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Robert Czech,(1) Shiyang Huang,(2) Dong Lou(3) and Tianyu Wang(4)

Abstract

We study investor trading behaviour and yield patterns in the UK government bond market during the recent Covid crisis. We show that the yield spike in mid-March 2020 was accompanied by heavy selling of gilts by UK-based insurance companies and pension funds (ICPFs), which we argue was an indirect result of the US dollar's global prominence. Non-US institutions invest a large portion of their capital in dollar assets and hedge their dollar exposures by selling dollars forward through FX derivatives. In crisis periods, dollars appreciate against other currencies. To meet margin calls on these short-dollar FX positions, non-US institutions sell their domestic safe assets, thereby contributing to the yield spikes in domestic markets.

Key words: Covid crisis, gilt yields, variation margin, FX derivatives, global reserve currency, currency hedging.

JEL classification: F31, G11, G12, G15, G22, G23.

(1) Bank of England. Email: robert.czech@bankofengland.co.uk
(2) University of Hong Kong. Email: huangsy@hku.hk
(3) London School of Economics and CEPR. Email: d.lou@lse.ac.uk
(4) Tsinghua University. Email: wangty6@sem.tsinghua.edu.cn

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Bank of England, Threadneedle Street, London, EC2R 8AH
Email enquiries@bankofengland.co.uk

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1 Introduction

Government bonds issued by developed countries (e.g., US, Germany, UK) are viewed by many as the safest and most liquid financial assets. In crisis periods, these high-quality assets traditionally experience large buying demand from investors and consequently appreciate in value – a phenomenon labelled "flight to safety" (e.g., Vayanos, 2004). In the recent COVID-19 crisis, however, there was a global selloff of these liquid, safe financial assets. As shown in Figures 1 and 11, the 10-year government bond yields across developed economies rose by more than 50bps in a nine-day window between the 10th and 18th of March 2020.

This surprising observation has inspired a volume of academic research. Much of the existing work focuses on the US Treasury market. Haddad et al. (2021) and Ma et al. (2021), for example, show that open-end mutual funds experienced large outflows and sold more than \$200bn of US Treasuries in the first quarter of 2020 to meet investor redemptions. In the same quarter, foreign investors sold nearly \$300bn and US households nearly \$200bn of US Treasuries. In face of this unprecedented selloff, dealer banks – many of whom were facing binding balance sheet constraints – were unable to quickly absorb the selling pressure (e.g., Duffie, 2020; He et al., 2021). As a result, a large disruption occurred in the US Treasury market in mid-March 2020. The market stabilized only after the emergency intervention by the Federal Reserve – the Fed bought over \$700bn of Treasury securities between the 20th and 31st of March 2020.

We complement these earlier studies by examining investor trading in, and return patterns of, UK government bonds (gilts) during the COVID crisis. Our empirical setting has two main advantages. First, unlike prior research on the US Treasury market that uses low-frequency (monthly or quarterly) investor holding and trading data, we have access to detailed and granular information on every transaction in the UK gilt market. This allows us to examine and delineate exactly what happened in the few days between the 10th and 18th of March 2020: for example, which groups of investors were buying, which groups were selling, by how much, and the associated return effect. Second and more importantly, given the global reserve currency status of the US dollar, the price patterns of US safe assets in crisis periods may not reflect the experience of safe assets in other countries. Consequently, a careful examination of investor trading and return patterns in the UK gilt market during the COVID crisis can provide useful insights for government bonds in other developed, non-US economies.

Our analyses reveal a number of intriguing patterns. First, between March 10th and 18th of 2020, the 10-year gilt yield rose by more than 50bps.[1] Second, this large yield spike was accompanied by heaving selling of two groups of agents in the secondary market: mutual funds sold nearly £4.5bn and insurance companies and pension funds (ICPFs) sold an additional £3.8bn of gilts. At the same time, the UK's Debt Management Office (DMO) issued over £4bn of gilts in the primary market through pre-scheduled auctions. Third, this selling of over £12bn of gilts in a window of seven trading days was entirely absorbed by banks and hedge funds.

The behavior and price impact of mutual funds and issuing authorities in government bond markets are less of a surprise. It is well known from prior research that Treasury issuance (e.g., Lou et al., 2013) and mutual fund flow-induced trading (e.g., Coval and Stafford, 2007; Lou, 2012) can have significant price impact in the secondary market.[2] Our focus is therefore on the activity of insurance companies and pension funds, who are typically passive gilt investors in normal times. We argue and further show that the abnormal trading behavior of insurance companies and pension funds in the COVID period was likely due to the US dollar's global prominence.

As the global reserve currency, the dollar serves two roles and has two advantages: to clear cross-border transactions and to attract investment in dollar denominated assets. Indeed, many non-US institutions invest a large amount of capital in dollar assets, particularly in

[1] We focus on the period up to March 18, because the BoE's Monetary Policy Committee decided to cut the base rate to 0.1% and to increase its holdings of UK government and corporate bonds by £200bn at a special meeting on March 19.

[2] Ma et al. (2021) further show that mutual fund flow-induced selling was partly responsible for the US Treasury market turmoil in the COVID-19 crisis. We show similar results for the UK gilt market in Table A4 of the Internet Appendix.

risky dollar assets. For example, UK insurers at the end of Q4 2019 had total assets of £2tn, nearly £250bn of which was invested in dollar denominated securities (such as stocks and corporate bonds). Not surprisingly, these institutions hedge their dollar exposures using foreign exchange derivatives – by selling USD forward. At the end of Q4 2019, the set of insurers in our sample hedged nearly 50 cents for every dollar of exposure to USD assets.

During the COVID crisis, two forces in particular had a large and negative impact on non-US institutions. First, asset values across the world dropped precipitously, including dollar denominated assets. Second, there was also a liquidity crisis – many investors were scrambling for dollars (the global reserve currency) to pay for bills and clear transactions. Consequently, USD appreciated substantially against other major currencies in this period; for example, the dollar saw a 10% rise against the pound between March 10th and 18th of 2020. As a result of this large foreign exchange rate movement, many UK-based institutions received margin calls on their foreign exchange derivatives holdings. For example, insurance companies and pension funds in our data collectively lost £6.4bn in variation margin (VM) on their FX derivatives holdings.

To meet these margin calls, these institutions had a number of choices: to sell their US holdings (most of which were in risky assets and had fallen significantly in value), to sell their risky UK holdings, and/or to sell their safe UK assets. As highlighted in Ma et al. (2021), investors tend to follow a pecking order of liquidation in crisis periods – that is, to sell their safe and liquid holdings first. Indeed, in the few days between March 10th and 18th, insurance companies and pension funds collectively sold nearly £4bn worth of gilts. A simple cross-sectional analysis suggests that a one-standard-deviation increase in ICPFs' selling is associated with a 30bps increase in long-term gilt yields during the COVID crisis.

In sum, our analyses and findings reveal a novel mechanism through which the reserve currency status of the US dollar can have large impact on non-US government bond yields. Since nearly half of all global financial assets are dollar denominated, non-US institutions invest a large portion of their capital in dollar assets. They then hedge their dollar exposures by selling dollars forward through FX derivatives. In crisis periods, because of the global reserve currency status, the dollar appreciates against other major currencies. Non-US institutions are doubly hurt in these periods – suffering losses from both their dollar investments and FX hedging positions. To meet margin calls, these institutions liquidate their domestic safe assets, thereby contributing to the yield spikes in domestic markets.

Our empirical results and proposed mechanism have useful implications for investors as well as policymakers in all non-US markets, including developed markets. As the costs of investing in foreign assets, especially USD assets, have kept falling in the last few decades, more investors hold dollar denominated assets today than at any time in history. While investors enjoy the diversification benefit of investing globally, we show in this paper a potential downside to this trend – the global reserve currency status of the USD may exacerbate crises in domestic markets through a currency hedging channel.

It is important to note, however, that UK-based ICPFs remained solvent and were able to meet their obligations during the COVID-19 crisis. Nevertheless, the question arises whether policymakers could help ICPFs to better manage their liquidity in crisis periods by enhancing the sector's liquidity preparedness and by making margin calls more predictable, e.g. through more transparent margin calculations for both centrally cleared and non-centrally cleared derivatives. Such measures may help to prevent a similar liquidity drain in the ICPF sector in future downturns, and reduce the likelihood of an adverse impact of US dollar appreciation on prices and liquidity in non-US government bond markets.

Related Literature. Our study contributes to several strands of the literature. First, our study is related to some contemporaneous studies on the economic mechanisms underlying the COVID-19 treasury market turmoil in March 2020. For example, Duffie (2020) emphasizes frictions in the market-making mechanisms, whereas Schrimpf et al. (2020) highlight the role of margin spirals. He et al. (2021) focus on the interaction between leveraged investors who obtain financing via repo and dealers who are subject to balance sheet constraints. Ma et al. (2021) compare the liquidity management behaviors of fixed-income mutual funds and commercial banks during the COVID-19 pandemic, and find that fixed-income mutual funds are more aggressive than commercial banks in selling liquid assets, i.e. treasuries. Huang et al. (2021a) directly link the liquidity management behaviors of fixed-income mutual funds to the excess return comovement in Treasury securities.

We complement this strand of literature by at least three aspects. First, we depart from the literature by focusing on the UK gilt market - the fourth largest government bond market in the world. Rather than focusing on mutual funds, we focus on ICPFs and find that the trading of ICPFs also plays an important role in the government bond market turmoil during the COVID crisis. Second, unlike prior research on the US treasury market that uses low-frequency (monthly or quarterly) investor holding and trading data, we have access to detailed and granular information on every transaction in the UK gilt market. This allows us to examine and disentangle exactly what happened in the few days between 10th and 18th of March 2020 – who were buying, who were selling, by how much, and the associated price effect. Third, our granular data allows us to pin down the driving forces for the trading of different investor types during the COVID period. While we also find that mutual funds' selling of gilts was largely driven by investor redemptions, we uncover a novel channel for ICPFs' selling of gilts. As the dollar appreciated against sterling, many ICPFs had to meet large VM calls on their extensive USD FX hedging positions. This liquidity demand induced investors to heavily sell their domestic government bonds, thereby contributing to the turmoil in the UK gilt market. Our study does not only provide a detailed anatomy of the turmoil in the gilt market during the COVID crisis, but it also uncovers an unintended consequence of holding dollar assets.[3]

Our paper is also related to the large body of literature on the role of institutional trading in generating price impacts and financial fragility. Edmans et al. (2012) and Lou (2012) show that fund flow-induced trading has a significant price impact on stock markets. Anton and

[3]Our findings also echo recent evidence from other legislations such as the eurozone or Norway, where ICPFs were also exposed to large VM calls due to their substantial FX hedging positions (e.g., Alstadheim et al., 2021; Rousová et al., 2020).

