLG), the FTA Government Stocks (<5 years) index (FTSG), and the FTSE All-Share Index (FTGS) between January 4th, 2000, and June 30th, 2024. These plots are used to visually assess the degree of normality and the presence of skewness or outliers in the distribution of daily returns.



[30] Bonds may leave the short-term index on March 7, June 7, September 7, and December 7, as each of these four dates is when the majority of UK bonds mature. Additionally, medium-term bonds whose maturity falls below five years are added to the short-term index. There are obvious irregularities in the bond index data as a result of these changes to the index components, which are made seven working days before the bond maturity dates.

5.2.1.1. Outlier detection and treatment

Excessive kurtosis and volatility clustering are common features of high-frequency financial time series. The GARCH model, which was first presented by Engle (1982) and Bollerslev (1986), is frequently used to model similar characteristics. Studies like Terasvirta (1996) and Baillie and Bollerslev (1989) have observed that GARCH model residuals often retain excess kurtosis, indicating the existence of outliers in financial data that the model is unable to sufficiently capture. The accuracy of the time series is called into question by these unusual findings. Outliers can pose serious estimation problems, as shown by studies such as Chang et al. (1988), Chen and Liu (1993), Franses and Van Dijk (2000), and Tsay et al. (2000). When such outliers are present in a time series, they can contribute serious errors in estimating and forecasting and cause significant distortions in parameter estimates.

The methodology to identify and treat the outliers in the data used in this chapteris exactly the same as outlined in research by Franses and Ghijsels (1999), and it has been implemented in R, with the corresponding code provided in the appendix. This approach ensures consistency in addressing data irregularities while maintaining the integrity of financial time series for analysis.

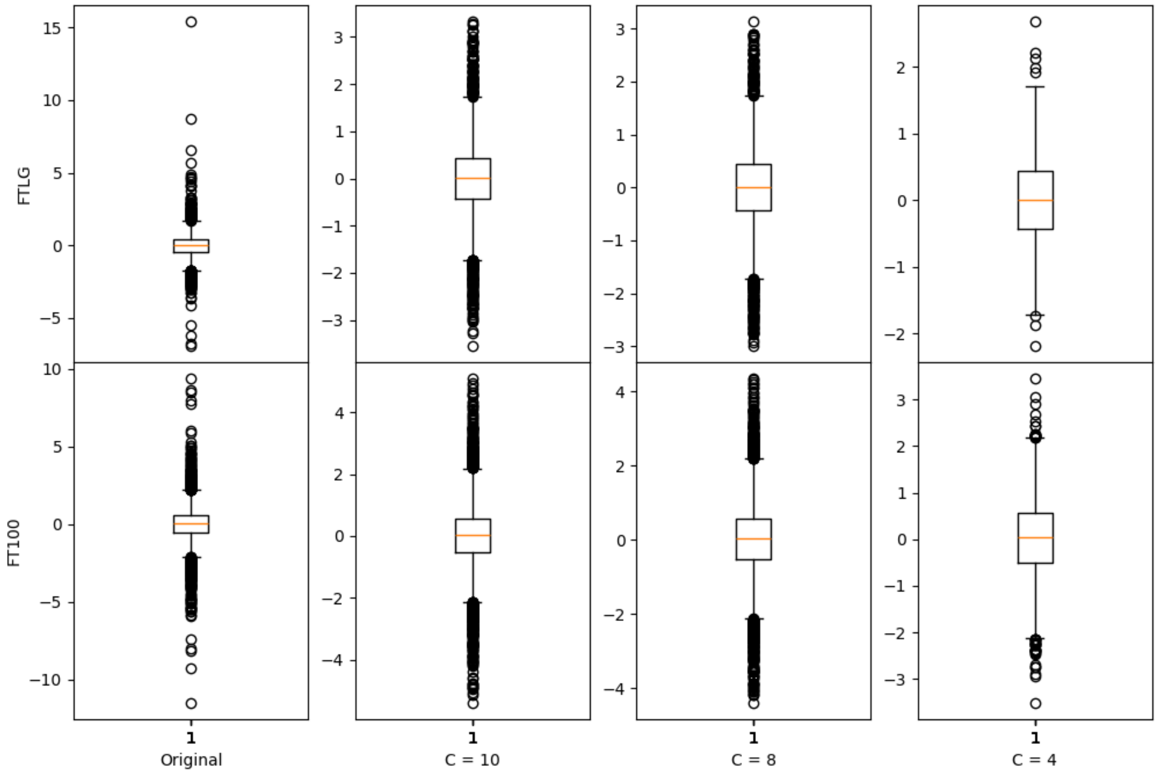
Outlier Detection and Correction Algorithm:

- The **AO detection** method computes standardized residuals from an initial GARCH model.
- Residuals exceeding a critical threshold (Tau statistic) are flagged as potential outliers.
- Corrected values are then re-estimated iteratively until no further outliers remain.

We tried several critical values for outlier detection and settled on **C = 10**. The process of adjusting the threshold is shown in the following figure, which compares the impact of different thresholds. As the critical value C increases, fewer outliers are corrected, and the variance of the data becomes more consistent. After testing different values, **C = 10** provided the most stable model fit while avoiding over-correction. The original data had several extreme outliers, which were successfully moderated with this threshold. For the FTSG market, no outliers were detected when observations corresponding to days where the index change dummy variable equals one were excluded. As a result, no additional treatment or correction of data was necessary for this market. This indicates that the previously identified anomalies were primarily driven by the structural adjustments related to index changes, and once these were accounted for, the dataset exhibited no further irregularities.

Figure 46: Comparison of critical values in outlier detection

This figure displays box plots for the return series of FTLG and FTSE, illustrating the effect of different critical values (C) used for outlier detection. The unit of the data is percentage return, measured as the daily log difference in price. The first column presents the original data, while the subsequent panels show the distributions after applying thresholds of C = 10, C = 8, and C = 4, respectively.



The summary statistics for long-term gilt index and stock market after treating the outliers are shown in table 76. Following the treatment of additive outliers, the FTLG market's kurtosis (from 28.38 to 4.619) and standard deviation (from 0.84 to 0.76) significantly decreased, suggesting a more stable and less heavy-tailed distribution. As a result of eliminating positive outliers that had previously hidden underlying negative performance, the mean return dropped from -0.215 to -0.737. The effect was less noticeable but still noticeable for the FTSE market, where the mean moved marginally from 0.265 to 0.671 and the kurtosis and standard deviation dropped from 11.07 to 5.598 and 1.15 to 1.08, respectively. The dependability of the summary statistics is increased by these modifications, which demonstrate how well outlier treatment works in both markets.

Table 76: Summary statistics after outlier treatment

Returns are calculated from daily observations on the FTA Government Stocks (<5 years) index (FTSG), the FTA Government Stocks (>15 years) index (FTLG) and the FTSE 100 share index (FTSE), between January 4th, 2000 and June 30th, 2024. Mean, Std. Dev., Skew., and Kurt., are the sample mean and standard deviation, both $\times 10^2$, skewness and kurtosis of the return's series. Min., Max., and Med., are the two extreme and central values of the return's distribution, and Q1 and Q3 are the lower and upper quartile values. The cross autocorrelation at lag τ is the correlation coefficient between the returns of the first named series in period t with the return on the second named series in period t-τ.

	Observation	Mean	SD	Min	P25	P50	P75	Max	Skewness	Kurtosis
FTLG	6190	-0.737	0.76	-3.55	-0.43	0.01	0.44	3.33	-.105	4.619
FTSE	6190	0.671	1.08	-5.39	-0.51	0.04	0.57	5.09	-.216	5.598

The following sections explain the explanatory variables including the monetary policy announcement, QE activity, and QT activity variables.

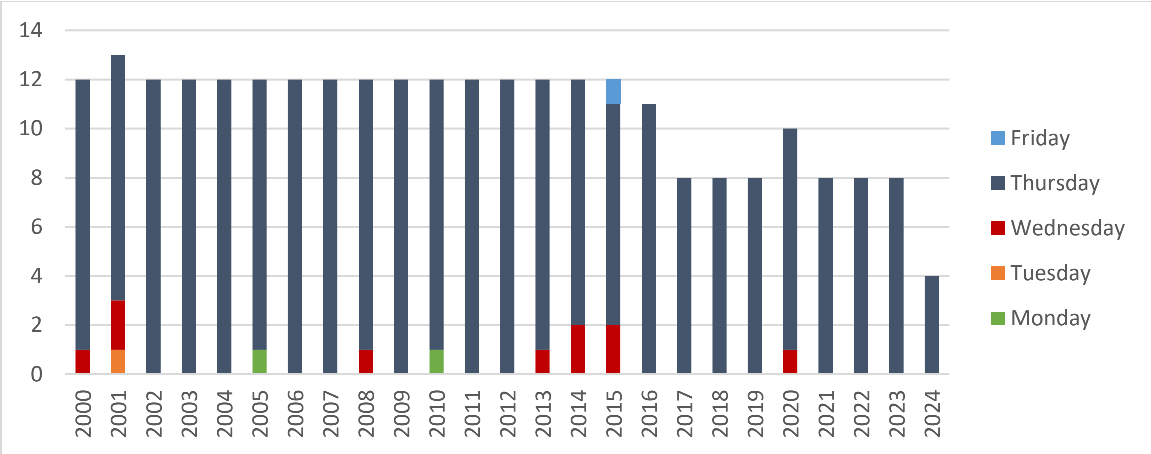
5.2.2. Monetary policy announcements

The frequency of monetary policy announcements in the UK, with a particular emphasis on the results of the monthly meetings of the Monetary Policy Committee (MPC), is represented by the variable MPC_t. Changes to the Bank of England's monetary policy, such as decisions on interest rates and other conventional or unconventional monetary measures, are mostly decided at these meetings. The variable MPC_t is set to take a value of 1 on the days that these policy announcements are made because they are usually issued at the end of the MPC's monthly meetings, which usually take place on Thursdays. MPC_t takes the value of 0 on all other days. Since monetary policy decisions are known to affect asset prices, volatility, and investor behaviour, it is crucial that this variable be included in the analysis to account for the possible market impact. The UK Debt Management Office (DMO) website provided the data for this variable, guaranteeing precision and reliability in determining when these announcements occurred. This variable aids in separating the effects of these pivotal events on financial markets within the dataset by taking into consideration conventional (such as interest rate changes) and unconventional (such as quantitative easing) monetary policy decisions.

The distribution of UK Monetary Policy Committee (MPC) statements across weekdays is depicted in the figure 47; Thursdays account for the majority of these announcements, which is consistent with the monthly meetings' regular schedule. Although the majority of announcements follow this pattern, certain meetings took place on various weekdays in different years. It is possible that the non-Thursdays are to avoid significant public events, such as Elections, major government announcements / budget statements, royal weddings and funerals, and public holidays. Additionally, there were more announcements in 2020, most likely as a result of the COVID-19 pandemic's economic effects, which necessitated more frequent monetary policy actions. After 2016, there was a noticeable drop in the overall number of announcements, which most likely reflected either a shift in announcement patterns or a decrease in policy activity. This regularity in Thursday announcements is consistent with the regular meeting schedule of the MPC.

Figure 47: Distribution of UK MPC Announcements by Weekday and Year

The figure covers the sample period from 2000 to 2024, with the x-axis representing calendar years and the y-axis showing the number of announcements per year (count data). Each bar is color-coded to indicate the weekday (Monday to Friday) on which the announcements were made.