Polk (2014) show that fund common ownership forecasts return correlation between stocks. Greenwood and Thesmar (2011) estimate the correlation between fund flows among mutual funds and link the correlated fund flows to stock return comovement. Huang et al. (2021b) document that the correlation between fund flows among mutual funds contributes to a large portion of the variance-covariance in anomaly returns.

The remainder of this paper is organized as follows. Section 2 describes the various data sources and presents summary statistics. Section 3 presents our main results. Section 4 provides further robustness checks and suggestive global evidence for our proposed mechanism. We conclude in Section 5.

2 Data Sources and Summary Statistics

In this section, we first introduce the various data sources in Section 2.1. We then present summary statistics in Section 2.2.

2.1 Data Sources

We collect data from various sources. First, we collect supervisory data on asset and derivatives holdings of UK insurers subject to the Solvency II Directive. Second, we obtain transaction-level data on government bond and repo trades from the regulatory MiFID II and Sterling Money Market databases, respectively. Finally, we add data on estimated variation margin calls based on derivatives data from the regulatory EMIR Trade Repository Data; as well as data on mutual fund flows from Morningstar. The various data sources are described in more detail below.

First, we use granular data on asset and derivatives holdings of insurance companies regulated by the UK's Prudential Regulation Authority (PRA) and subject to the Solvency II Directive. Insurers within scope of the Solvency II Directive are required to submit annual and quarterly returns, with the exception of some smaller firms with quarterly waivers. The reports include detailed information on the holdings of a given insurer, such as the instrument's ISIN, quantity, currency, issuer country, asset category and rating. For derivatives holdings, the reports also include trade-level information on the identity of the counterparty, underlying security, notional amount, derivative category (e.g. FX forward), and swap delivered/received currencies. We consider both unit-linked and non-unit-linked portfolios. The data are available from 2016 Q1.

To analyse trading in the gilt market, we use the transaction-level MiFID II database, maintained by the UK's Financial Conduct Authority (FCA). The MiFID II data provide detailed reports of all secondary-market trades of UK-regulated firms, or branches of UK firms regulated in the European Economic Area (EEA). Given that all dealers are UK-domiciled and hence FCA-regulated institutions, our data cover virtually the entire trading activity in the gilt market. Each transaction report contains information on the transaction date and time, ISIN, execution price, transaction size, and the legal identities of the buyer and seller. We allocate investors to an investor group (e.g. hedge funds) using a best-endeavour sectoral classification, which is naturally subject to uncertainties (e.g. allocation of insurer with asset management arm).

Derivative users are required to settle changes in the market value of the trade at least once a day via variation margin (VM). For each trading day in March 2020, VM calls of individual insurers, hedge funds, and mutual funds are estimated using the EMIR Trade Repository Data on interest rate swaps, forward rate agreements, inflation swaps, and cross-currency basis swaps. The estimates are based on the methodology used in Bardoscia et al. (2021). We observe derivatives trades meeting one of the following conditions: i) one of the counterparties is a UK-regulated entity, ii) any leg of the trade is denominated or paid for in Sterling, iii) the trade is cleared by a UK supervised CCP, or iv) the underlying security is a UK entity.

Finally, we collect international government bond yields and foreign exchange rates from Bloomberg. To obtain mutual fund flows, we first use the MiFID II bond transaction data to find the legal entity identifiers (LEIs) of all asset managers that are active in the gilt market. Out of these >2,000 LEIs, we are able to manually match more than 900 LEIs to the corresponding fund ISINs in Morningstar. Finally, we collect the daily fund flows for these fund ISINs from Morningstar.

2.2 Summary Statistics

The summary statistics for our sample are presented in Table 1. Panel A shows that the total dollar denominated asset holdings of UK insurers on average amount to £257bn in the period from 2016 Q1 to 2020 Q4 (out of their total capital of around £2tn, see Figure 2), and the average USD hedging notionals add up to more than £50bn across all insurers. For other non-dollar denominated foreign assets, the corresponding figures are £237bn and £71bn, respectively. As shown in Figure 3, more than half of insurers' dollar denominated assets are typically equity investments, but the share of corporate and government bond investments increased steadily in recent years.

Panel B of Table 1 shows the average daily gilt yield changes for different periods in March 2020. During the 'flight to safety' period (March 1-9), yields decreased by 4.3bps each day on average in the gilt market. On the contrary, during the 'dash for cash' (March 10-18), yields sharply increased by 8.2bps each day on average. The average yield change across both periods amounts to a 2.4bps daily increase. As shown in Figure 1, even the highly liquid 10-year gilt reached a level of almost 80bps on March 18 – a jump of more than 50bps in only nine days since March 10.

Summary statistics on the average daily estimated VM calls for the period March 1-18 are presented in Panel C of Table 1. On the sectoral level, VM calls were most pronounced for insurance companies and pension funds with an average daily VM call of £16m per investor. For mutual funds and hedge funds, the figures are notably smaller with £6m and £4m, respectively. When analysing the different types of derivatives, it becomes evident that the largest share of VM calls can be attributed to FX derivatives with an average VM call of £8m per day and investor, followed by interest rate derivatives (£5m) and inflation swaps (£3m). As shown in Figures 6 and 7, VM calls increased sharply during the dash for cash, having remained relatively subdued (or even negative) during the flight to safety.

Panel D of Table 1 presents the average investor order flows in the gilt market for the period March 1-18. Importantly, both the ICPF sector as well as the mutual fund sector were on average net sellers of gilts, while non-dealer banks and hedge funds helped to stabilise the market by being net buyers.

3 Main Results

We describe our main results in this section. In Section 3.1, we describe the FX hedging behavior of UK insurance companies. In Section 3.2, we link insurers' USD FX hedging positions to their VM demands in March 2020. In Section 3.3, we show that these VM demands induced ICPFs to sell gilts in this period. In Section 3.4, we examine how the ICPF selling pressure affected gilt yields.

3.1 USD Asset Holdings and FX Hedging Positions

In this section, we focus on UK insurers and examine their FX derivative hedging behavior. When institutional investors invest in foreign assets, they tend to hedge their foreign asset portfolios against currency risks. In fact, many countries have regulations that restrict currency risks and provide guidance for FX hedging (see the detailed institutional background in Liao and Zhang, 2021). In the UK market, insurers are regulated by the UK's Prudential Regulation Authority (PRA) and are subject to the Solvency II Directive. The Solvency II Directive also incentivizes UK insurers to hedge their currency risks.

To get a better idea of their FX hedging behavior, we start by describing UK insurers' derivative holdings. As shown in Figure 4, UK insurers predominantly hold interest rate swaps and FX derivatives. This is not surprising, given that insurers can use interest rate swaps to increase their portfolio duration with limited upfront payments. Moreover, insurers use FX derivatives to hedge the currency risk of their foreign asset holdings. In Figure 5, we focus on insurers' FX derivatives and find that the most heavily hedged foreign currency is the US dollar, which is consistent with the finding in Figure 2 that dollar denominated assets are predominant in insurers' foreign asset portfolios.

We now turn to examine to what extent UK insurers hedge the currency risk of their foreign asset holdings. Specifically, we run the following panel regression:

$$FX\ Derivative\ Hedging\ Position_{i,j,t} = \beta_0 + \beta_1 \times Foreign\ Asset\ Holdings_{i,j,t} + FE + \varepsilon_{i,j,t}, \tag{1}$$

where $FX\ Derivative\ Hedging\ Position_{i,j,t}$ is insurer i's net notional FX derivative holdings in currency j/GBP in quarter t, and $Foreign\ Asset\ Holdings_{i,j,t}$ is insurer i's total asset holdings in foreign currency j in quarter t. We follow Sialm and Zhu (2021) and add insurer fixed effects, time fixed effects, and insurer×time fixed effects. We calculate standard errors clustered by time.

Table 2 reports the results. We have several important findings. First, as shown in Panel A (incl. all foreign asset holdings), we find that UK insurers indeed hedge a large part of the currency risks of their foreign assets holdings. For example, when a UK insurer holds £1 in a particular foreign currency (e.g, USD), the insurer hedges £0.26 of the currency risk on average. This result is robust to the inclusion of insurer fixed effects, time fixed effects, and insurer×time fixed effects. The second observation is that insurers hedge their US dollar assets to a larger extent. Specifically, in Panel B, we split the sample into non-USD assets and a sample with only USD assets. We find that UK insurers hedge more of the currency risk of their US dollar assets. That is, as shown in Columns (1)–(3), when a UK insurer holds £1 in a foreign currency (excl. USD), it hedges £0.20 of the currency risk. In contrast, as shown in Columns (4)–(5), when a UK insurer holds £1 in dollar denominated assets, it hedges £0.50 of the currency risk.

3.2 FX Hedging and Variation Margin

In this section, we link USD FX hedging positions to estimated variation margins of UK insurers in March 2020. As shown in Figure 1, the 10-year gilt yield rose by more than 50bps in a nine-day window between the 10th and 18th of March 2020. In the same time window, GBP depreciated by about 10% relative to USD. Although several mechanisms may have contributed to the simultaneous spike in gilt yields and dollar appreciation, the striking correlation between these two series during the COVID crisis serves as motivation for the following empirical analyses. Unsurprisingly, when USD appreciated relative to GBP, UK insurers who were net hedgers of USD incurred large losses on their USD FX hedging positions.

To formally show how insurers' USD FX hedging positions affect VM demands, we focus on the window of between the 1st and 18th of March 2020. We first run the following regression:

$$VM_{i,t} = \beta_0 + \beta_1 \times Indicator\_Top_i + \varepsilon_{i,t}, \tag{2}$$

where $VM_{i,t}$ is insurer i's estimated variation margin on its FX derivatives on day t (positive values mean that the investor was a net payer of VM, and negative values mean that the investor was a net receiver of VM), and $Indicator\_Top_i$ is an indicator variable equal to one if a particular insurance company's USD FX derivative hedging position is above the sample median at the end of 2019Q4, and zero otherwise. We use robust standard errors.