5.2.3. Quantitative Easing Variables

5.2.3.1. Phases of QE

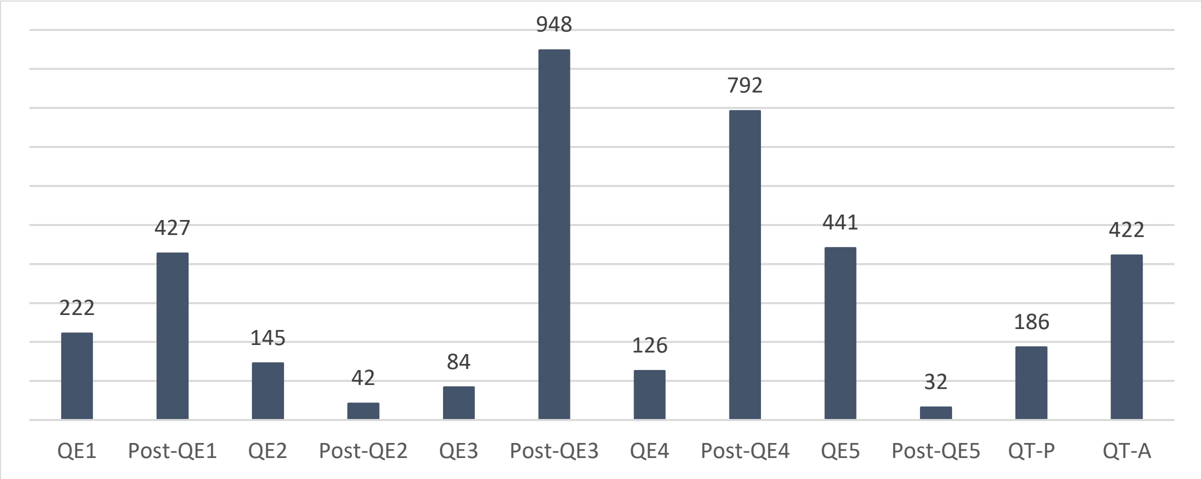
The variable *QEDUM* is an indicator variable designed to take a value of 1 during periods corresponding to the Bank of England's asset purchase programs under QE and 0 otherwise. This variable captures the impact of QE purchases, with seven key announcements marking the commencement of different QE phases, as outlined in the previous chapter. Following the 2008 financial crisis, the Monetary Policy Committee (MPC) initiated the QE program in 2009 through the Bank's Asset Purchase Facility, with the most recent QE round beginning in November 2020 in response to the COVID-19 crisis. Since the last three asset purchase programs in 2020 were announced close together, they are grouped as a single QE round.

The sample in this chapter extends beyond the previous chapters, covering the period from December 2022 to June 2024. As a result, the QT-Active phase is extended accordingly to reflect ongoing active sales by the Bank of England. QT-P means no longer buying back bonds (but not yet selling them) and QT-A means intending to or actually selling them back into the market. The definitions of the QE phases remain the same as established earlier (see Chapter 3, Section 3.2.1). There are 186 days in the QT-Passive period (3rd February 2022 to 4th May 2022) and 422 days in the QT-Active period (5th May 2022 to 30th June 2024).

The number of days in each sub-period related to the QE and QT phases is shown in Figure 48. With 948 and 792 days, respectively, the post-QE3 and post-QE4 periods have the longest durations, indicating extended periods of policy stabilisation after QE phases. Post-QE2 and Post-QE5 periods, on the other hand, contain significantly fewer days (42 and 32, respectively), suggesting shorter periods of inactivity or changes in policy. The Bank's transition to policy normalisation is marked by the QT-Passive (186 days) and QT-aggressive (422 days) periods, with QT-Active signifying a longer period of determined tightening. These variations demonstrate the changing nature of monetary policy implementation and the varying durations of the QE and QT phases, which are probably impacted by the state of the economy and the objectives of policy.

Figure 48: Number of Days in Each Sub-Periods

This figure displays the number of calendar days within each monetary policy sub-period, covering the phases of Quantitative Easing (QE) and Quantitative Tightening (QT). The x-axis lists the sub-period labels (e.g., QE1, Post-QE1, QT-A), the sub-periods are: QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 30th June 2024. Since, while the y-axis shows the number of days (unit: days).



5.2.3.2. QE Intensity

Beyond the general phases that dummy variables can represent, QE intensity is designed to quantify the daily impact of quantitative easing (QE) activity. This metric is based on the size of gilt purchases in relation to the size of their outstanding issue because the Bank of England's QE program was largely focused on buying gilts. The purchase amount of each gilt is divided by the total amount of its outstanding issuance (both in term of face value) for each day of reverse auction activity. The QE intensity is then determined by averaging this ratio across all gilts purchased on that day.

The cumulative gilt purchases over time are shown in Figure 49, which is calculated at the end of each month and contrasted with the higher bounds (boundaries) set for QE activity. The chart illustrates how these boundaries were nearly reached by the total transactions, leaving limited space for more purchases. This highlights the intensity of the program during significant times of economic intervention and highlights the primacy of gilt purchases in the Bank of England's QE policy.

The QE intensity variable gives a detailed assessment of how forceful the Bank's actions were on particular days by capturing local variations in QE activity. This degree of specificity supports more general metrics like dummy variables and enables a more accurate evaluation of QE's immediate market impact. The variable, which focusses on the ratio of purchases to issuance, is a strong tool for assessing the efficiency of QE since it captures the relative importance of each purchase in the context of the market. The UK Debt Management Office provided the issuance data and the Bank of England's public archives provided the purchase details used to generate this variable.

The average QE intensity for each sub-period is depicted in Figure 50, which demonstrates a notable variation throughout the various QE stages. With QE1 (0.788%) and QE5 (0.630%) showing the highest averages, the intensity values are greater during periods of active asset purchase programs, such as QE1, QE2, QE4, and QE5. This indicates the Bank of England's vigorous intervention to solve economic issues during these periods. On the other hand, the intensity ratio is 0 during sub-periods that have no active gilt purchases, such as pre-QE1, Post-QE1, Post-QE2, Post-QE5, QT-Active, and QT-Passive. Interestingly, QE intensity stays over zero during Post-QE3 (0.031%) and Post-QE4 (0.185%) because proceeds from matured gilts that were previously bought under the QE program are reinvested. Even without the acquisition of new assets, this reinvestment approach maintained market stability.

49: Accumulated Gilt Purchases and QE Boundaries

This figure shows the accumulated gilt purchases under the Bank of England's quantitative easing (QE) program over time, measured at the end of each month, alongside the maximum QE boundaries established for each phase. Both are in million £.

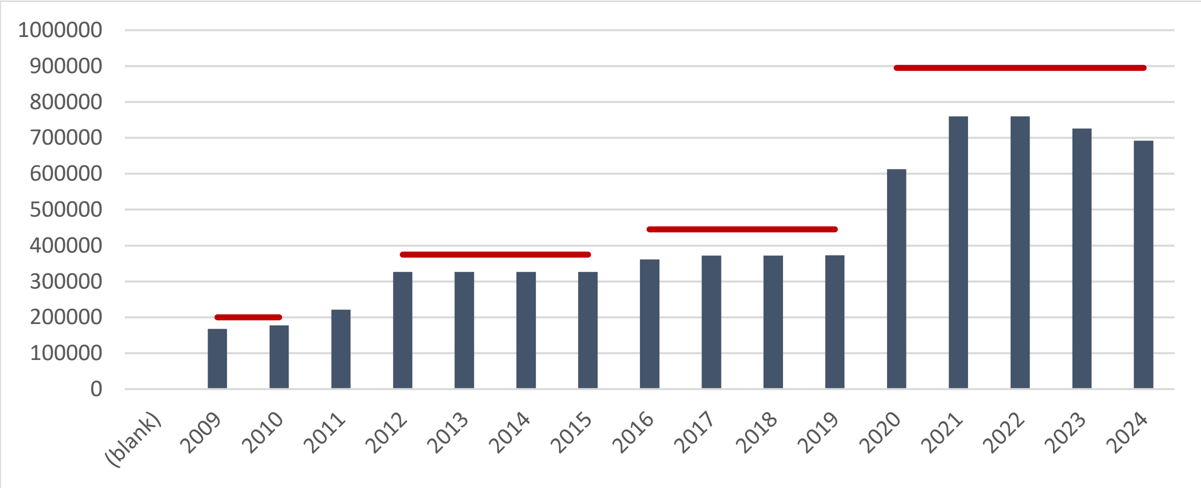
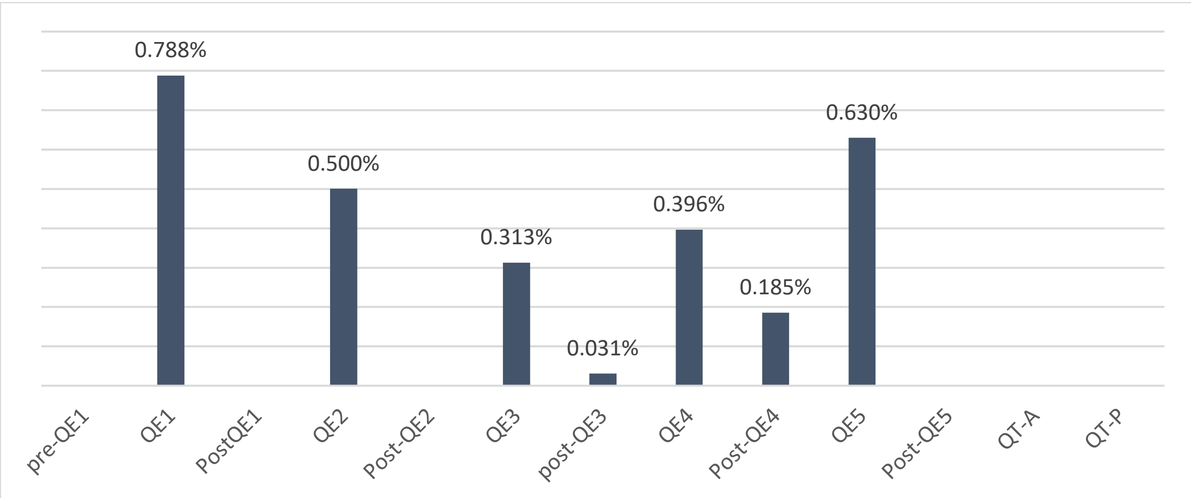


Figure 50: Average QE Intensity Across Sub-Periods

This figure displays the average QE intensity for each sub-period, calculated as the ratio of gilt purchases to their outstanding issuance size. It highlights the variation in QE activity across different phases, including active QE periods, post-QE periods, and QT phases. The x-axis lists the sub-period labels (e.g., QE1, Post-QE1, QT-A), the sub-periods are: QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 30th June 2024. Since, while the y-axis shows the number of days (unit: days).



5.2.4. Quantitative Tightening Variables

5.2.4.1. Phases of QT

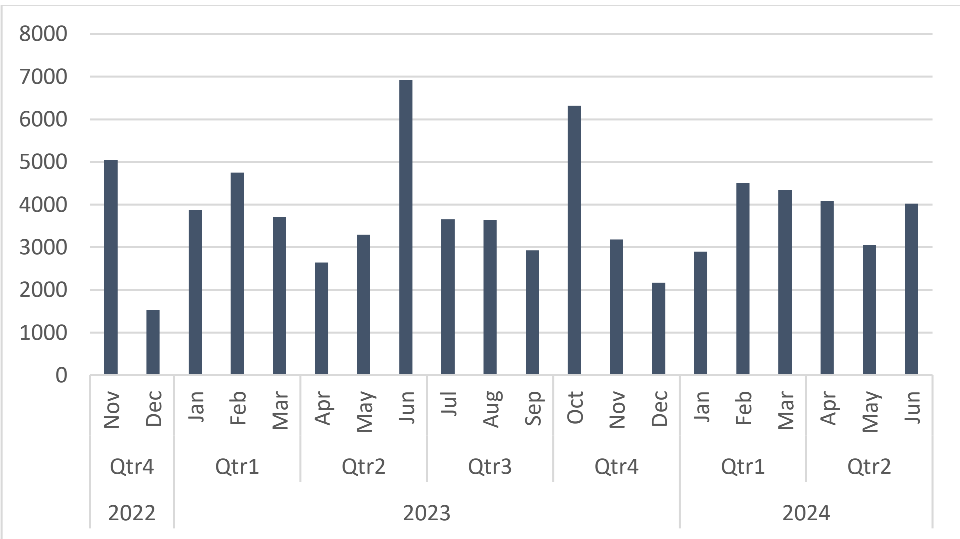
An indicator variable entitled *QTDUM* was created to track the times when the Bank of England applied QT. During QT phases, it takes the value of 1, and otherwise, it takes the value of 0. As the Bank actively decreases its balance sheet by either actively selling assets (QT-Active) or allowing purchased gilts to mature without reinvestment (QT-Passive), QT signifies the reverse of quantitative easing (QE). There are 186 days in the QT-Passive period (3rd February 2022 to 4th May 2022) and 422 days in the QT-Active period (5th May 2022 to 31st June 2024).

Since these times reflect a shift from a supporting monetary policy to a more restrictive perspective intended to control inflation and normalise monetary conditions, this variable is crucial for capturing the impacts of QT on financial markets. Because the central bank is less active as a buyer in the gilt market, QT periods are anticipated to have a major effect on market liquidity, asset prices, and yield spreads. QTDUM offers a targeted metric for examining the particular market dynamics and macroeconomic implications of quantitative tightening by separating these periods.

The Bank of England's total monthly gilt sales throughout the period of active QT from November 2022 to June 2024 are depicted in Figure 51. Periods of increased QT activity are indicated by the sales quantities, which fluctuate with noteworthy peaks in June 2023 and October 2023. The Bank's determined efforts to control its balance sheet reduction while reacting to market conditions and preserving financial stability are shown in the volatility in monthly sales.

Figure 51: Monthly Gilt Sales Under Active QT (in Millions)

This figure shows the total monthly sales of gilts by the Bank of England under active quantitative tightening (QT) from November 2022 to June 2024, measured in million £.



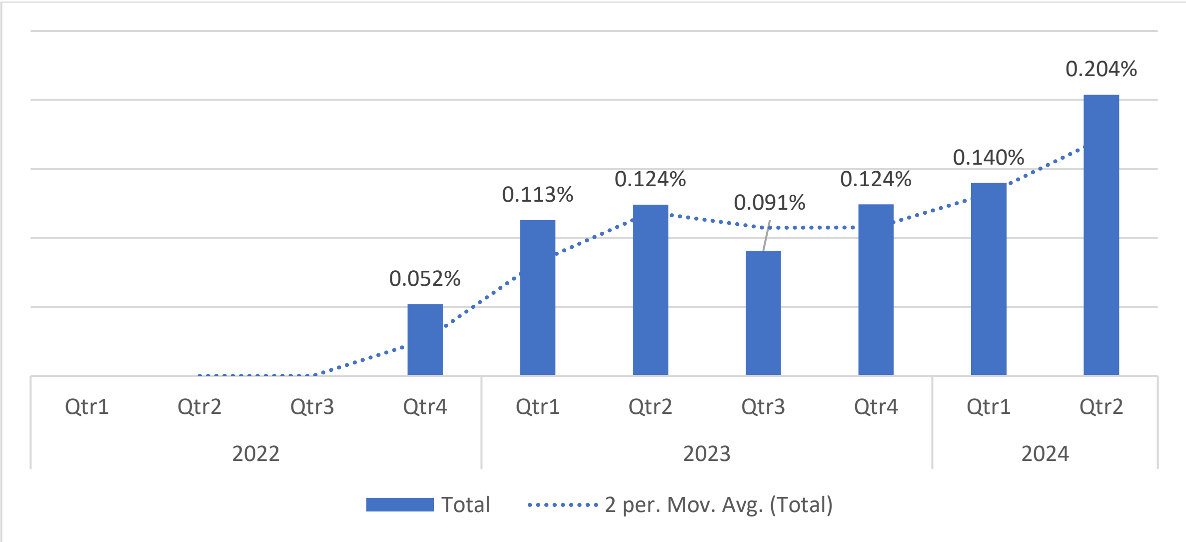
5.2.4.2. QT Intensity

Using the same methods as QE Intensity, the variable QT Intensity gauges the size of gilt sales accomplished by the Bank of England during the QT era. The amount sold for each gilt is divided by the total amount of gilts that are still outstanding (face value) for each gilt sale day. The relative size of the sale for that gilt is shown by this ratio. The ratios for every gilt sold in the reverse auction are averaged to determine the daily QT Intensity. This variable, which records the percentage of outstanding issuance sold back into the market, offers a detailed assessment of the level of QT activity on a particular day. QT Intensity provides insights into the efficacy and market reaction to the Bank's QT operations by concentrating on this ratio, which represents the relative impact of each sale within the market context. The Bank of England's public archives provide the sales information used to generate this variable, while the UK Debt Management Office provides the issuance information.

In addition to a two-period moving average trend line, Figure 52 displays the quarterly average of QT intensity ratios over the quantitative tightening (QT) period. The early phases of active QT are reflected in the QT intensity ratio, which starts in Q4 2022 at a low level of 0.052%. It then gradually rises till it reaches 0.204% in Q2 2024. A steady increase in QT intensity is highlighted by the two-period moving average, suggesting a slow increase in gilt sales in relation to their outstanding issue.

Figure 52: Quarterly Average of QT Intensity Ratio

This figure displays the quarterly average of the QT Intensity ratio from Q4 2022 to Q2 2024, along with a two-period moving average to highlight trends in the intensity of gilt sales during the quantitative tightening period. QT Intensity is measured by he amount sold for each gilt is divided by the total amount of gilts that are still outstanding (face value) for each gilt sale day; a value of 1.0 indicates that the entire outstanding stock of the gilt was sold, representing the maximum possible intensity for that sale.



5.2.5. Index Change

The variable *IndexChgt* captures the effects of changes in the composition of the two bond indexes, notably the short-term bond index, where these changes are most noticeable. Bonds may leave the short-term index on March 7, June 7, September 7, and December 7, as each of these four dates is when the majority of UK bonds mature. Additionally, medium-term bonds whose maturity falls below five years are added to the short-term index. There are obvious irregularities in the bond index data as a result of these changes to the index components, which are made seven working days before the bond maturity dates. This impact is addressed by introducing the variable $IndexChg_t$ as a dummy variable, which takes a value of 0 otherwise and 1 on days when index constituents are altered. This variable helps to control for the distortions caused by such changes in the bond indices and that can be seen in Figure 43 earlier.

5.3. Modelling Capital Market Integration

5.3.1. Univariate GARCH Models

Bollerslev (1986) developed the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models, which are now a fundamental tool in financial econometrics for simulating and predicting time-varying volatility. When it comes to financial time series, the GARCH model works especially well because it can model volatility clustering—high volatility followed by high volatility and low volatility followed by low volatility— which occurs frequently in actual dataIt represents the conditional variance as a function of past squared returns and past variances. Asymmetries in volatility are further accommodated by GARCH model variations like EGARCH (Nelson, 1991) and TGARCH (Zakoian, 1994), which capture the leverage effect, according to which negative shocks often increase future volatility more than positive shocks of the same magnitude.

To model the variance processes of returns in the three markets—short-term bond, long-term bond, and equity markets—we adopt a GARCH framework. The model consists of two main components:

$$R_{i,t} = \alpha_{i,1} + \alpha_{i,2}MPC_t + \alpha_{i,3}IndexChg_t + \alpha_{i,4}QEDUM_t + \alpha_{i,5}QTDUM_t + \alpha_{i,6}QTInt_t + \alpha_{i,7}QEInt_t + \sum_{k=1}^{5}\sum_{i=1}^{3}\beta_{i,k}R_{i,t-k} + \varepsilon_{i,t} \quad (7)$$

where $\varepsilon_{i,t}|\Omega_{t-1} \sim N(0, h_{i,t})$, and

$$h_{i,t} = \omega_{i,i} + b_{i,i}\varepsilon_{t-1}^{2} + c_{i,i}h_{i,t-1} + \gamma_{i,i,1}MPC_t + \gamma_{i,i,2}QEDUM_t + \gamma_{i,i,3}QTDUM_t + \gamma_{i,i,4}QTInt_t + \gamma_{i,i,5}QEInt_t \quad (8)$$

where $R_{i,t}$ is daily the return from market i in day t, and the $i = 1,2,3$ markets are the short-term bond market, the long-term bond market and the equity market. The information set, Ω_{t-1}, includes all information known at time $t-1$. The variables include monetary policy announcements (MPC_t), changes to bond index constituents ($IndexChg_t$), quantitative easing intensity (QEInt_t), QE phases ($QEDUM_t$), quantitative tightening intensity ($QTInt_t$), and QT phases ($QTDUM_t$). By incorporating up to five lags of historical returns, the model also takes autocorrelation in returns into account. This methodology guarantees the reduction of bias or inefficiency resulting from autocorrelation or cross-autocorrelation in the return series. It is assumed that the error term ($\varepsilon_{i,t}$) in the mean equation has a normal distribution with mean zero and conditional variance $h_{i,t}$.

The conditional variance $h_{i,t}$ is modelled separately to capture the time-varying volatility of returns. The GARCH variance equation includes lagged squared residuals and lagged variance terms to model volatility dynamics. Additionally, exogenous variables such as monetary policy (MPC_t), QE phases ($QEDUM_t$), QE intensity ($QEInt_t$), QT phases ($QTDUM_t$), and QT intensity ($QTInt_t$) are incorporated to evaluate their direct impact on return volatility. To ensure stationarity, the model imposes constraints on the sum of the coefficients, requiring it to be less than one, $\omega_{i,i} > 0$, $b_{i,i}, c_{i,i} > 0$, $b_{i,i} + c_{i,i} + \sum_{j=1}^{5} \gamma_{i,i,j} < 1$.

In order to solve potential problems with negative coefficients that can occur in standard GARCH models, Nelson (1991) proposed the EGARCH model, which models the logarithm of variance rather than its level. Without imposing non-negativity constraints on the coefficients, the EGARCH model guarantees that the variance stays positive by using the log of variance. The model is now more adaptable and reliable in capturing volatility dynamics as a result of this improvement. We apply the EGARCH model for the univariate analysis of the separate markets, but without the asymmetry option that featured in its original form, which we found was not needed for our indices. Estimation of the models is done using the software Estima-RATS.

5.3.2. Modelling Time-Varying Correlations

We use a multivariate framework to examine how correlations between the three markets—equities, long-term bonds, and short-term bonds—have changed over time and how QE and QT have affected these relationships. Initially, the mean and variance equations (8) and (9) are used to model each market separately. However, we jointly estimate the three markets inside a multivariate GARCH framework in order to reflect the interdependencies and dynamic interactions among the markets.

Financial market volatility spillovers have been extensively analysed using GARCH models, which provide information on risk transmission and market interdependence. To illustrate the interdependence of the stock, bond, and money markets, Aftab et al. (2019) used a multivariate GARCH framework to evaluate volatility interactions between these asset classes. In a similar vein, Arouri et al. (2011) examined the transmission of volatility between oil prices and stock sectors using a VAR-GARCH model, finding unidirectional spillovers in European markets and bidirectional spillovers in

U.S. markets. Zhang et al. (2020) investigated the geographical dimension of volatility spillovers by using a GARCH-BEKK model to examine the networks of volatility among G20 stock markets, focussing on hierarchical and time-varying patterns in spillovers. Furthermore, Ewing and Malik (2016) showed that, after controlling for structural discontinuities in variance, there were notable volatility spillovers between oil prices and U.S. stock markets. These studies demonstrate how well GARCH models capture both direct and indirect transmission of volatility, offering vital information for financial stability assessments, hedging tactics, and portfolio management.

In multivariate settings, modelling correlations usually requires estimating a lot of parameters. For example, even a simple GARCH (1,1) specification applied within a multivariate setting such as VECH or BEKK may need about 50 parameters, which makes it difficult to construct and computationally complicated. We employ Engle (2002) Dynamic Conditional Correlation (DCC) model to address this. The DCC model allows for time-varying correlations between the markets while drastically reducing the number of parameters to evaluate. This method balances the flexibility required to model changing market dynamics with computing efficiency. Bollerslev (1990) developed the CCC-GARCH model, which is a simpler method for examining volatility interdependencies because it assumes continuous correlations between assets. However, the DCC-GARCH was created as a result of the CCC-GARCH model's inability to capture time-varying relationships. Gamba-Santamaria et al. (2017), for instance, constructed volatility spillover indices using the DCC-GARCH framework and shown a notable temporal variance in spillovers among major global stock markets, especially during times of market instability. In a similar vein, Bala and Takimoto (2017) investigated volatility spillovers between emerging and established markets during financial crises using a DCC-GARCH model with skewed-t distributions, discovering that the impacts were higher during times of global stress. In order to better identify systemic risks, diversify portfolios, and create risk management plans, these models have shown to be extremely useful in capturing the magnitude and direction of volatility transmission in interconnected markets.