Table 3 reports the results. We find strong evidence that UK insurers with more pronounced USD FX hedging positions at the end of 2019 received variation margin on their FX derivatives during the flight to safety (March 1-9) on average, but then had to pay variation margin on their FX derivatives during the dash for cash (March 10-18). Specifically, as shown in Column (1) of Panel A, during the flight to safety, an insurer with a USD FX hedging position above the sample median at the end of 2019 received about £15m more in VM per day than those with USD FX hedging positions below the sample median. This is consistent with Figure 1, which shows that GBP slightly appreciated relative to USD in the period from March 1-9. In contrast, as shown in Column (2) of Panel A, during the dash for cash, an insurer with a USD FX hedging position above the sample median at the end of 2019 paid about £62m more in VM per day than those with USD FX derivative hedging position below the sample median. Again, this is consistent with Figure 1, which shows that GBP depreciated significantly relative to USD in the period from March 10-18. In Column (3), we use an indicator variable to confirm that the reversed patterns in the dash for cash period are statistically significant. Furthermore, we illustrate this pattern in Figure 8.[4]

To further explore the economic magnitude of the impact of USD FX hedging positions on insurers' FX VM demands, we run the following regression:

$$VM_{i,t} = \beta_0 + \beta_1 \times USD\ FX\ Holdings_i + \varepsilon_{i,t}, \tag{3}$$

where $USD\ FX\ Holdings_i$ is insurer i's USD FX hedging position at the end of 2019. Intuitively, β_1 estimated from Equation (3) describes how much FX variation margin a particular insurer needs to pay or receive for each pound of its USD FX hedging positions held at the end of 2019.

Panel B of Table 3 reports the results. First, as shown in Column (1), the point estimate of β_1 is -10bps (t-statistics $= -4.969$), suggesting that insurers receive £0.001 for each £1 of their USD FX hedging positions during the flight to safety. Second, as shown in Column (2), the point estimate of β_1 is 50bps (t-statistics $= 4.574$), suggesting that an insurer needs to pay £0.005 for every £1 of its USD FX hedging positions during the dash for cash. It is also worth noting that the variation in FX VM can largely be explained by insurers' USD

[4]In Figure 8, for comparison, we also plot the dynamics of estimated VM demands on interest rate swaps and inflation swaps separately for the top/bottom group of USD FX hedgers, and we do not observe a similar pattern for either instrument. Furthermore, in Table A1 of the Internet Appendix, we again use the regression specification in Equation (2), but use VM demands on interest rate swaps and inflation swaps as a placebo test. We find no significant difference in interest rate / inflation swap VM for insurers with USD FX hedging positions above the sample median at the end of 2019, and those with USD FX hedging positions below the sample median. This highlights that the increased FX VM demands on insurers was not due to other confounding factors, but can indeed be attributed to insurers' USD FX hedging positions.

FX derivative hedging positions at the end of 2019. More precisely, as shown in Column (1), the R^2 in the regression of FX variation margin on USD FX hedging positions is about 0.63. Such a high R^2 confirms that a large part of insurers' FX VM can be attributed to their USD FX hedging positions.

3.3 Variation Margin and Gilt Trading

After having established the relation between FX hedging positions and variation margins, we now investigate the impact of variation margins on gilt trading volumes and prices.

As shown in the previous section, the ICPF sector is a net payer of VM during the dash for cash period with a total VM of £11.78bn. In general, insurers have various options to meet their VM demands, for example by using their cash holdings, by borrowing via repo, or by selling risky or safe assets, for instance government bonds. As shown in Figure 9, we find that the ICPF sector sold £3.84bn in the government bond market in the dash for cash period. In addition, we also find that mutual funds were net sellers of gilts, while non-dealer banks and hedge funds were net buyers during the dash for cash. To test the statistical pattern, we now examine whether VM demands affect ICPF trading in the gilt market by conducting the following panel regression:

$$Net\ Volume_{i,t} = \beta_0 + \beta_1 \times VM_{i,t} + FE + \epsilon_{i,t} \tag{4}$$

where the dependent variable is the daily gilt net trading volume and the main independent variable is the daily VM demand on each institution i. Positive (negative) values mean that the investor was a net payer (receiver) of VM. We cover the whole COVID period (March 1-18), but also run the regression separately for the flight to safety (March 1-9) and dash for cash periods (March 10-18). The indicator variable $Dash\ for\ Cash$ is equal to one if the date of the observation is between March 10-18, and zero otherwise. VM(>0) truncates the independent variable, VM, at zero, and equals the original value when VM is positive, and zero otherwise. VM(<0) is equal to the original value when VM is negative, and zero otherwise. Both gilt net trading volume and the variation margins are adjusted using the inverse hyperbolic sine method (see, e.g., Bellemare and Wichman, 2020). We also control for time fixed effects.

Table 4 reports the results of these regressions. Panel A shows the results for the entire COVID period (March 1-18), and also separately for the flight to safety (March 1-9) and dash for cash (March 10-18) periods. Across all specifications, VM has a significant negative effect on net gilt trading volumes in the dash for cash period. In other words, ICPFs sell government bonds when they have to meet their VM calls. For example, as shown in Panel A, during the dash for cash, the OLS coefficient estimate of VM is -0.142 and significant at the 5% level. The results remain significant when including time fixed effects. For comparison, the coefficient is positive but insignificant during the flight to safety period, when ICPFs' VM demands are negative (i.e. they were net receivers of VM). Furthermore, we explore the asymmetric effect of VM demands. To this end, we split the sample based on the sign of the VM demand (VM payer (VM>0) and VM receiver (VM<0)), and find that ICPFs sell government bonds when they have to pay VM, but do not buy bonds when they are net receivers of VM.[5]

In addition, we also analyse whether the impact on gilt trading volumes is more pronounced for VM demands on FX derivatives, interest rate swaps, or inflation swaps during the dash for cash period. Panel B of Table 4 reports the results of these regressions. We find that VM on FX derivatives has the largest impact on gilt trading volumes, with the most negative coefficient (-0.382) and highest significance level (1%). The coefficient estimate is negative but only weakly significant (10%) for VM on interest rate swaps, although the VM payments on interest rate swaps have a similar magnitude compared to the VM calls on FX derivatives during the dash for cash, as shown in Figure 7. A potential reason could be that

[5]In Table A2 of the Internet Appendix, we analyse the impact of VM demands on gilt trading volumes of mutual funds and hedge funds. We find that VM demands had no significant impact on the gilt trading volumes of these two investor types.

ICPFs may choose to terminate interest rate swaps straightaway, while they still need FX derivatives to hedge their foreign currency exposures. Lastly, the coefficient estimate for VM on inflation swaps is insignificant, which is unsurprising given that the magnitude of VM demands on inflation swaps is relatively small, as shown in Figure 7.

Variation Margin and Gilt Trading: Bond Level Analysis

We further explore the impact of VM demands on gilt trading using a regression specification on the institution-bond level, which enables us to account for the heterogeneity in liquidity across gilts. We conduct the following regression:

$$Net\ Volume_{i,j,t} = \beta_0 + \beta_1 \times VM_{i,t} + \beta_2 \times VM_{i,t} \times Liquid\ Bond_j + FE + \epsilon_{i,j,t} \tag{5}$$

where the dependent variable is the daily gilt net trading volume at the institution (i)-bond (j) level and the main independent variable is the daily VM demand for each institution. The indicator variable $Liquid\ Bond_j$ is equal to one if a gilt's trading volume is above the sample median, and zero otherwise. We also include time and bond fixed effects.

Table 5 reports the results of these regressions. Similar to the institution-level analysis, we find that VM demands have a significant negative effect on net gilt trading volumes during the dash for cash period. Furthermore, we also find that the coefficient for the whole COVID period is negative and significant, while it remains insignificant for the flight to safety period. In the cross-section, we find that our estimates are more pronounced for more liquid bonds. For instance, in Column (5) of Panel A of Table 5, the coefficient is -0.037 (t-statistics = -3.25) for VM, and the coefficient is -0.042 (t-statistics = -1.862) for the interaction term. In other words, the magnitude is twice as high for more liquid gilts. The results remain robust when we include fixed effects. Panel B of Table 5 reports the regression results for VM demands on different derivative types. Similar to the regression results at the institution-level, only VM on FX derivatives has a strongly significant effect on gilt trading volumes, while VM demands on interest rate swaps only have a weakly significant effect on gilt trading. Again, the net selling pressure is more pronounced for relatively liquid gilts.

3.4 Gilt Trading and Yields

In this section, we turn to the impact of the selling pressure on gilt prices. We start with a regression of gilt yield changes on investors' contemporaneous daily order flows. We examine the price impact of ICPFs as well as that of other investor types. We estimate the following regression at the daily frequency:

$$\Delta Yield_{j,t} = \beta_0 + \beta_1 \times Trading_{s,j,t} + Controls + \epsilon_{s,j,t} \tag{6}$$

where the dependent variable $\Delta Yield_{j,t}$ is the yield change in each gilt maturity bucket j from the previous trading day (t-1) to the current trading day (t). The main independent variables are order flows in maturity bucket j of insurance companies and pension funds (*ICPF Trading*), mutual funds (*Mutual Fund Trading*), non-dealer banks (*Non-Dealer Bank Trading*), and hedge funds (*Hedge Fund Trading*). We calculate the order flow as the total net trading volume (buy volume minus sell volume) of a given investor type scaled by the total trading volume across all investor types. The list of control variables includes the logarithm of the total client trading volume and gilts' time-to-maturity. In order to mitigate the noise in the trading of individual bonds, we calculate equally-weighted yields and order flows across all gilts in each maturity bucket (1-3 years, 3-5 years, 5-7 years, 7-10 years, 10-15 years, 15+ years, and index-linked).

Panel A of Table 6 reports the results of these regressions. The results show that order flows of ICPFs are negatively and significantly correlated with gilt yield changes in the period of March 1-18. The coefficient estimate (-0.382) is also economically large: a one standard deviation increase (decrease) of ICPF order flow is associated with a gilt yield decrease (increase) of 3.2bps (8.27% $\times$ 0.382) per day. As shown in Table 1, the average daily yield change is 4.34bps during the flight to safety period and 8.23bps during the dash for cash period. Mutual fund trading is also highly correlated with gilt yield changes with a coefficient of -0.224 (significant at the 1% level). Therefore, both ICPFs and mutual funds demanded liquidity in the gilt market in March 2020. Non-dealer bank and hedge funds were net liquidity providers, and the coefficients for the order flows of these two sectors are both positive and significant.