The conditional variance processes for every market in the DCC framework are described in equation (9). However, a quasi-correlation matrix, Q_t, is used to model the covariance processes. The conditional covariances can be written as follows:

$$h_{i,m,t} = q_{i,m,t} \sqrt{h_{i,t} h_{m,t}} / \sqrt{q_{i,t} q_{m,t}} \tag{10}$$

where, $q_{i,t}$ and $q_{i,m,t}$ are, respectively, the diagonal and off-diagonal elements of a quasi-correlation matrix, Q, that as a whole follows a "GARCH (1,1)" process, depending on just two parameters a and b, such that the diagonal elements are given by

$$q_{i,t} = (1 - a - b) q_{0,i} + a\varepsilon_{i,t-1}^2 + b q_{i,t-1} \tag{11}$$

and the off-diagonal elements are given by

$$q_{i,m,t} = (1 - a - b)q_{0,i,m} + a\varepsilon_{i,t-1}\varepsilon_{m,t-1} + bq_{i,m,t-1} \tag{12}$$

5.3.3. Modelling Persistence in Variance and Correlation Processes

An important indicator of how rapidly volatility reacts to and recovers from market shocks is the persistence of shocks to the variance process, which is determined by adding the coefficients $b + c$ in the variance equation. Particularly during times of economic instability like the pre-QE crisis or during the several stages of QE and QT, this persistence might not hold steady over the course of the sample period. We add phase-specific elements to the variance model in equation (2) to account for possible persistence changes, producing the enhanced equation (6).

$$\begin{aligned} h_{i,t} = \omega_{i,i} + b_{i,i}\varepsilon_{t-1}^2 + c_{i,i}h_{i,t-1} + \varphi_{j,i,i}(QEDUM_t + QTDUM_t)\varepsilon_{t-1}^2 + \gamma_{i,i,1}\mathrm{MPC}_t \\ + \gamma_{i,i,2}QEDUM_t + \gamma_{i,i,3}QTDUM_t + \gamma_{i,i,4}QTInt_t + \gamma_{i,i,5}QEInt_t \end{aligned} \tag{13}$$

According to this definition, shock persistence is represented by $b + c + \varphi$, where φ permits the persistence to change over time, including the QE and QT phases. The model may detect transient changes in volatility dynamics linked to particular stages of monetary policy intervention due to the addition of φ terms that interact with phase-specific dummy variables *QEDUM* and *QTDUM*. This method provides an adaptable framework for identifying structural changes in the variance process, building on Chu (1995) parameter constancy test for GARCH models.

5.4. Results

5.4.1. Univariate GARCH Results

The results of the univariate GARCH are shown in Table 77. The intercepts $\hat{\alpha}_1$, which represent a baseline level of returns inherent to each asset type, are statistically significant across all indexes. The FTSE index has the largest intercept, which is consistent with the higher predicted returns linked to stocks because of their higher risk. The smaller intercepts of both short-term (FTSG) and long-term (FTLG) bonds are indicative of their reduced risk profiles. These findings demonstrate the essential distinctions between the risk and return dynamics of bonds and stocks.

It appears that monetary policy statements, $\hat{\alpha}_2$, have no effect on any of the indexes, indicating that the markets mostly predict how these announcements would turn out. This suggests that monetary policymaking is very transparent and credible, and that market players are adequately equipped to handle shifts in interest rates or associated policies. This result is in line with efficient markets theory, which holds that asset prices promptly integrate information that is readily available to the public.

The coefficient on the dummy variable for quantitative easing, $\hat{\alpha}_4$, is significant and negative for FTLG, but insignificant for FTSG and FTSE. This implies that the central bank's emphasis on acquiring longer-dated securities during asset purchase programs is the main reason why QE phases affect long-term bond returns. This lower yield, which has a detrimental effect on long-term bond returns. The lack of effect on short-term bonds and stocks suggests that, in contrast to long-term bond markets, these markets are less directly impacted by the widespread occurrence of QE. Further evidence of QE impact on long-term bond market is provided by significant quantitative easing intensity for long-term bonds (FTLG) at the 5% level indicates that QE has a positive impact on long-dated assets, most likely by lowering risk premiums and yields through central bank purchases. It does not, however, have a significant effect on short-term bonds (FTSG) or stocks (FTSE), suggesting that the intensity of QE does not have the same direct effect on these asset classes. However, the negative impact of QEDUM implies that lower long-term bond returns generally correspond with the occurrence of QE phases. This might be the consequence of market reactions to the macroeconomic environment in general during QE periods, such as central banks indicating deflationary pressures or recession, which could lower investor confidence. Additionally, even though QE stabilised the bond market, the decrease in bond yields brought on by central bank purchases may result in lower returns for long-term bonds. On the other hand, the direct impact of liquidity injections during times of active asset purchases is captured by the positive impact of QE Intensity. More active interventions are implied by higher QE intensity, which raises demand for long-term bonds and temporarily raises prices. The QE phase's overall downward pressure may be outweighed by this localised increase in bond prices. Therefore, the intensity of active bond purchases has a positive effect but only significant for FTLG, presumably reflecting rapid market reactions to increased liquidity and lower risk premiums, but the total QE term (as measured by QEDUM) has a dampening effect.

As a dummy variable, quantitative tightening has a positive and significant effect on short-term bond returns (FTSG), suggesting that greater returns for short-term bonds are correlated with tighter monetary policy. This can be a result of reinvestment possibilities or increasing yields during QT periods. On the other hand, QT has a very large and negative effect on long-term bonds (FTLG), indicating that tighter monetary circumstances have a negative influence on long-term bond returns, most likely as a result of heightened sensitivity to fluctuations in interest rates and liquidity restrictions. The intensity of quantitative tightening (QT) has a negative and highly significant influence on long-term bond returns (FTLG), while it has a weakly significant (10% level) negative effect on short-term bonds (FTSG) and stocks (FTSE), indicating that QT has a wide range of negative effects on financial markets. Since QT phases cause longer-duration securities to reprice significantly, the strong negative impact on long-term bonds reflects their high sensitivity to liquidity withdrawal and rising interest rates.

Although short-term bonds are less susceptible to fluctuations in interest rates, they are nonetheless impacted negatively by the tightening of liquidity circumstances, as evidenced by the smaller but still negative influence on these bonds.

Lagged Returns $\beta_{i,k}$ underscore the interconnected nature of financial markets, where past movements in one asset class can propagate to others, influenced by portfolio rebalancing, risk sentiment, and macroeconomic linkages. Across all index series, the dummy variable that measures how bond maturity changes affect the components of the bond indices is highly significant.

The variance equation of the GARCH model also includes variables that account for both QT and QE activity, providing a more comprehensive view than previous studies. The c parameter (the coefficient on the lagged conditional variance) being near 1 indicates that the results show substantial persistence in volatility across all indices. Financial theory, which holds that volatility tends to cluster and persist, especially during uncertain economic times, is consistent with this.

Across all indices, the MPC announcement variable $\hat{\gamma}_1$ does not exhibit statistical significance. This finding implies that monetary policy meetings do not directly cause meaningful increases in volatility, even though they are crucial for communicating central bank actions. This might be an example of efficient market behaviour, in which investors primarily use pre-meeting communications and economic data to predict the results of MPC meetings. This is theoretically consistent with the Efficient Market Hypothesis, which holds that markets quickly modify asset values to reflect available information, reducing the direct effect of such announcements on volatility.

The fact that the QE dummy $\hat{\gamma}_2$ is not significant across the indices suggests that there were no statistically significant increases in volatility during the QE periods. This result provides evidence for the idea that QE, in spite of its unconventional nature, contributed to market stabilisation by lowering systemic risks and introducing liquidity. An additional indication that the QE activities does not further increase volatility beyond what is seen during the initial announcement phase is supplied by QE intensity $\hat{\gamma}_4$, which does not demonstrate a statistically significant influence. Because it affects investor expectations and risk sentiment at the time of announcement rather than during the implementation phase, this study supports the idea that QE has a greater impact at that stage. The outcome is also consistent with theories that highlight the stabilising function of QE since liquidity injections lower systemic risk and uncertainty, especially in bond markets.

For some indices, like the short-term gilt indices, the QT dummy $\hat{\gamma}_3$ is significant and positive, indicating that QT periods were associated with increased volatility. This result is consistent with the theoretical prediction that when market players adapt to tighter monetary conditions, the withdrawal of liquidity under QT creates uncertainty. The strong correlation with volatility during QT also draws attention to potential risks of the quick normalisation of monetary policy, as market players can find it difficult to adjust their expectations. Changes in monetary policy and liquidity conditions have a significant impact on short-term bonds. Due to their close ties to financing markets and expectations for short-term interest rates, short-term bonds are more volatile during QT as supply rises and liquidity is removed. Short-term instruments react more strongly to monetary tightening, according to theoretical frameworks such as the liquidity preference and term structure of interest rates. This effect is further amplified during QT by market segmentation and demand-supply mismatches. This explains why short-term bonds are more volatile during QT periods and emphasises how important they are in communicating policy changes. On the other hand, we observe a declining trend in Figure 53 on the variance estimated by the model which is in contrast with the impact of QT on short term gilts. The apparent inconsistency could be explained by the fact that when QT started in February 2022, markets were adjusting to the central bank's reduction in its balance sheet, which was a time of increased uncertainty. Increased volatility may have resulted from this initial shock, which the GARCH model accounts for through the positive volatility shock captured by the conditional variance. Further evidence for the negative impact of QT is provided by the variable QT intensity $\hat{\gamma}_4$ which is negative and significant in short term gilt market. This outcome emphasises the stabilising effect of QT, most likely as a result of its function in restoring normal market conditions by eliminating excess liquidity. QT operations promote a return to fundamentally driven pricing by reducing uncertain behaviour. This result supports hypotheses that claim QT-induced liquidity withdrawal encourages market discipline and reduces volatility in the bond and equities markets. Initially, the announcement and early stages of QT create heightened volatility due to uncertainty and liquidity withdrawal, especially affecting short-term bonds. However, as QT progresses and markets adjust to the new monetary environment, volatility tends to decrease as excess liquidity is removed, promoting a return to more fundamentally driven pricing. The former effect is being captured by the positive γ_3, while the negative effect is being captured by the negative γ_4.

The squared residuals of only the long-term bond index returns show some residual autocorrelation, according to diagnostic statistics. This residual autocorrelation could not be eliminated by alternative specifications that used various lag parameters among the previous squared residuals in equation (9) or the past returns in equation (8). At the bottom of Table 77, the correlations between the standardised residuals from the three models are presented. The expectations theory of the term structure of interest rates is supported by the correlation of 0.725 between the short- and long-term bonds, which shows an anticipated positive long-term relationship between these two markets. In contrast, the equity index and bond indexes have a negative connection, with the longer-term bonds exhibiting a higher negative correlation coefficient. These suggest that during the sample period, there might have been some opportunities for hedging between the two markets. We now analyse the findings of the multivariate DCC GARCH model, which may detect time fluctuation in the correlations between the markets, to see whether this long-term connection showed notable short-term variance.

Table 77: Univariate GARCH models

This table contains the estimated coefficients from the model, $R_{i,t} = \alpha_{i,1} + \alpha_{i,2}MPC_t + \alpha_{i,3}IndexChg_t + \alpha_{i,4}QEDUM_t + \alpha_{i,5}QTDUM_t + \alpha_{i,6}QTInt_t + \alpha_{i,7}QEInt_t + \sum_{k=1}^{5}\sum_{i=1}^{3}\beta_{i,k}R_{i,t-k} + \varepsilon_{i,t}$, $\varepsilon_{i,t}|\Omega_{t-1} \sim N(0, h_{i,t})$, $log h_{i,t} = \omega_{i,i} + b_{i,i}\frac{|\varepsilon_{t-1}|}{\sqrt{h_{i,t-1}}} + c_{i,i}log h_{i,t-1} + +\gamma_{i,i,1}MPC_t + \gamma_{i,i,2}QEDUM_t + \gamma_{i,i,3}QTDUM_t + \gamma_{i,i,4}QTInt_t + \gamma_{i,i,5}QEInt_t$, where $R_{i,t}$ is the return at time t on index i, i ∈ {FTSG,FTLG,FTSE} as defined in Table 75. Estimated parameters are indicated by a caret, and ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The variable MPC_t is a dummy variable taking the value unity on days of MPC meetings and is zero otherwise, and $IndexChg_t$ is a dummy variable that controls for the effects of quarterly changes to the bond index constituents. $QEInt_t$ is a measure of the intensity of QE activity on these purchase auction days and is measured as the purchase amount of each gilt divided by the total amount of its outstanding issuance (both in term of face value) for each day of reverse auction activity, expressed as a percentage, A value of 1.0 means that the amount of gilts sold on that day equals the entire outstanding face value of that gilt. $QEDUM_t$ is a dummy variable that takes value one during the phases of QE, and $QTDUM_t$ is a dummy variable that takes value one during the phases of QT. $QTInt_t$ is a measure of the intensity of QT activity on these sale auction days, expressed as a percentage, measured by the amount sold for each gilt is divided by the total amount of gilts that are still outstanding (face value) for each gilt sale day ; a value of 1.0 indicates that the entire outstanding stock of the gilt was sold, representing the maximum possible intensity for that sale. Log-L is the maximized value of the log-likelihood function (assuming Normally distributed errors) using the Levenberg-Marquardt non-linear optimization algorithm. Q(10) [$Q^2(10)$] is the Box-Ljueng test for autocorrelation applied to the standardized [squared] residuals. SBC is the Schwartz Bayesian criterion.

Coefficient	FTSG	FTLG	FTSE
$\hat{\alpha}_1$	0.0036***	0.0218***	0.0475***
MPC	0.0105	-0.0070	0.0161
IndexChg	-0.8482***	-0.9154***	-0.1962***
$QEDUM$	0.0001	-0.0534**	0.0180
$QTDUM$	0.0120*	-0.1060***	0.0346
$QTInt$	-3.6916*	-19.3424**	-11.7009*
$QEInt$	0.1360	5.1875***	0.4069
$\hat{\beta}_{1,1}$	0.0489***	0.0232***	0.0234
$\hat{\beta}_{1,2}$	-0.0016	-0.0312***	0.1546**
$\hat{\beta}_{1,3}$	-0.0074	-0.0402***	-0.0610*
$\hat{\beta}_{1,4}$	0.0106	-0.0212***	-0.0614
$\hat{\beta}_{1,5}$	-0.0027	-0.0196***	0.0125
$\hat{\beta}_{2,1}$	-0.0131***	-0.0598***	0.0347**
$\hat{\beta}_{2,2}$	-0.0034*	0.0079	0.0167
$\hat{\beta}_{2,3}$	-0.0036**	0.0251	0.0375***
$\hat{\beta}_{2,4}$	0.0009	0.1628***	0.0582***
$\hat{\beta}_{2,5}$	-0.0008	0.0831**	0.0167
$\hat{\beta}_{3,1}$	-0.0003	0.0052	-0.0309**
$\hat{\beta}_{3,2}$	-0.0004	0.0024	-0.0271**
$\hat{\beta}_{3,3}$	-0.0024*	-0.0012	-0.0222**
$\hat{\beta}_{3,4}$	0.0011	0.0024	0.0021
$\hat{\beta}_{3,5}$	0.0024*	0.0225***	-0.0145
$\widehat{\omega}$	-0.0408***	-0.0727***	-0.1687***
$\hat{b}$	0.0286***	0.0810***	0.2166***
$\hat{c}$	0.9949***	0.9932***	0.9770***
MPC	-0.0192	0.0809	-0.0179
$QEDUM$	-0.0019	-0.0017	-0.0035
$QTDUM$	0.0126***	0.0115*	0.0077
$QTInt$	-11.6610***	-4.4069	-16.8271
$QEInt$	0.0957	0.3391	1.0361
Log-L	4386.5702	-6435.1130	-8211.6377
SBC	-1.376	2.125	2.699
Q(10)	41.18	47.01	50.09
$Q^2(10)$	12.05	60.10**	47.37
		Cross correlations of standardized residuals	
FTLG	0.663		
FTSE	-0.159	-0.226	

5.4.2. Multivariate GARCH Results

Based on the results reported in Table 78, our empirical findings indicate that Monetary Policy Committee meetings have a considerable beneficial impact on all three markets, with significant coefficients of 0.041 for FTSG, 0.133 for FTLG, and 0.279 for FTSE. These steady positive reactions imply that markets react favourably to monetary policy communication events in general. This result is consistent with monetary policy's Information Effect Theory, which contends that market players can learn important information about the state of the economy via central bank communications. Additionally, these findings are consistent with the Policy Signalling Channel theory, which holds that communication and transparency from central banks influence market expectations and lower uncertainty.

Our examination of changes in index composition shows that there are notable negative impacts in all markets, but the short-term bond market is more significantly affected. The effects of quarterly bond index recomposing are captured by the IndexChg variable, which displays significant negative coefficients in both univariate and multivariate models. Since these adjustments mostly impact the short-term bond index, where bonds mature and medium-term bonds with maturities below five years are introduced, the higher negative effects in FTSG and FTLG relative to FTSE make economic sense. This pattern suggests substantial price pressure during rebalancing periods as investors modify their portfolios to reflect the new index composition, which is consistent with the literature on Market Microstructure Theory and Index Inclusion Effects (see Koijen et al. (2021)). Due to their direct exposure to these indices change events, short-term markets (FTSG, FTLG) have greater magnitude effects than the FTSE. This validates Market Segmentation Theory by showing that the markets most immediately impacted by index changes have the biggest price impacts.

According to the findings, markets react to QE intensity and phases in interesting ways. The DCC model indicates that the phases of QE programs do not significantly affect returns, as the QE dummy variable (α_4) exhibits limited significant impacts across markets. However, QE intensity (α_7) shows notable positive coefficients, especially in FTLG and FTSG, suggesting that the quantity and actual implementation of QE purchases have a greater market influence than phases of QE. We find comparable trends, albeit of varying magnitudes, when comparing these findings with the CC model. The market's reaction to QE activities isn't constant, therefore taking time-varying correlations into account is crucial for capturing the full impact of QE operations, according to this difference between the DCC and CC models.

When examining the effects of QT on the FTSG market, the results reveal intriguing distinctions between the Constant Correlation (CC) and Dynamic Conditional Correlation (DCC) models. The QT dummy variable has a positive value (0.0161) in the CC model and a negative coefficient (-0.0070) in the DCC model. This discrepancy implies that the CC model's assumption of constant correlations does not fully explain the market's time-varying reaction to QT activity. Because the DCC model can take dynamic correlations into account, it gives a more accurate picture, showing that FTSG generally reacts negatively to QT phases as investors rebalance their holdings. Notably the univariate GARCH analysis revealed that the QT dummy had a positive but marginally significant impact on FTSG, emphasising the significance of taking cross-market dynamics into account when evaluating the results of monetary policy actions.

In the volatility equation, based on DCC model, the results reveal that QE phases (QEDUM) and intensity (QEInt) have distinct effects on market volatility. For short-term gilts (FTSG), QEDUM significantly reduces volatility, reflecting the stabilizing effect of liquidity injections during QE phases, which anchor yields and calm short-term funding markets. In contrast, QEDUM increases volatility in the long-term gilt market (FTLG), likely due to the uncertainty introduced by large-scale asset purchases that disrupt yield dynamics and create price fluctuations. The intensity of QE (QEInt) significantly reduces volatility in both short-term (FTSG) and long-term gilt markets (FTLG), indicating that a higher share of gilts purchased by the Bank of England reduces uncertainty and market fragmentation, particularly in the bond markets. However, QEInt has a positive and marginally significant impact on equity volatility (FTSE), suggesting that the risk-taking channel of QE, which encourages investors to reallocate funds into equities, amplifies fluctuations in equity markets. We could not find any significant impacts for QE variables through the CC model.

The results reveal an important divergence in the effects of QT phases (*QTDUM*) and QT intensity (*QTInt*) on market volatility, as reflected in their opposite signs. QT phases (*QTDUM*) are associated with a positive and significant impact on volatility across all markets in the CC model, suggesting that the announcement of QT introduces uncertainty and disrupts market dynamics. This can be explained by the fact that *QTDUM* encompasses both types of QT: passive QT (where the government stops reinvesting proceeds from matured bonds) and active QT (where the Bank of England actively sells bonds purchased during the Asset Purchase Facility). Passive QT has a relatively milder impact on liquidity as it reduces the balance sheet gradually, whereas active QT directly withdraws liquidity from markets, intensifying its disruptive effects. On the other hand, QT intensity (*QTInt*), which measures the scale of active QT, shows a negative and significant impact on volatility across all markets. This reflects the stronger liquidity impact of active QT, where bond sales actively normalize market conditions, reduce speculative activity, and stabilize volatility through systematic liquidity withdrawal. The difference in signs between *QTDUM* and *QTInt* highlights that while QT announcements introduce uncertainty and increase volatility due to their broad scope, the targeted implementation of active QT through bond sales has a more pronounced stabilizing effect on financial markets. This underscores the importance of distinguishing between passive and active QT when assessing their impacts on market dynamics.

Table 78: Multivariate GARCH models

This table contains the estimated coefficients from the model, $R_{i,t} = \alpha_{i,1} + \alpha_{i,2}MPC_t + \alpha_{i,3}IndexChg_t + \alpha_{i,4}QEDUM_t + \alpha_{i,5}QTDUM_t + \alpha_{i,6}QTInt_t + \alpha_{i,7}QEInt_t + \sum_{k=1}^{5}\sum_{i=1}^{3}\beta_{i,k}R_{i,t-k} + \varepsilon_{i,t}$, $\varepsilon_{i,t}|\Omega_{t-1} \sim N(0, h_{i,t})$, $h_{i,t} = \omega_{i,i} + b_{i,i}\varepsilon_{t-1}^2 + c_{i,i}h_{i,t-1} + \gamma_{i,i,1}MPC_t + \gamma_{i,i,2}QEDUM_t + \gamma_{i,i,3}QTDUM_t + \gamma_{i,i,4}QTInt_t + \gamma_{i,i,5}QEInt_t$, and in Panel A $h_{i,m,t} = \rho_{i,m,t}\sqrt{h_{i,t}h_{m,t}}$, $\rho_{i,m,t} = q_{i,m,t}/\sqrt{q_{i,i,t}q_{m,m,t}}$, $q_{i,m,t} = q_{i,m}(1-a-b) + a\varepsilon_{i,t-1}\varepsilon_{m,t-1} + bq_{i,m,t-1}$, while in Panel B, $h_{i,m,t} = \rho_{i,m}\sqrt{h_{i,t}h_{m,t}}$, where $R_{i,t}$ is the return at time t on index i, $i \in$ {FTSG,FTLG,FTSE} as defined in Table 75. Estimated parameters are indicated by a caret, and ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The variable MPC_t is a dummy variable taking the value unity on days of MPC meetings and is zero otherwise, and $IndexChg_t$ is a dummy variable that controls for the effects of quarterly changes to the bond index constituents. $QEInt_t$ is a measure of the intensity of QE activity on these purchase auction days and is measured as the purchase amount of each gilt divided by the total amount of its outstanding issuance (both in term of face value) for each day of reverse auction activity, expressed as a percentage, A value of 1.0 means that the amount of gilts sold on that day equals the entire outstanding face value of that gilt. $QEDUM_t$ is a dummy variable that takes value one during the phases of QE, and $QTDUM_t$ is a dummy variable that takes value one during the phases of QT. $QTInt_t$ is a measure of the intensity of QT activity on these sale auction days, expressed as a percentage, measured by the amount sold for each gilt is divided by the total amount of gilts that are still outstanding (face value) for each gilt sale day ; a value of 1.0 indicates that the entire outstanding stock of the gilt was sold, representing the maximum possible intensity for that sale. Log-L is the maximized value of the (multivariate) log-likelihood function (assuming Normally distributed errors) using the Levenberg-Marquardt (CC) or BFGS (DCC) non-linear optimization algorithm. Q(10) [$Q^2(10)$] is the Box-Ljueng test for autocorrelation applied to the standardized [squared] residuals.