We further compare the price impact during the COVID period to the previous, non-stress period (January to February 2020). We estimate the following specification:

$$\begin{aligned} \Delta Yield_{j,t} = \beta_0 + \beta_1 \times Trading_{s,j,t} + \beta_2 \times Trading_{s,j,t} \times COVID\ Period_t \\ + \beta_3 \times COVID\ Period_t + Controls + \epsilon_{s,j,t} \end{aligned} \tag{7}$$

where $COVID\ Period_t$ is an indicator variable equal to one if the trading day is in the period of March 1-18, and zero otherwise. Panel B of Table 6 reports the results of these regressions. During the non-stress period, no sector has a significant impact on prices. For instance, the coefficients from Column (1) to (4) are all very small and statistically insignificant. In contrast, the coefficients on the interaction term $Trading_{s,j,t} \times COVID\ Period_t$ are significant for all sectors.

Short-term vs Long-term Gilts

As highlighted in Figure 1, the 10-year gilt yield changes were dramatically larger compared to the 2-year gilt yield changes, which is consistent with global evidence that short-term bonds were less affected during the dash for cash period. In this subsection, we further examine the variation in trading intensity and contemporaneous yield changes for short-term and long-term gilts. We divide all gilts in our sample into two groups. The short-term gilt subsample includes gilts with a residual time-to-maturity of less than or equal to five years; the long-term gilt subsample includes the remaining gilts. Table 7 reports the results of these regressions. As shown in Panel A, daily order flows of ICPFs weakly affect future gilt yields of short-term gilts, with a coefficient of -0.187 (t-statistics = -2.169). The effects are insignificant for mutual funds and the non-dealer bank sector. In striking contrast, the results are much stronger for all sectors in the case of long-term gilts. For instance, for the ICPF sector the coefficient is -0.547 (t-statistics = -3.387) and almost three times larger than the one in the short-term gilt sample. For the order flow of mutual funds, the coefficient is -0.473 (t-statistics = -3.564) in the long-term gilt sample, while it is -0.081 (t-statistics = -1.045) in the short-term gilt sample.

Long-term Gilt Yield Changes

A natural question is whether investors' price impact is temporary or permanent. If the correlation between investors' order flows and gilt prices is driven by short-term liquidity needs, then we should observe a mean reversal of gilt prices over time. On the contrary, if the correlation is driven by superior information on future gilt price movements, then we should observe a permanent effect on prices (e.g., Czech et al., 2021). To answer this important question, we regress future gilt yield changes at different horizons on ICPF order flows:

$$\Delta Yield_{j,k} = \beta_0 + \beta_1 \times Trading_{s,j,t} + Controls + \epsilon_{j,k} \tag{8}$$

where the dependent variable, $\Delta Yield_{j,k}$ is the yield change from day t-1 to day t+k, with k=1, 5, 10, 15, 21. Table 8 reports the results of these regressions. Across all samples, we find a very strong price reversal pattern within 21 trading days. As can be seen from Panel A, the coefficients are negative at day t+1 and day t+5, but they become positive at day t+10 and thereafter. At day t+21, the cumulative yield change is statistically not different from zero for short-term gilts, while it is positive and significant for the long-term gilt sample. In sum, these strong reversal patterns confirm the price pressure channel.

Repo Trading

In addition to selling government bonds directly, an alternative way to meet VM calls is via borrowing through the repo market. In Figure 10, we report the total borrowing and lending activities of ICPFs and other sectors during the COVID period. In total, ICPFs' net borrowing increases by £2bn in the flight to safety period of March 1-9 (£4bn additional borrowing – £2bn additional lending), and increases by another £2bn in the dash for cash period of March 10-18. Hedge funds and mutual funds were also net borrowers during this period.

4 Additional Analyses

In this section, we first conduct additional robustness checks in Section 4.1. We then present suggestive global evidence for our proposed mechanism in Section 4.2.

4.1 Robustness checks

In the price impact section, we calculate equally weighted average yield changes and order flows in a given maturity bucket. A significant concern is the potential bias induced by the relatively small trading volumes of some gilts. Therefore, we conduct several robustness checks. First, we use value-weighted average yield changes and order flows. The results are very similar to those in Table 6, as shown in Panel A of Table A3 in the Internet Appendix. Furthermore, our results remain robust if we use more granular maturity buckets, or if we allocate all gilts trading on day t into a single bucket.

In addition, to compare the price impact during the COVID period and previous calmer periods, we classify January and February 2020 as a 'non-stress period' in Section 3.4. For robustness, we also compare the regression results for the crisis period to the 2019 sample, and our results remain robust. The results are reported in Panel B of Table A3 in the Internet Appendix.

4.2 Global Evidence

Thus far, we have shown that dollar denominated asset holdings of the UK insurance sector may have an unintended consequence for the gilt market. More precisely, UK insurers hold large amounts of dollar denominated assets and they are incentivized to hedge the inherent currency risk. When the dollar appreciated relative to pound sterling (between March 10-18), UK insurers needed to pay a large amount of variation margin on their FX hedging positions, which in turn induced them to sell gilts and thereby contribute to the rapid increase of gilt yields.

Since it is common practice for investors worldwide (e.g., insurance companies and pension funds) to hedge currency risks, other non-US institutions might have also faced large losses on their FX hedging positions, similar to UK insurers. In turn, this might have also induced these non-US institutions to sell their domestic assets, particularly domestic government bonds. In Figure 11, we focus on G10 countries other than the UK, and we plot the exchange rate between the dollar and the local currency of these countries, as well as the domestic 2-year and 10-year government bond yields. Surprisingly, we find that the correlation between the exchange rate and government bond yields in other G10 countries is similar to the dynamics in UK: when the local currency depreciated relative to the dollar between March 10th and 18th, the domestic government bond yields increased dramatically. Admittedly, many potential economic mechanisms could drive the patterns in Figure 11, but the similarity between Figure 11 and Figure 1 suggests that there are at least some common economic forces at play.

5 Conclusion

In this paper, we study investor trading and return patterns of UK government bonds during the recent COVID crisis. Our analyses reveal a number of intriguing patterns. Between March 10th and 18th of 2020, the 10-year gilt yield rose by more than 50bps. This large yield spike was accompanied by the selling activity of three groups of agents: HM Treasury auctioned and issued over £4bn of gilts, mutual funds sold nearly £4.5bn and ICPFs sold an additional £3.8bn of gilts. We conjecture and empirically show that the abnormal trading behavior of insurance companies and pension funds was a result of the US dollar's global dominance.

Our findings reveal a novel mechanism through which the reserve currency status of the US dollar can have a large impact on non-US government bond yields. Since nearly half of all global financial assets are dollar denominated, non-US institutions invest a large portion of their capital in dollar assets. They then hedge their dollar exposures by selling dollars forward through FX derivatives. In crisis periods, dollars appreciate against most other currencies. To meet margin calls, non-US institutions sell off their domestic safe assets, thereby contributing to the yield spikes in domestic markets. Our results and proposed mechanism have important implications for investors and policymakers in virtually all non-US countries, both developed and developing, as long as investors in these countries invest in dollar denominated assets.

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Table 1: Summary Statistics

This table reports the summary statistics for our sample. Panel A reports the UK insurance companies' quarterly aggregate foreign assets holdings and their quarterly aggregate FX derivative hedging positions, the sample period is from 2016Q1 to 2020Q4. Panel B reports the summary statistics of the daily gilt yield changes from March 1-18 2020. Panel C reports the summary statistics of daily estimated variation margins per investor for different investor types (e.g., insurance companies and pension funds (ICPF), mutual funds, and hedge funds), and the sample period is March 1-18 2020. Panel C also reports the daily variation margin per investor for FX derivatives, interest rate swaps, and inflation swaps. Panel D reports the summary statistics of daily order flows of different investor types. The order flow of a particular investor type is the total net trading volume (buy volume minus sell volume) of this investor type scaled by the total trading volume across all types of investors.

		Mean	Std.Dev	Q25	Q50	Q75
Panel A: Insurers' Holdings and Hedging Positions						
Foreign Asset Holdings (£ bn) (excl. USD)		236.65	19.53	222.41	238.26	247.34
FX Derivative Hedging Positions (£ bn) (excl. USD)		70.78	62.78	26.17	35.26	128.80
USD Asset Holdings (£ bn)		257.30	27.07	243.89	252.85	277.06
USD Derivative Hedging Positions (£ bn)		52.60	33.58	31.08	48.97	75.16
Panel B: Gilt Yield Change						
△Yield (March 1—18) (bps)		2.43	8.82	-3.47	-0.40	7.62
△Yield (March 1—9) (bps)		-4.34	4.00	-5.22	-3.66	-1.90
△Yield (March 10—18) (bps)		8.23	7.60	3.37	7.20	11.72
Panel C: Estimated Daily Variation Margin per Investor						
By sector (£m)	ICPF	16.023	165.061	-1.63	0.23	5.79
	Mutual Fund	6.196	75.33	-0.09	0	0.15
	Hedge Fund	4.026	24.629	-1.33	0	1.68
By derivative type (£m)	FX	7.986	44.745	-0.090	0.000	0.320
	Interest Rate	5.416	157.371	-1.820	0.000	5.330
	Inflation	2.621	16.882	-0.060	0.000	1.560
Panel D: Gilt Trading						
Order Flow	ICPF	-2.15%	8.27%	-7.51%	-2.01%	2.10%
	Mutual Fund	-2.02%	9.09%	-6.90%	-2.15%	2.84%
	Non-dealer Bank	0.49%	3.63%	-2.19%	0.20%	1.98%
	Hedge Fund	2.60%	13.06%	-2.78%	2.10%	10.53%

Table 2: Foreign Assets Holdings and Derivative Hedging Positions

This table reports results of regressions of insurers' net FX hedging positions on asset holdings in the corresponding currency. The sample period is from 2016Q1 to 2020Q4, and the observations are at the insurer-currency-quarter level. The dependent variable is an insurer's net FX Notional in a foreign currency in each quarter. The key independent variable is total asset holdings in the given foreign currency. Panel A includes insurers' asset holdings and FX derivative hedging positions across all foreign currencies. Columns (1)-(3) of Panel B include insurance companies' asset holdings and FX derivative hedging positions across all currencies excluding USD, columns (4)-(5) of Panel B only include insurers' asset holdings and FX derivative hedging positions in USD. *T*-statistics are based on standard errors clustered by time and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Foreign Asset Holdings and Hedging Positions

	(1)	(2)	(3)
DepVar:	Derivative Hedging Positions		
Foreign Asset Holdings	0.262***	0.262***	0.262***
	(9.811)	(9.805)	(9.896)
Insurer FE	Yes	Yes	No
Time FE	No	Yes	No
Insurer×Time FE	No	No	Yes
No. of Obs	17,740	17,740	17,518
Adj. R^2	0.191	0.191	0.139

Panel B: Comparison between Hedging Position for USD Assets and Assets in Other Currencies