	FTSG	FTLG	FTSE	FTSG	FTLG	FTSE
	Panel A: Dynamic Conditional Correlation (DCC)			Panel B: Constant correlation (CC)		
$\hat{\alpha}_1$	-0.002	-0.019	0.044*	0.002**	0.003	0.032***
MPC	0.041***	0.134**	0.279***	-0.007	0.028**	0.012**
IndexChg	-0.519***	-0.707***	-0.228*	-0.618***	0.040	-0.824***
$QEDUM$	-0.003	-0.058	0.053	-0.038*	-0.225***	0.002
$QTDUM$	0.012**	-0.057	0.016	-0.078**	0.021	0.011*
$QTInt$	-2.464	-14.167	-7.731	-18.429	0.029	-3.142
$QEInt$	1.197***	9.789***	0.431	5.245***	-10.142	0.151
$\hat{\beta}_{1,1}$	0.077***	-0.109	0.205*	-0.112***	-0.153	0.041***
$\hat{\beta}_{1,2}$	-0.028*	0.143*	-0.103	-0.007	0.089	-0.008
$\hat{\beta}_{1,3}$	-0.032*	-0.031	0.337***	0.041	0.122*	-0.007
$\hat{\beta}_{1,4}$	0.018	0.044	-0.022	0.141***	-0.090	0.005
$\hat{\beta}_{1,5}$	-0.042***	-0.116	0.202*	0.061	-0.052	-0.007
$\hat{\beta}_{2,1}$	-0.014***	0.023	0.032	-0.012***	-0.029	0.018
$\hat{\beta}_{2,2}$	0.002	-0.040**	0.050**	-0.003*	-0.025**	0.018
$\hat{\beta}_{2,3}$	-0.004	-0.050**	0.013	-0.004**	-0.047***	0.043***
$\hat{\beta}_{2,4}$	0.003	0.010	0.094***	0.0001	-0.026**	0.060***
$\hat{\beta}_{2,5}$	0.007***	0.015	-0.026	0.0001	-0.020*	0.018
$\hat{\beta}_{3,1}$	0.0003	0.025**	-0.029	0.0004	0.009	-0.031**
$\hat{\beta}_{3,2}$	-0.0005	-0.004	-0.033*	-0.0001	0.007	-0.019
$\hat{\beta}_{3,3}$	-0.004***	0.000	-0.066***	-0.003**	-0.003	-0.022*
$\hat{\beta}_{3,4}$	-0.002	-0.019*	0.013	0.001	0.004	0.001
$\hat{\beta}_{3,5}$	0.003*	0.031***	-0.019	0.003***	0.024***	-0.013
$\widehat{\omega}$	0.021***	3.097***	4.503***	0.005***	0.352***	2.501***
$\hat{b}$	0.008***	0.053***	0.113***	0.0060***	0.030***	0.100***
$\hat{c}$	0.988***	0.921***	0.857***	0.991***	0.963***	0.874***
MPC	0.104	-1.828	-5.954	-0.008	-1.637	-3.365
$QEDUM$	-0.010***	2.923***	-1.851	0.001	0.076	0.406
$QTDUM$	-0.002	-0.307	-0.655	0.034***	1.568***	1.525**
$QTInt$	-0.153***	1.283	-11.045***	-0.293***	-7.430*	-10.879***
$QEInt$	-0.016***	-2.436***	4.204*	-0.002	0.291	1.040
Log-L	Dynamic Conditional Correlation Parameters			Constant Conditional Correlations		
$\hat{a}$	0.009***			FTSG	0.66***	-0.232***
$\hat{b}$	0.324***			FTLG	-0.170***	
Log-L	-4681.17			-8408.7671		
Q(10)	48.70	48.87	50.69	45.20	47.48	47.07
$Q^2(10)$	10.43	56.61	39.85	10.55	55.57*	44.39

5.4.3. Results of Persistence in Variance and Correlation Processes

The results focus on how QE ($\hat{\varphi}_{1,i,i}$) and QT ($\hat{\varphi}_{1,i,i}$) phases influence the persistence of volatility in the short-term gilt index (FTSG), long-term gilt index (FTLG), and FTSE 100 index (FTSE). The significance of these variables highlights the role of QE and QT in shaping the duration of volatility shocks across different markets.

The negative φ_1 coefficient for FTSG implies that QE phases shorten the duration of volatility shocks in the short-term gilt market. This finding aligns with the portfolio balance channel of monetary policy, where QE reduces market uncertainty by injecting liquidity and anchoring yields, particularly for short-term instruments that are more sensitive to liquidity conditions. The significant negative effect of φ_1 on FTSE highlights QE's stabilizing role in equity markets. By increasing liquidity and reducing systemic risk, QE lowers the persistence of volatility in equities, allowing markets to recover more quickly from shocks. This finding supports the risk-taking channel, where lower yields during QE drive investors into equities, promoting stability by improving market confidence. For FTLG, φ_1 is not statistically significant, indicating that QE phases do not significantly affect the persistence of volatility in long-term gilts. This could reflect the structural nature of long-term bonds, where expectations about future interest rates and macroeconomic conditions dominate the effects of QE phases.

The coefficient φ_2, representing the QT dummy, is significant and negative only for FTSE, indicating that QT phases reduce the persistence of volatility in equity markets. The negative φ_2 coefficient for FTSE suggests that QT phases stabilize equity markets by reducing the persistence of volatility shocks. As QT withdraws excess liquidity, it discourages speculative behaviour and promotes normalization in the stock market. This finding reflects the normalization effect of QT, where markets transition to more fundamental-driven dynamics as excess liquidity is removed. For both FTSG and FTLG, φ_2 is not significant, indicating that QT phases do not significantly impact the persistence of volatility in short- or long-term gilts. This may be due to the bond market's reliance on broader macroeconomic and interest rate expectations, which outweigh the direct liquidity effects of QT phases. Our findings are in line with the results of Steeley (2015) who found for QE1,2and3, that persistence declines, but that now we have found this more broadly across all phases of QE and also for QT.

Table 79: Time-varying Persistence in Volatility and Correlation

This table contains the estimated persistence coefficients $\varphi_{j,i,m}$,from the model, $\mathrm{R}_{\mathrm{i,t}} = \alpha_{\mathrm{i,1}} + \alpha_{\mathrm{i,2}}\mathrm{MPC}_{\mathrm{t}} + \alpha_{\mathrm{i,3}}\mathrm{IndexChg}_{\mathrm{t}} + \alpha_{\mathrm{i,4}}\mathrm{QEDUM}_{\mathrm{t}} + \alpha_{\mathrm{i,5}}\mathrm{QTDUM}_{\mathrm{t}} + \alpha_{\mathrm{i,6}}\mathrm{QTInt}_{\mathrm{t}} + \alpha_{\mathrm{i,7}}\mathrm{QEInt}_{\mathrm{t}} + \sum_{\mathrm{k=1}}^{5}\sum_{\mathrm{i=1}}^{3}\beta_{\mathrm{i,k}}\mathrm{R}_{\mathrm{i,t-k}} + \varepsilon_{\mathrm{i,t}}, \varepsilon_{i,t}|\Omega_{t-1}\sim N(0,h_{i,t})$, and $h_{i,t} = \omega_{i,i} + b_{i,i}\varepsilon_{t-1}^2 + c_{i,i}h_{i,t-1} + \varphi_{j,i,i}(QEDUM_t + QTDUM_t)\varepsilon_{t-1}^2 + \gamma_{i,i,1}MPC_t + \gamma_{i,i,2}QEDUM_t + \gamma_{i,i,3}QTDUM_t + \gamma_{i,i,4}QTInt_t + \gamma_{i,i,5}QEInt_t$, *and* $h_{i,m,t} = \rho_{i,m}\sqrt{h_{i,t}h_{m,t}}$, where $R_{i,t}$ is the return at time t on index i, $i \in$ {FTSG,FTLG,FTSE} as defined in Table 75. Estimated parameters are indicated by a caret, and ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The variable $\mathrm{MPC}_{\mathrm{t}}$ is a dummy variable taking the value unity on days of MPC meetings and is zero otherwise, and $\mathrm{IndexChg}_{\mathrm{t}}$is a dummy variable that controls for the effects of quarterly changes to the bond index constituents. $\mathrm{QEInt}_{\mathrm{t}}$ is a measure of the intensity of QE activity on these purchase auction days and is measured as the purchase amount of each gilt divided by the total amount of its outstanding issuance (both in term of face value) for each day of reverse auction activity, expressed as a percentage, A value of 1.0 means that the amount of gilts sold on that day equals the entire outstanding face value of that gilt. $\mathrm{QEDUM}_{\mathrm{t}}$ is a dummy variable that takes value one during the phases of QE, and $\mathrm{QTDUM}_{\mathrm{t}}$ is a dummy variable that takes value one during the phases of QT. $\mathrm{QTInt}_{\mathrm{t}}$ is a measure of the intensity of QT activity on these sale auction days, expressed as a percentage, measured by the amount sold for each gilt is divided by the total amount of gilts that are still outstanding (face value) for each gilt sale day ; a value of 1.0 indicates that the entire outstanding stock of the gilt was sold, representing the maximum possible intensity for that sale. Log-L is the maximized value of the (multivariate) log-likelihood function (assuming Normally distributed errors) using the Levenberg-Marquardt non-linear optimization algorithm. Q(10) [$Q^2(10)$] is the Box-Ljueng test for autocorrelation applied to the standardized [squared] residuals. SBC is the Schwartz Bayesian criterion.

	Panel A: Constant Conditional Correlation		
(CC)	FTSG	FTLG	FTSE
FTSG		0.66***	-0.17***
FTLG			-0.23***
$\hat{\varphi}_{1,i,i}$	-0.001***	-0.002	-0.011**
$\hat{\varphi}_{2,i,i}$	-0.0003	-0.002	-0.014**
LogL	-8401.48		
Q(10)	44.66	47.02	47.03
$Q^2(10)$	12.04	54.50*	44.62

5.5. Conclusion

This chapter provides a comprehensive analysis of how monetary policy interventions, specifically quantitative easing (QE) and quantitative tightening (QT), influence financial markets. By examining short-term bonds (FTSG), long-term bonds (FTLG), and equities (FTSE) through univariate and multivariate GARCH models, the findings highlight key distinctions between asset classes and the nuanced effects of these interventions on returns and volatility.

The results reveal significant differences in risk-return dynamics across asset classes. Stocks (FTSE) exhibit higher returns, consistent with their elevated risk levels, while short-term (FTSG) and long-term bonds (FTLG) show lower returns, reflecting their safer profiles. Monetary policy announcements, captured through the Monetary Policy Committee (MPC) variable, have no significant impact on returns, suggesting that markets are efficient and able to anticipate and integrate policy decisions. This aligns with the Efficient Market Hypothesis, which posits that asset prices incorporate publicly available information promptly.

Quantitative easing exhibits mixed effects across asset classes. QE phases have a negative impact on long-term bond returns (FTLG), likely due to reduced yields caused by central bank purchases. However, the intensity of QE positively influences long-term bond returns, reflecting increased demand and localized price increases during active interventions. Short-term bonds (FTSG) and equities (FTSE) are less affected, indicating that QE's impact is more pronounced in long-term bond markets. In contrast, QT phases positively influence short-term bond returns, reflecting reinvestment opportunities and yield adjustments, while exerting significant negative effects on long-term bonds due to heightened sensitivity to liquidity withdrawals and interest rate changes. The intensity of QT further exacerbates these negative effects on long-term bonds, while also weakly affecting short-term bonds and equities.

The analysis of volatility dynamics highlights the stabilizing role of QE and the normalizing role of QT. QE phases reduce volatility in short-term bonds by anchoring yields and enhancing market confidence, while QE intensity further lowers bond market volatility but marginally increases equity volatility through risk-taking behaviour. QT phases, on the other hand, introduce uncertainty and increase volatility across markets during the transition, reflecting the disruptive nature of liquidity withdrawal. However, QT intensity stabilizes markets by systematically reducing excess liquidity, mitigating speculative activity, and promoting normalization.

Market interdependencies and time-varying correlations further illuminate the transmission mechanisms of monetary policy. Lagged returns across indices reveal significant cross-market linkages driven by portfolio adjustments and macroeconomic factors. The negative correlation between equities and bonds suggests hedging opportunities, while the dynamic correlations captured by the DCC model underscore the importance of considering time-varying market reactions, particularly during QT phases.

Overall, the findings underscore the complex and differentiated impacts of monetary policy interventions on financial markets. QE generally stabilizes markets by reducing systemic risks and providing liquidity, while QT fosters a return to fundamental pricing but introduces transitional volatility. The study highlights the importance of distinguishing between passive and active QT, as active QT plays a more pronounced stabilizing role (which is determined by the intensity of sale). These insights contribute to a deeper understanding of monetary policy transmission mechanisms, offering valuable implications for policymakers, investors, and researchers navigating unconventional policy environments.

5.6. Appendix

Figure 53: Estimated Conditional Variance Processes from univariate GARCH models

The figure displays the estimated conditional variance processes for the Short-Term Gilt Index, Long-Term Gilt Index, and the FTSE 100 Share Index using univariate GARCH models. The x-axis covers the sample period from 2000 to 2024, and the y-axis indicates the conditional variance, expressed in squared percentage returns (% return) ^2, reflecting time-varying volatility. Each panel includes shaded bands corresponding to Quantitative Easing (QE) and Quantitative Tightening (QT) sub-periods, allowing for a comparison of volatility dynamics across different monetary policy regimes. The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive.

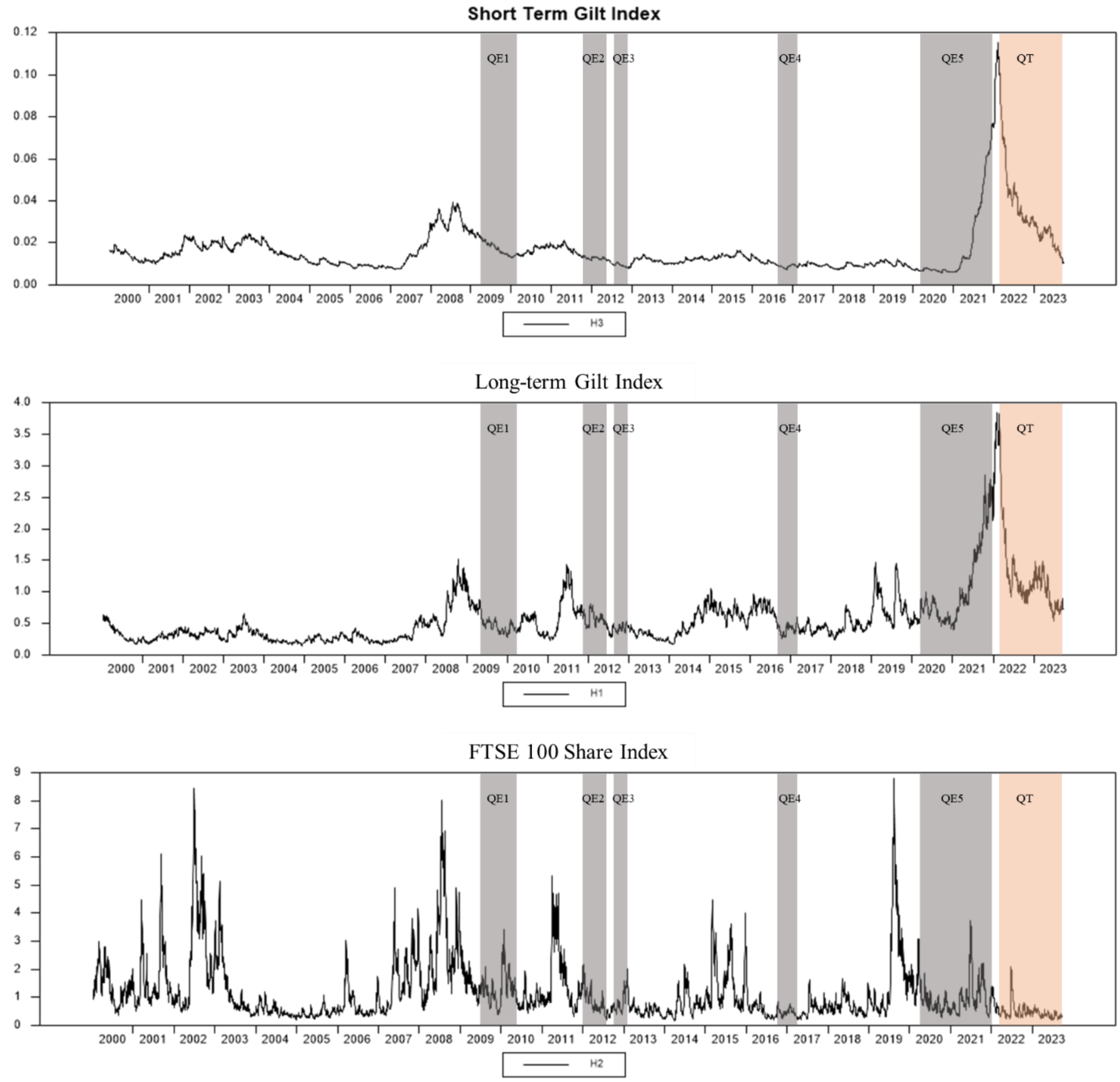
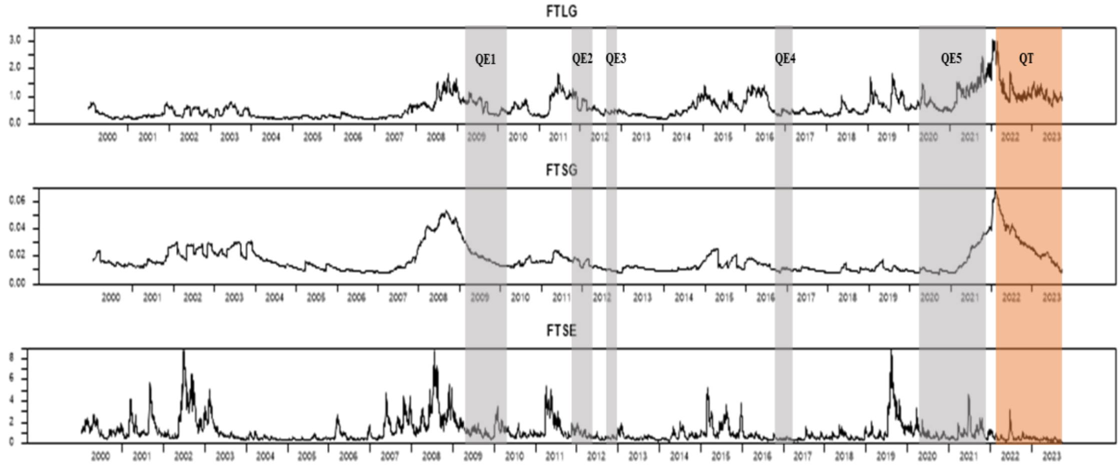


Figure 54: Estimated Conditional Variances from multivariate DCC GARCH

presents the estimated conditional variances a multivariate DCC-GARCH model. The **y-axes** in the first three panels represent **conditional variances of daily percentage returns**. The **x-axis** across all panels indicates **time**, covering the period from **2000 to 2024**. The sub-periods are: Pre-crisis - the start of the sample until the collapse of the Northern Rock bank on September 14th 2007; Crisis – September 14th 2007 to March 10th 2009; QE1 – March 11th 2009 to 26th January 2010; Post-QE1 – 27th January 2010 to 9th October 2011; QE2and3 – 10th October 2011 to 30th October 2012; Post QE3 – 31st October 2012 to 7th August 2016; QE4 – 8th August 2016 to 1st February 2017; Post QE4 – 2nd February 2017 to 18th March 2020; QE5 – 19th March 2020 to 15th December 2021; Post QE5 – 16th December 2021 to 2nd February 2022; QT-Passive– 3rd February 2022 to 4th May 2022; QT-Active – 5th May 2022 to 31st December 2022. Since the Post-QE5 episode lasts for a short time and only includes two auctions, it is combined with QT-Passive.



Conditional Correlations

5.6.1. Code in R for outlier treatment

```
fix_outliers <- function(returns2, indexchg, C = 10) {
  returns <- returns2
  outlier_count <- 0
  repeat {
    # Step 1: Fit GARCH
    garch_spec <- ugarchspec(variance.model = list(garchOrder = c(1,1)),
                            mean.model = list(armaOrder = c(0,0)),
                            distribution.model = "norm")
    garch_fit <- ugarchfit(spec = garch_spec, data = returns)

    # Step 2: Calculate h and z
    h_t <- sigma(garch_fit)^2
    z_t <- returns^2 - h_t
    n <- length(z_t)

    # Step 3: Calculate sigma_a for standardizing omegas
    sigma_a <- numeric(n)
    for (t in 1:n) {
      z_t_excluded <- z_t[-t]
      sigma_a[t] <- sd(z_t_excluded)
    }

    # Step 4: calculate tau test
    tau <- z_t / sigma_a
    outlier_t <- which.max(abs(tau))

    if ((abs(tau[outlier_t]) >= C)) {
      outlier_count <- outlier_count + 1

      old_value <- returns[outlier_t]
      new_value <- sign(returns[outlier_t]) * sqrt(h_t[outlier_t])
      returns[outlier_t] <- new_value

      print(paste("Outlier #", outlier_count, ": Found at point", outlier_t,
            "with tau test value", tau[outlier_t],
            "— correcting. Old value:", old_value, "New value:", new_value))
    } else {
      break
    }
```

```
  }

  return(returns)
}
```