	Excluding USD Assets			USD Assets Only	
	(1)	(2)	(3)	(4)	(5)
DepVar:	Derivative Hedging Positions				
Foreign Asset Holdings	0.202***	0.202***	0.201***	0.542***	0.507***
	(9.572)	(9.609)	(9.710)	(3.446)	(3.002)
Insurer FE	Yes	Yes	No	Yes	Yes
Time FE	No	Yes	No	No	Yes
Insurer×Time FE	No	No	Yes	No	No
No. of Obs.	15,994	15,994	15,549	1,737	1,737
Adj. R^2	0.061	0.062	0.042	0.782	0.782

Table 3: USD Hedging Positions and Variation Margin

This table reports results of regressions of estimated variation margins of insurance companies on USD FX derivative hedging positions. The sample period is from March 1st to 18th 2020, and the observations are at the insurer-day level. The dependent variable is an insurer's variation margin (VM) demands on FX derivatives on each day (in £ million). Positive (negative) values mean that the investor was a net payer (receiver) of VM. In Panel A, the key independent variable is $Indicator\_Top$, which is an indicator variable equal to one if the insurer's USD FX hedging position is above the sample median at the end of 2019Q4, and zero otherwise. $Dash\_for\_Cash$ is an indicator variable equal to one if the date of the observation is between March 10-18 2020, and zero otherwise. In Panel B, the key independent variable is an insurer's USD FX hedging position at the end of 2019Q4. T-statistics are based on robust standard errors and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Comparison of Variation Margin Between Top and Bottom USD Hedgers

	Flight to safety period (March 1 - 9)	Dash for cash period (March 10 - 18)	March 1 - 18
	(1)	(2)	(3)
DepVar:	VM	VM	VM
$Indicator\_Top$	-14.975**	61.512***	-14.975***
	(-2.599)	(3.085)	(-2.605)
$Dash\_for\_Cash$			76.487***
			(3.680)
$Indicator\_Top \times Dash\_for\_Cash$			16.453***
			(2.859)
No. of Obs.	74	105	179
Adj. R^2	0.062	0.067	0.150

Panel B: USD FX Derivative Holdings and Variation Margin

	Flight to safety period (March 1 - 9)	Dash for cash period (March 10 - 18)	March 1 - 18
	(1)	(2)	(3)
DepVar:	VM	VM	VM
USD FX Derivative Holdings	-0.001***	0.005***	-0.001***
	(-4.969)	(4.574)	(-4.981)
$Dash\_for\_Cash$			0.006***
			(5.604)
USD FX Derivative Holdings $\times Dash\_for\_Cash$			26.855***
			(3.710)
No. of Obs.	74	105	179
Adj. R^2	0.625	0.537	0.582

Table 4: Variation Margin and Government Bond Trading Volume

This table reports the results of panel regressions of the gilt net trading volume of insurance companies and pension funds (ICPFs) on estimated daily variation margins. The sample period is from March 1st to 18th 2020, and the observations are at the investor-day level. The dependent variable is the daily gilt net trading volume (in £ million) of a particular ICPF. In Panel A, the main independent variable is the daily variation margin (in £ million) of the given ICPF, and this variable is denoted as VM. Positive (negative) values mean that the investor was a net payer (receiver) of VM. The indicator variable $Dash\_for\_Cash$ is equal to one if the date of the observation is between March 10-18, and zero otherwise. VM(>0) truncates the independent variable, VM, at zero, and equals the original value when VM is positive and zero otherwise. VM(<0) is equal to the original value when VM is negative and zero otherwise. In Panel B, the main independent variables include a given ICPF's daily variation margin separately for FX derivatives, interest rate swaps, and inflation swaps. The dependent variable and the variation margins are adjusted using the inverse hyperbolic sine method. We also control for time fixed effects. *T*-statistics are based on robust standard errors and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Variation Margin (VM) and Net Gilt Trading Volume

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	March 1 - 18	Flight to safety period (March 1 - 9)	Dash for cash period (March 10 - 18)		March 1 - 18			
DepVar:	Net Gilt Trading Volume							
VM	-0.044	0.130	-0.142**	-0.163**	0.131	0.11	0.268	0.095
	(-0.855)	(1.547)	(-2.138)	(-2.278)	(1.551)	(1.261)	(1.239)	(0.651)
VM × $Dash\_for\_Cash$					-0.273***	-0.273**		
					(-2.544)	(-2.412)		
VM(>0) × $Dash\_for\_Cash$							-0.742***	
							(-3.041)	
VM(<0) × $Dash\_for\_Cash$								0.215
								(1.020)
$Dash\_for\_Cash$					-0.071			
					(-0.252)			
Time FE	No	No	No	Yes	No	Yes	Yes	Yes
No. of Obs.	435	174	261	261	435	435	237	84
Adj. R^2	0.002	0.021	0.025	0.046	0.024	0.047	0.127	0.118

Panel B: Variation Margin on Different Derivative Groups and Net Gilt Trading Volume					
	(1)	(2)	(3)	(4)	(5)
	Dash for cash period (March 10 - 18)				
DepVar:	Net Gilt Trading Volume				
VM on FX Derivatives	-0.382***			-0.406***	-0.420***
	(-3.820)			(-4.233)	(-4.115)
VM on Interest Rate Swaps		-0.096		-0.120*	-0.132*
		(-1.414)		(-1.865)	(-1.919)
VM on Inflation Swaps			0.008	0.036	0.092
			(0.068)	(0.314)	(0.743)
Time FE	No	No	No	No	Yes
No. of Obs.	261	261	261	261	261
Adj. R^2	0.066	0.011	0.000	0.085	0.106

Table 5: Variation Margin and Government Bond Trading Volume: Bond-Level Analysis

This table reports the results of panel regressions of gilt net trading volume of insurance companies and pension funds (ICPFs) on variation margins. The sample period is from March 1-18 2020, and the observations are at the investor-bond-day level. The dependent variable is the daily gilt net trading volume (in £ million) of a given ICPF. In Panel A, the main independent variable is the daily variation margin (in £ million) of the given ICPF, and this variable is denoted as VM. Positive (negative) values mean that the investor was a net payer (receiver) of VM. In Panel B, the main independent variables include a given ICPF's daily variation margin separately for FX derivatives, interest rate swaps, and inflation swaps. The indicator variable, $Liquid\_Bond$ is equal to one if the particular gilt's trading volume is above the sample median, and zero otherwise. The dependent variables and the variation margins are adjusted using the inverse hyperbolic sine method. We also control for time and bond fixed effects. *T*-statistics are based on robust standard errors and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Variation Margin (VM) and Net Gilt Trading Volume						
	(1)	(2)	(3)	(4)	(5)	(6)
	March 1 - 18	Flight to safety period (March 1 - 9)	Dash for cash period (March 10 - 18)			
DepVar:	Net Gilt Trading Volume					
VM	-0.036***	0.003	-0.055***	-0.058***	-0.037***	-0.036***
	(-4.457)	(0.238)	(-5.131)	(-5.041)	(-3.250)	(-2.899)
VM × $Liquid\_Bond$					-0.042*	-0.049**
					(-1.862)	(-2.186)
$Liquid\_Bond$					-0.001	
					(-0.006)	
Time FE	No	No	No	Yes	No	Yes
Bond FE	No	No	No	Yes	No	Yes
No. of Obs.	2,615	1,019	1,596	1,596	1,596	1,596
Adj. R^2	0.007	0.000	0.017	0.112	0.019	0.115

Panel B: Variation Margin (VM) on Different Derivative Groups and Net Gilt Trading Volume				
	(1)	(2)	(3)	(4)
	Dash for cash period (March 10 - 18)			
DepVar:	Net Gilt Trading Volume			
VM on FX Derivatives	-0.102***	-0.094***	-0.043*	-0.037
	(-5.153)	(-4.233)	(-1.828)	(-1.408)
VM on Interest Rate Swaps	-0.045***	-0.047***	-0.020*	-0.019
	(-4.096)	(-4.080)	(-1.712)	(-1.552)
VM on Inflation Swaps	0.031	0.056	-0.015	0.016
	(1.068)	(1.242)	(-0.464)	(0.336)
VM on FX Derivatives			-0.150***	-0.141***
$\times$ $Liquid\_Bond$			(-3.650)	(-3.325)
VM on Interest Rate Swaps			-0.063***	-0.069***
$\times$ $Liquid\_Bond$			(-2.691)	(-2.912)
VM on Inflation Swaps			0.102*	0.091
$\times$ $Liquid\_Bond$			(1.712)	(1.527)
$Liquid\_Bond$			0.187	
			(1.495)	
Time FE	No	Yes	No	Yes
Bond FE	No	Yes	No	Yes
No. of Obs.	1,596	1,596	1,596	1,596
Adj. R^2	0.026	0.117	0.041	0.130

Table 6: Order Flows and Government Bond Yields

This table reports the results of panel regressions of bond yield changes on contemporaneous order flows of ICPFs, mutual funds, non-dealer banks and hedge funds. The sample period in Panel A is from March 1-18 2020; the sample period in Panel B is from January 1 - March 18 2020. The observations are at the gilt maturity bucket-day level. The dependent variable is the yield change from the previous trading day to the current trading day. The main independent variables are order flows of insurance companies and pension funds (ICPF $\text{Trading}_{j,t}$), mutual funds (Mutual Fund $\text{Trading}_{j,t}$), non-dealer banks (Non-Dealer Bank $\text{Trading}_{j,t}$), and hedge funds (Hedge Fund $\text{Trading}_{j,t}$). We calculate the order flow of a particular investor type as the total net trading volume (buy volume minus sell volume) of this investor type scaled by the total trading volume across all types of investors. We then calculate the equal-weighted average yield change and order flows within each maturity bucket (1-3 years, 3-5 years, 5-7 years, 7-10 years, 10-15 years, 15+ years, and index-linked). In Panel B, $COVID\_Period_t$ is an indicator variable, which equals one if the day is between March 1-18 2020, and zero otherwise. Control variables include the logarithm of total client volume and gilts' time-to-maturity. T-statistics are based on robust standard errors and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: March 1 - 18				
	(1)	(2)	(3)	(4)
DepVar:		$\triangle\text{Yield}_{j,t}$		
ICPF $\text{Trading}_{j,t}$	-0.382***			
	(-3.725)			
Mutual Fund $\text{Trading}_{j,t}$		-0.224***		
		(-3.008)		
Non-Dealer Bank $\text{Trading}_{j,t}$			0.559***	
			(2.732)	
Hedge Fund $\text{Trading}_{j,t}$				0.128**
				(2.236)
$\text{Log(volume)}_{j,t}$	-0.030	-0.017	-0.013	-0.013
	(-1.639)	(-0.868)	(-0.634)	(-0.639)
$\text{Maturity}_{j,t}$	0.003*	0.002	0.002	0.002
	(1.840)	(1.231)	(1.218)	(1.265)
Constant	0.635	0.359	0.276	0.280
	(1.639)	(0.888)	(0.651)	(0.653)
No. of Obs.	91	91	91	91
Adj. R^2	0.135	0.070	0.070	0.052

Panel B: January - March 18				
	(1)	(2)	(3)	(4)
ICPF Trading$_{j,t}$	-0.019			
	(-0.806)			
Mutual Fund Trading$_{j,t}$		-0.019		
		(-0.960)		
Non-Dealer Bank Trading$_{j,t}$			-0.021	
			(-0.376)	
Hedge Fund Trading$_{j,t}$				-0.019
				(-1.347)
ICPF Trading$_{j,t}$	-0.308***			
$\times COVID\_Period_t$	(-3.292)			
Mutual Fund Trading$_{j,t}$		-0.197**		
$\times COVID\_Period_t$		(-2.551)		
Non-Dealer Bank Trading$_{j,t}$			0.560***	
$\times COVID\_Period_t$			(2.672)	
Hedge Fund Trading$_{j,t}$				0.132**
$\times COVID\_Period_t$				(2.299)
$COVID\_Period_t$	0.025***	0.027***	0.029***	0.029***
	(2.892)	(2.884)	(3.105)	(2.947)
Controls	Yes	Yes	Yes	Yes
No. of Obs.	378	378	378	378
Adj. R^2	0.133	0.103	0.102	0.089

Table 7: Order Flows and Government Bond Yields: Short- and Long-Term Bonds

This table reports the results of panel regressions of gilt yield changes on contemporaneous order flows of ICPFs, mutual funds, non-dealer banks and hedge funds. The sample period is from March 1-18 2020. The bond sample in Panel A is comprised of short-term gilts with a remaining time-to-maturity of equal to or less than five years, and the bond sample in Panel B is comprised of long-term gilts with a remaining time-to-maturity of more than five years. The observations are at the gilt maturity bucket-day level. The dependent variable is the yield change from the previous trading day to the current trading day. The main independent variables are order flows of insurance companies and pension funds (ICPF $Trading_{j,t}$), mutual funds (Mutual Fund $Trading_{j,t}$), non-dealer banks (Non-Dealer Bank $Trading_{j,t}$), and hedge funds (Hedge Fund $Trading_{j,t}$). We calculate the order flow of a particular investor type as the total net trading volume (buy volume minus sell volume) of this investor type scaled by the total trading volume across all types of investors. We then calculate the equal-weighted average yield change and order flows within each maturity bucket (1-3 years, 3-5 years, 5-7 years, 7-10 years, 10-15 years, 15+ years, and index-linked). Control variables include the logarithm of total client volume and gilts' time-to-maturity. T-statistics are based on robust standard errors and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Short-Term Bonds				
	(1)	(2)	(3)	(4)
DepVar:	$\triangle Yield_{j,t}$			
ICPF $Trading_{j,t}$	-0.187**			
	(-2.169)			
Mutual Fund $Trading_{j,t}$		-0.081		
		(-1.045)		
Non-Dealer Bank $Trading_{j,t}$			0.168	
			(0.716)	
Hedge Fund $Trading_{j,t}$				0.185*
				(1.849)
Controls	Yes	Yes	Yes	Yes
No. of Obs.	26	26	26	26
Adj. R^2	0.244	0.166	0.151	0.236

Panel B: Long-Term Bonds				
ICPF $Trading_{j,t}$	-0.547***			
	(-3.387)			
Mutual Fund $Trading_{j,t}$		-0.473***		
		(-3.564)		
Non-Dealer Bank $Trading_{j,t}$			0.914***	
			(2.915)	
Hedge Fund $Trading_{j,t}$				0.105
				(1.583)
Controls	Yes	Yes	Yes	Yes
No. of Obs.	65	65	65	65
Adj. R^2	0.155	0.119	0.087	0.028

Table 8: Order Flows and Future Government Bond Yield Changes

This table reports the results of panel regressions of future bond yield changes on order flows of ICPFs. The sample period is from March 1-18 2020, and the observations are at the bond maturity bucket-day level. The dependent variable, △Yield (t-1,t+k), is the yield change from day $t-1$ to day $t+k$. The main independent variables are order flows of insurance companies and pension funds (ICPF $Trading_{j,t}$). We calculate the order flow of a particular investor type as the total net trading volume (buy volume minus sell volume) of this investor type scaled by the total trading volume across all types of investors. We then calculate the equal-weighted average yield change and order flows within each maturity bucket (1-3 years, 3-5 years, 5-7 years, 7-10 years, 10-15 years, 15+ years, and index-linked). Control variables include the logarithm of total client volume and gilts' time-to-maturity. T-statistics are based on robust standard errors and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Panel A: All Bonds					
DepVar:	△Yield(t-1,t+1)	△Yield(t-1,t+5)	△Yield(t-1,t+10)	△Yield(t-1,t+15)	△Yield(t-1,t+21)
ICPF $Trading_{j,t}$	-0.515***	-0.211	0.686***	0.110	0.206
	(-2.965)	(-0.576)	(2.784)	(0.733)	(1.496)
No. of Obs.	91	91	91	91	91
Adj. R^2	0.111	0.097	0.166	0.114	0.101
Panel B: Short-term Bonds					
ICPF $Trading_{j,t}$	-0.186	-0.405	0.202	-0.203	-0.022
	(-1.116)	(-1.472)	(1.003)	(-1.067)	(-0.135)
No. of Obs.	26	26	26	26	26
Adj. R^2	0.106	0.089	0.156	0.074	0.013
Panel C: Long-term Bonds					
ICPF $Trading_{j,t}$	-0.783**	0.036	1.013***	0.347*	0.398**
	(-2.540)	(0.059)	(2.679)	(1.941)	(2.030)
No. of Obs.	65	65	65	65	65
Adj. R^2	0.135	0.116	0.127	0.075	0.100

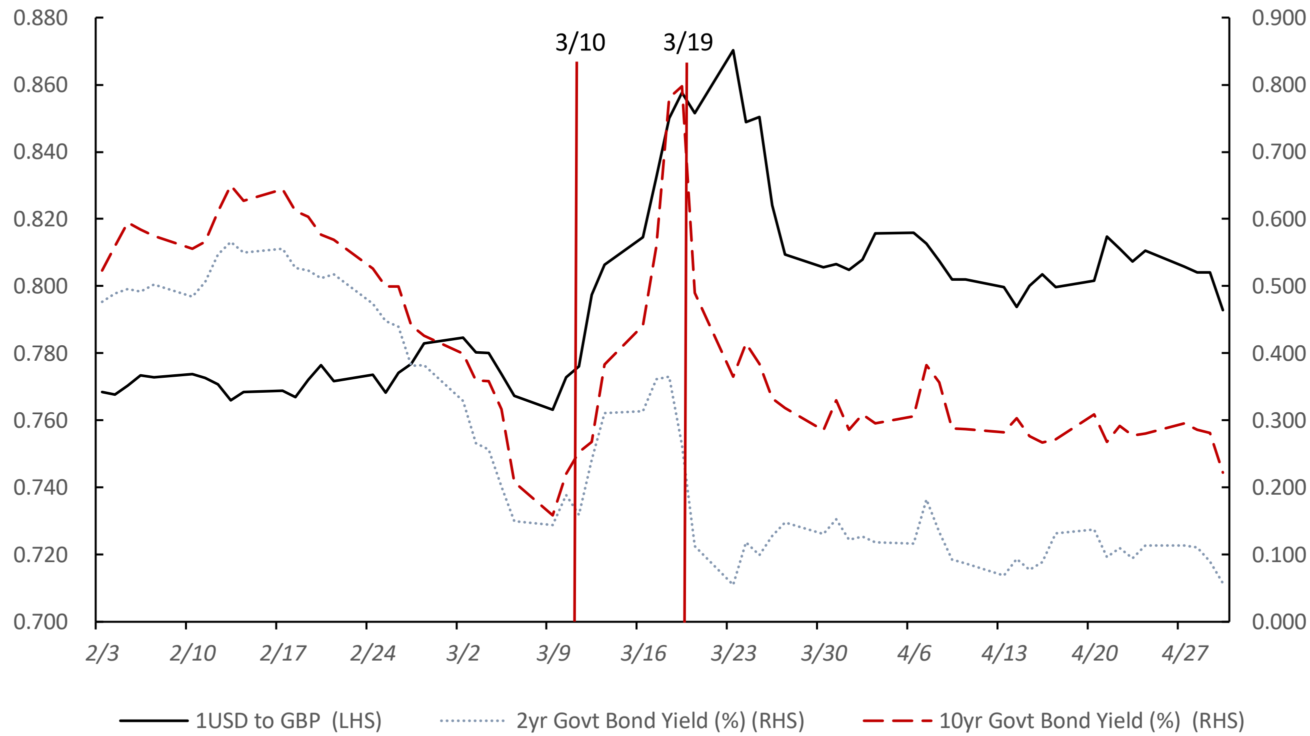


Figure 1: USD/GBP Exchange Rate and UK Government Bond Yields

This figure shows the dynamics of the USD/GBP exchange rate (shown on the left-hand-side axis) and UK gilt yields (shown on the right-hand-side axis) from February 3 to April 30 2020. March 10 2020 is the day before the WHO declared COVID-19 as a global pandemic. On March 19 2020 the Bank of England voted to cut Bank rate to 0.1% and increase its holdings of UK government and corporate bonds by £200 billion. The yield is in percentages.