5.6.2. Code in RATS for CC Model

```
compute gstart=6,gend=6190
compute n=3
dec vect[series] y(n) u(n)
dec vect[frml] resid(n)
set y(1) = FTLG
set y(2) = FTSG
set y(3) = FT100

dec vect b0(n) b1(n) b2(n) b3(n) b4(n) b5(n) b6(n) b7(n) b8(n) b9(n) $
        b10(n) b11(n) b12(n) b13(n) b14(n) b15(n) b16(n) b17(n) b18(n) $
        b19(n) b20(n) b21(n)
nonlin(parmset=meanparms) b0 b1 b2 b3 b4 b5 b6 b7 b8 b9 b10 b11 b12 b13 $
                       b14 b15 b16 b17 b18 b19 b20 b21
do i=1,n
   frml resid(i) = (y(andi)-b0(andi)-b1(andi)*FTLG{1}-b2(andi)*FTLG{2}-b3(andi)*FTLG{3}-
b4(andi)*FTLG{4} $
   -b5(andi)*FTLG{5}-b6(andi)*FTSG{1}-b7(andi)*FTSG{2}-b8(andi)*FTSG{3}-b9(andi)*FTSG{4} $
   -b10(andi)*FTSG{5}-b11(andi)*FT100{1}-b12(andi)*FT100{2}-b13(andi)*FT100{3}-b14(andi)*FT100{4}
$
   -b15(andi)*FT100{5}-b16(andi)*MPC-b17(andi)*QEDUM-b18(andi)*QEINT-b19(andi)*INDEXCH $
   -b20(andi)*QTDUM-b21(andi)*QTINT)
end do i

nlsystem(parmset=meanparms,resids=u) gstart gend resid## NL6. NONLIN Parameter B0(1) Has Not Been
Initialized. Trying 0


compute rr=%sigma

declare series[symm] h uu
declare symm hx(n,n)
declare vect ux(n)

gset h  * gend = rr
gset uu * gend = rr

declare frml[symm] hf

frml logl = $
   hx = hf(t) , $
   %do(i,1,n,u(i)=resid(i)) , $
   ux = %xt(u,t), $
   h(t)=hx, uu(t)=%outerxx(ux), $
   %logdensity(hx,ux)

dec symm qc(n-1,n-1)
dec vect vcv(n) vbv(n) vav(n)

function hfcccgarch time
 type symm hfcccgarch
 type integer time
 do i=1,n
   compute hx(i,i)=vcv(i)+vav(i)*h(time-1)(i,i)+vbv(i)*uu(time-1)(i,i)
```

```
  do j=1,i-1
    compute hx(i,j)=qc(i-1,j)*sqrt(hx(j,j)*hx(i,i))
  end do j
end do i
 compute hfcccgarch=hx
 end

frml hf = hfcccgarch(t)
nonlin(parmset=garchparms) vcv vbv vav qc
compute vcv=%xdiag(rr),vbv=%const(0.80),vav=%const(0.05),qc=%const(0.0)
maximize(parmset=meanparms+garchparms,pmethod=simplex,piters=10) logl gstart gend

dec symm qc(n-1,n-1)
dec vect vcv(n) vbv(n) vav(n) vdv(n) vev(n) vfv(n) vgv(n) vhv(n) viv(n) $
 vjv(n)
function hfcccgarch time
type symm hfcccgarch
type integer time
do i=1,n
compute hx(i,i)=vcv(i)+vav(i)*h(time-1)(i,i)+vbv(i)*uu(time-1)(i,i)+vdv(i)*mpc(time) $
   +vev(i)*qedum(time)+vfv(i)*qeint(time)+vgv(i)*qtdum(time)+vhv(i)*qtint(time)
do j=1,i-1
compute hx(i,j)=qc(i-1,j)*sqrt(hx(j,j)*hx(i,i))
end do j
end do i
compute hfcccgarch=hx
end

frml hf = hfcccgarch(t)
nonlin(parmset=garchparms) vcv vbv vav qc vdv vev vfv vgv vhv
compute vdv=vev=vfv=vgv=vhv=%const(0.0)
maximize(parmset=meanparms+garchparms,pmethod=simplex,piters=10,iters=400) logl gstart gend
```

5.6.3. Code in RATS for DCC Model

```
compute gstart=6,gend=6190
compute n=3
dec vect[series] y(n) u(n)
dec vect[frml] resid(n)
set y(1) = FTLG
set y(2) = FTSG
set y(3) = FT100

dec vect b0(n) b1(n) b2(n) b3(n) b4(n) b5(n) b6(n) b7(n) b8(n) b9(n) $
        b10(n) b11(n) b12(n) b13(n) b14(n) b15(n) b16(n) b17(n) b18(n) $
        b19(n) b20(n) b21(n)
nonlin(parmset=meanparms) b0 b1 b2 b3 b4 b5 b6 b7 b8 b9 b10 b11 b12 b13 $
                          b14 b15 b16 b17 b18 b19 b20 b21
do i=1,n
   frml resid(i) = (y(andi)-b0(andi)-b1(andi)*FTLG{1}-b2(andi)*FTLG{2}-b3(andi)*FTLG{3}-
b4(andi)*FTLG{4} $
   -b5(andi)*FTLG{5}-b6(andi)*FTSG{1}-b7(andi)*FTSG{2}-b8(andi)*FTSG{3}-b9(andi)*FTSG{4} $
   -b10(andi)*FTSG{5}-b11(andi)*FT100{1}-b12(andi)*FT100{2}-b13(andi)*FT100{3}-b14(andi)*FT100{4}
$
   -b15(andi)*FT100{5}-b16(andi)*MPC-b17(andi)*QEDUM-b18(andi)*QEINT-b19(andi)*INDEXCH $
   -b20(andi)*QTDUM-b21(andi)*QTINT)
end do i
```

```
nlsystem(parmset=meanparms,resids=u) gstart gend resid

compute rr=%sigma

declare series[symm] h uu q
declare symm hx(n,n)
declare symm qx(n,n)
declare vect ux(n)

gset h  * gend = rr
gset uu * gend = rr
gset q * gend = rr

declare frml[symm] hf
declare frml[symm] qf

frml logl = $
   hx = hf(t) , $
   qx = qf(t) , $
   %do(i,1,n,u(i)=resid(i)) , $
   ux = %xt(u,t), $
   h(t)=hx, uu(t)=%outerxx(ux), q(t)=qx, $
   %logdensity(hx,ux)

dec vect vcv(n) vbv(n) vav(n) vdv(n) vev(n) vfv(n) vgv(n) vhv(n) viv(n) vjv(n)

declare symm omega(n,n)
compute omega = rr
nonlin a b

function qcalculate time
   type symm qcalculate
   type integer time
   do i=1,n
   compute qx(i,i) = omega(i,i)*(1-a-b)+a*uu(time-1)(i,i)+b*h(time-1)(i,i)

   do j=1,i-1
   compute qx(i,j) = omega(i,j)*(1-a-b)+a*uu(time-1)(i,j)+b*h(time-1)(i,j)
   compute qcalculate=qx
end

function hfcccgarch time
   type symm hfcccgarch
   type integer time
   do i=1,n
   compute hx(i,i) = vcv(i)+vav(i)*h(time-1)(i,i)+vbv(i)*uu(time-1)(i,i)
   do j=1,i-1
   compute hx(i,j)=sqrt(hx(j,j)*hx(i,i))*qx(i,j)/sqrt(qx(i,i)*qx(j,j))

   end do j
   end do i
   compute hfcccgarch=hx
end

frml hf = hfcccgarch(t)
frml qf = qcalculate(t)
nonlin(parmset=garchparms) vcv vbv vav a b
compute vcv=%xdiag(rr),vbv=%const(0.05),vav=%const(0.8)
compute b=0.80,a=0.1
maximize(parmset=meanparms+garchparms,pmethod=simplex,piters=10,iters=400) logl gstart gend
```

```
function qcalculate time
   type symm qcalculate
   type integer time
      do i=1,n
      compute qx(i,i) = (1-a-b)*omega(i,i)+a*uu(time-1)(i,i)+b*h(time-1)(i,i)
      do j=1,i-1
      compute qx(i,j) = (1-a-b)*omega(i,j)+a*%xt(u,time-1)(i)*%xt(u,time-1)(j)+b*h(time-1)(i,j)
      end do i
      end do j
   compute qcalculate = qx
end

function hfcccgarch time
   type symm hfcccgarch
   type integer time
   do i=1,n
      compute hx(i,i) = vcv(i)+vav(i)*h(time-1)(i,i)+vbv(i)*uu(time-1)(i,i)+vdv(i)*mpc(time) $
            +vev(i)*qedum(time)+vfv(i)*qeint(time)+vgv(i)*qtdum(time)+vhv(i)*qtint(time)
      do j=1,i-1
      compute hx(i,j)=sqrt(hx(j,j)*hx(i,i))*qx(i,j)/sqrt(qx(i,i)*qx(j,j))
      end do i
      end do j
   compute hfcccgarch=hx
end

frml qf = qcalculate(t)
frml hf = hfcccgarch(t)
nonlin(parmset=garchparms) vcv vbv vav vdv vev vfv vgv vhv a b
compute vdv=vev=vfv=vgv=vhv=%const(0.0)
maximize(parmset=meanparms+garchparms,pmethod=simplex,piters=10,iters=400) logl gstart gend
```

6. Conclusion

This thesis has examined the effects of unprecedented monetary policy interventions, specifically Quantitative Easing (QE) and Quantitative Tightening (QT), on the UK gilt market, focusing on government debt issuance costs, auction demand dynamics, and financial market volatility. By employing robust empirical models and theoretical frameworks, it has provided a comprehensive understanding of how these unconventional policies influence sovereign debt markets and investor behaviour.

The findings from the first chapter reveal that QE phases, despite providing a willing buyer for gilts, were associated with higher issuance costs. This was largely driven by increased volatility and auction sizes, which placed pressure on GEMM inventories and reduced demand at prevailing prices. The results support supply-driven theories, such as the "inventory adjustment" mechanism, where the need to absorb increased issuance temporarily lowers gilt prices, raising issuance costs. Furthermore, segmentation analysis showed that long-term gilts, being more sensitive to interest rate risk, were disproportionately affected by volatility, while mechanisms like the Post Auction Option Facility (PAOF) proved effective in mitigating costs for short- and medium-term gilts by improving liquidity.

The second chapter builds on these insights by analyzing the determinants of auction demand, as measured by the bid-to-cover ratio. The results confirm that QE phases increased demand for gilts, particularly during QE4 and QE5. This aligns with the "liquidity channel" theory, where central bank purchases increase market confidence and reduce perceived risks, enhancing demand. However, periods of financial instability and larger auction sizes negatively impacted demand, reflecting heightened risk aversion and capacity constraints among GEMMs. The positive influence of PAOF and primary dealer turnover underscores the importance of liquidity and active market participation in sustaining demand. Yet, the contrasting findings for volatility—with stock market volatility having no significant impact—highlight the need for a more nuanced understanding of market-specific drivers of investor behavior.

The third chapter shifts the focus to financial market volatility, exploring how QE and QT influence risk dynamics across asset classes. Consistent with the findings of the first two chapters, QE phases reduced bond market volatility, particularly for short-term gilts, while increasing equity volatility, reflecting risk-taking behavior by investors. In contrast, QT phases heightened volatility across markets, with QT-active phases providing some stabilization by systematically reducing excess liquidity. These results support theories of "monetary policy transmission," where unconventional interventions influence asset prices through liquidity effects and risk premium adjustments. The increased volatility during QT also aligns with the "uncertainty hypothesis," highlighting the market's sensitivity to liquidity withdrawals and interest rate expectations.

The thesis findings contribute to the broader literature on sovereign debt markets by integrating theories of auction design, liquidity effects, and risk dynamics. The results emphasize the interplay between supply-side factors (e.g., auction size, maturity segmentation) and demand-side considerations (e.g., investor confidence, market liquidity) in shaping issuance costs and demand. For instance, the higher issuance costs during QE phases can be explained by the interaction of supply-induced pressure on inventories and the signaling effects of monetary policy easing. Similarly, the increase in demand during QE phases highlights the dual role of central bank purchases in reducing risk perceptions and enhancing market liquidity.

The analysis of volatility provides additional insights into the transmission mechanisms of monetary policy. The stabilizing effects of QE on bond markets align with the "portfolio rebalancing" channel, where central bank interventions lower yields and encourage investors to shift toward riskier assets. Conversely, the transitional volatility during QT underscores the challenges of liquidity normalization and the importance of clear communication to manage market expectations.

The findings have significant practical implications for policymakers and debt managers. The UK Debt Management Office (DMO) can reduce issuance costs by optimizing auction sizes, particularly for short-term gilts, and enhancing primary dealer activity to sustain demand. Liquidity-enhancing mechanisms like PAOF should be leveraged across maturity segments to mitigate the impact of volatility. During periods of QE, balancing the volume of issuance with the absorptive capacity of GEMMs is crucial to avoid excessive pressure on inventories. Similarly, during QT phases, gradual and predictable liquidity withdrawals can help stabilize markets and reduce transitional volatility.

This thesis underscores the complex and interconnected effects of QE and QT on the UK gilt market, demonstrating how unconventional monetary policies shape issuance costs, demand dynamics, and market volatility. By linking these findings through robust theoretical and empirical frameworks, it provides a holistic understanding of the challenges and opportunities in sovereign debt management during periods of economic turbulence. The results offer actionable insights for navigating the evolving landscape of monetary policy and its implications for financial stability, market behavior, and investor confidence.

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