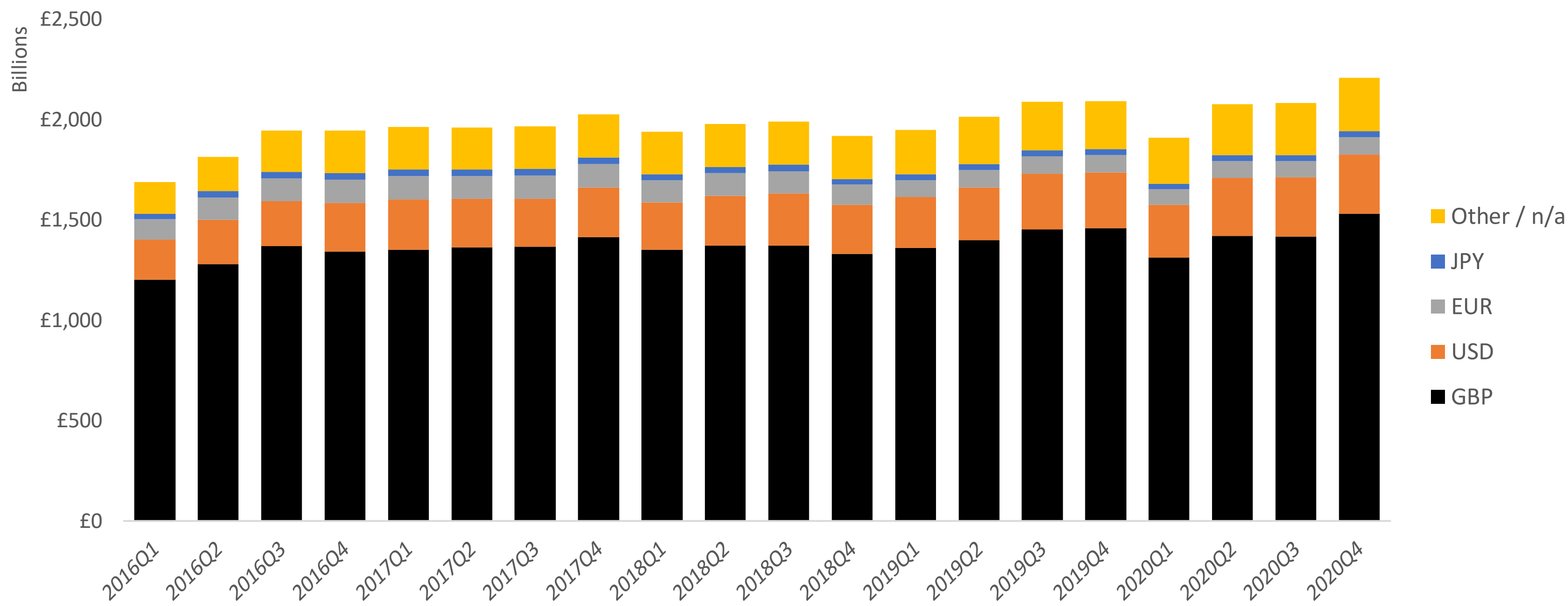


Figure 2: Total Asset Holdings of UK Insurance Companies

This figure shows the total asset holdings of UK insurance companies grouped by currency. The sample period is from 2016Q1 to 2020Q4. The asset holdings are in £ billions.

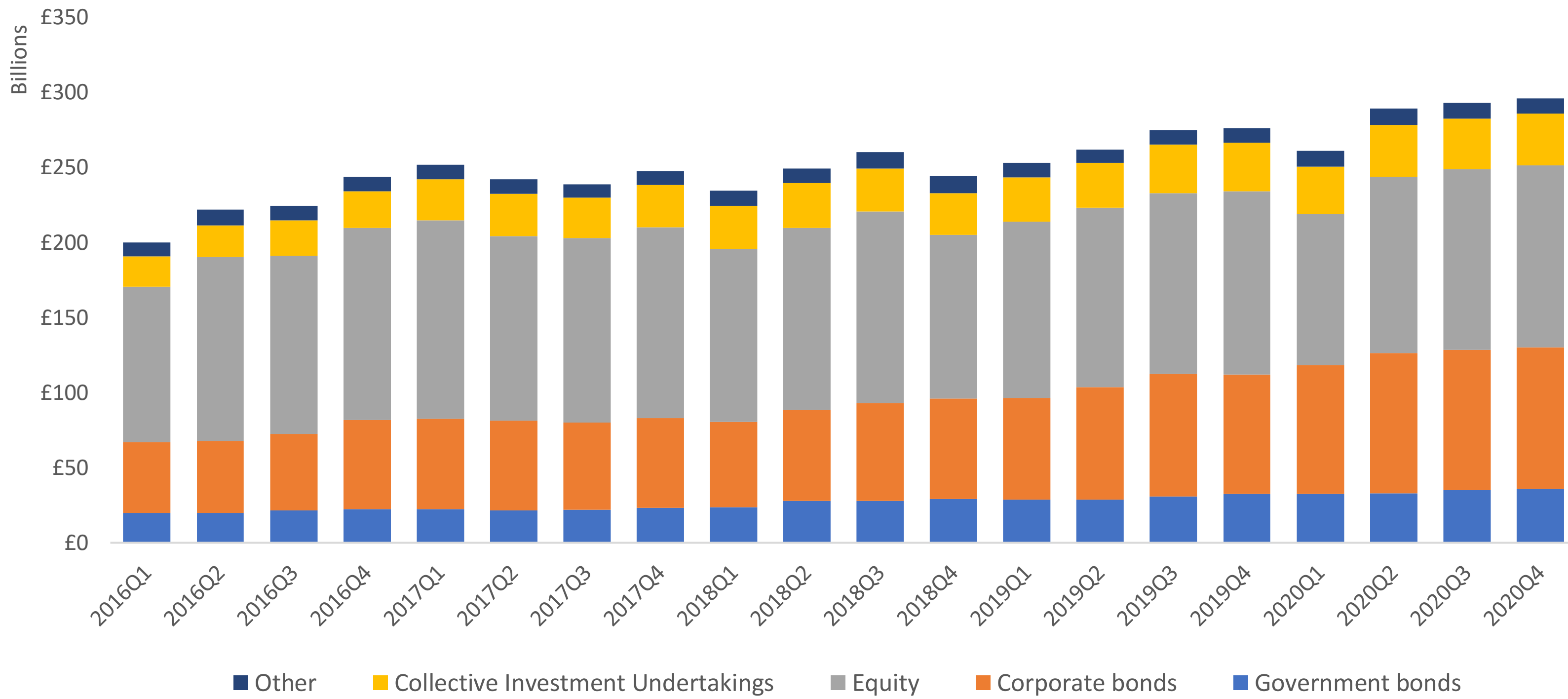


Figure 3: USD Asset Holdings of UK Insurance Companies

This figure shows the US dollar asset holdings of UK insurance companies grouped by asset class. The sample period is from 2016Q1 to 2020Q4. The asset holdings are in £ billions.

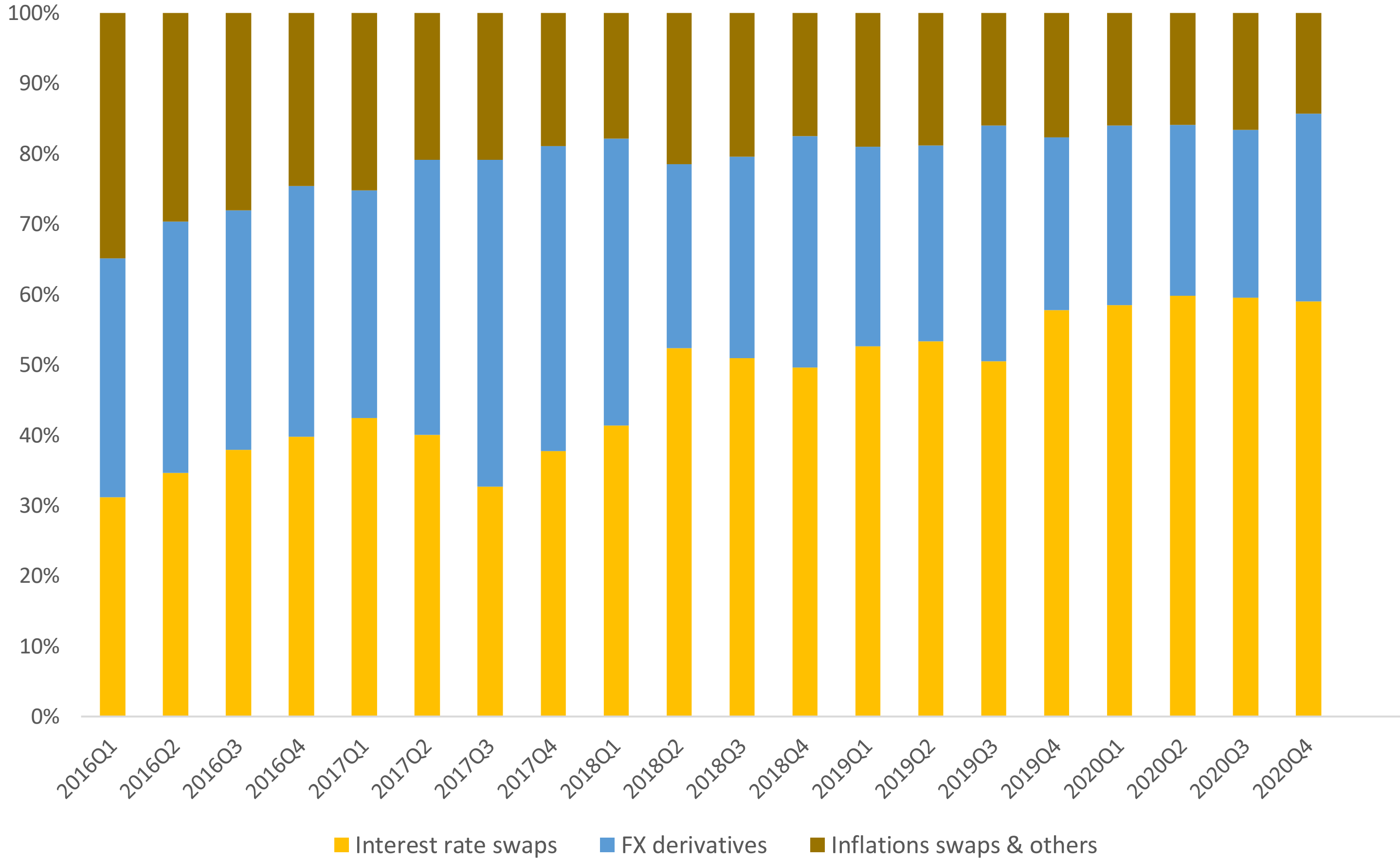


Figure 4: Composition of Derivative Holdings of UK Insurance Companies

This figure shows the composition of derivative holdings of UK insurance companies. The derivatives are grouped into interest rate swaps, FX derivatives, and inflation swaps/others. The sample period is from 2016Q1 to 2020Q4.

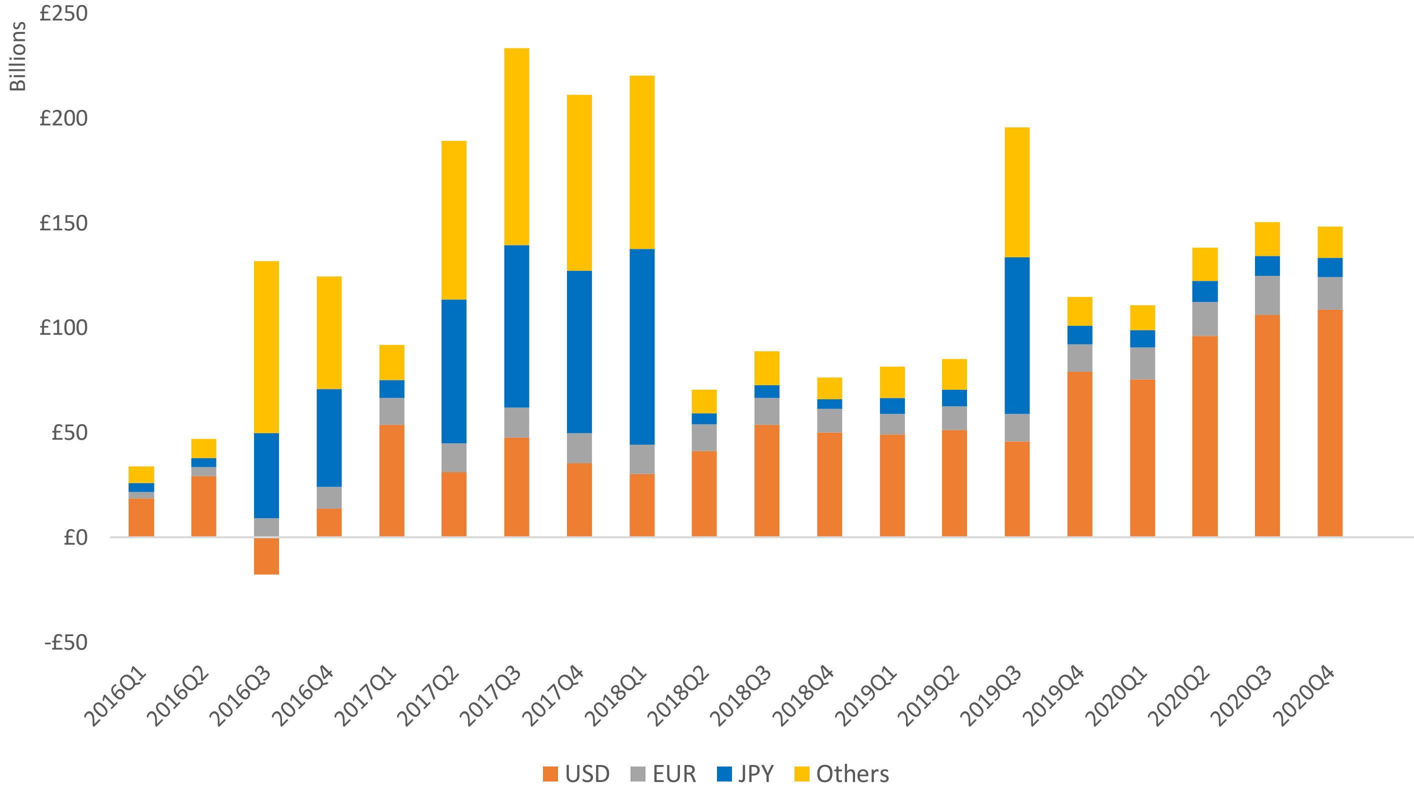


Figure 5: FX Derivative Net Exposure by Currency

This figure shows the foreign FX derivative net exposure of UK insurance companies grouped by currency. Positive values indicate that insurers deliver more than they receive of a given currency through their FX derivatives, i.e. a net hedging position. The sample period is from 2016Q1 to 2020Q4.

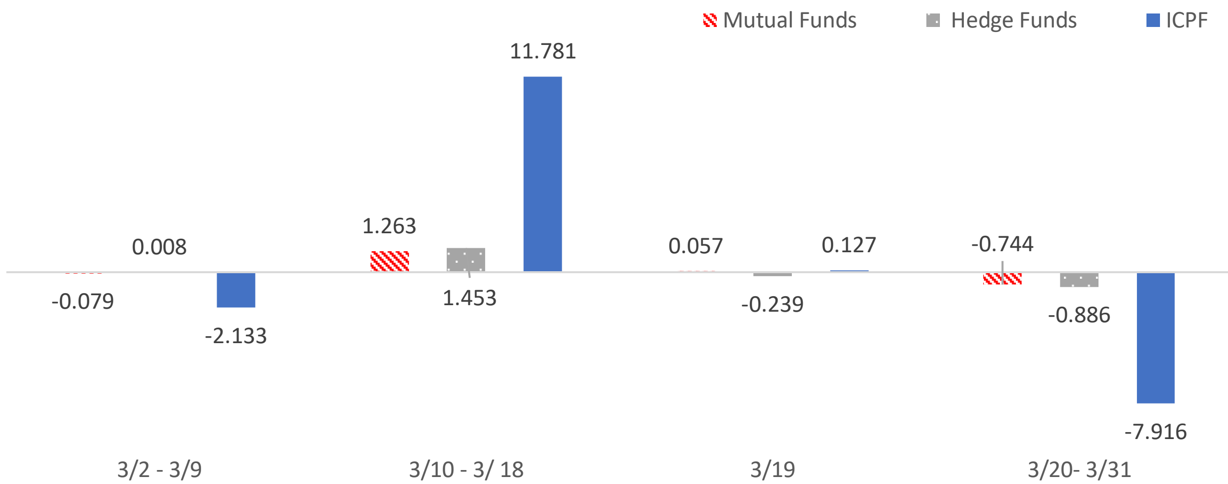


Figure 6: Total Variation Margin Demands on Different Investor Types

This figure shows the dynamics of the total variation margin (VM) demands on derivatives of different investor types (i.e., mutual funds, hedge funds, and insurance companies and pension funds (ICPFs)) in different periods of March 2020. VM calls are estimated using the EMIR Trade Repository Data on interest rate swaps, forward rate agreements, inflation swaps, and cross-currency basis swaps. Positive (negative) values mean that the investor group was a net payer (receiver) of VM. The estimates are based on the methodology used in Bardoscia et al (2020). The variation margin demands are in £ billion.

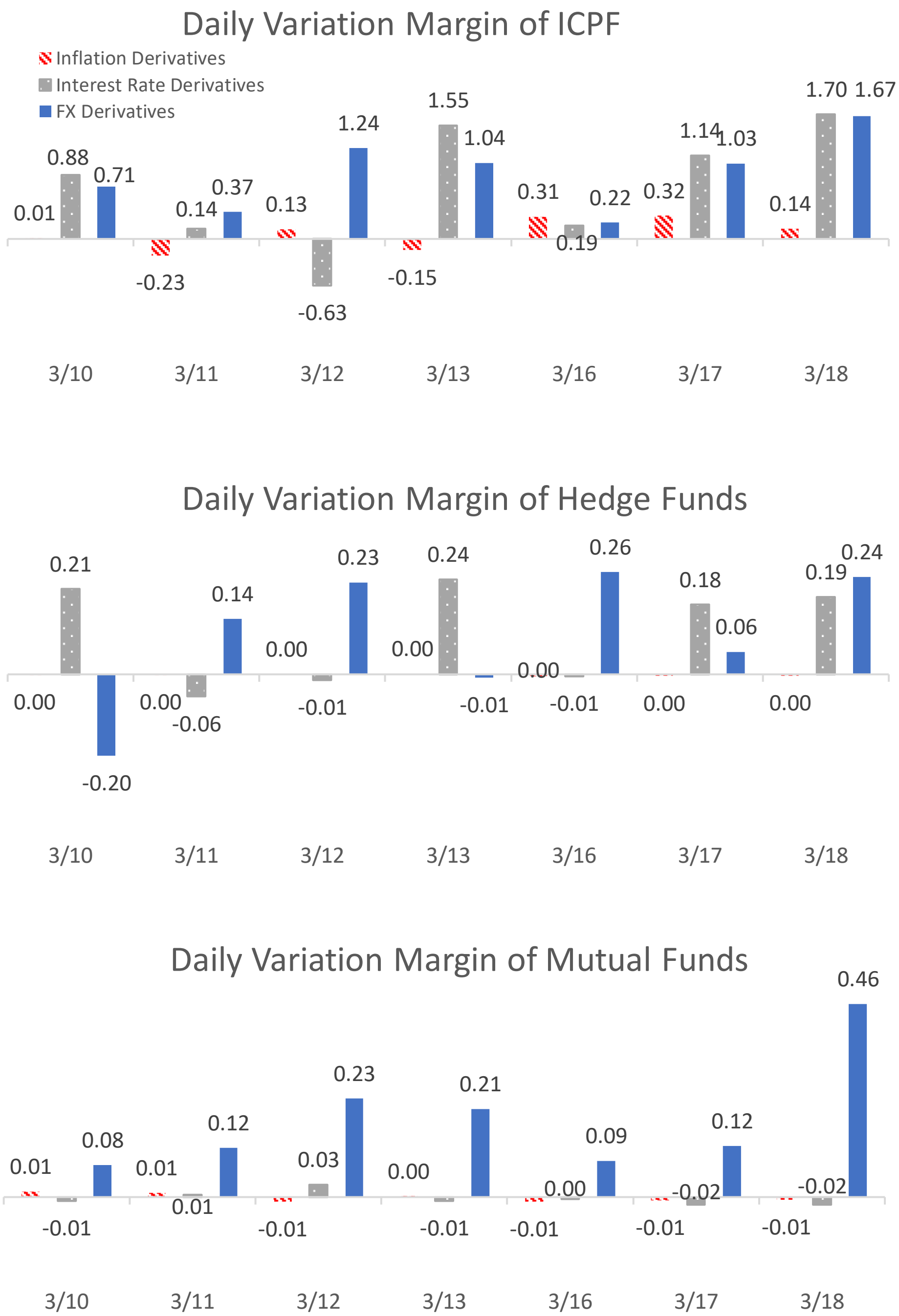


Figure 7: Daily Variation Margin Demands on Different Investor Types

This figure shows the dynamics of the total variation margins on different derivatives of insurance companies and pension funds (ICPFs), hedge funds and mutual funds from March 10-18 2020. VM calls are estimated using the EMIR Trade Repository Data on interest rate swaps, forward rate agreements, inflation swaps, and cross-currency basis swaps. Positive (negative) values mean that the investor group was a net payer (receiver) of VM. The variation margins are in £ billion.

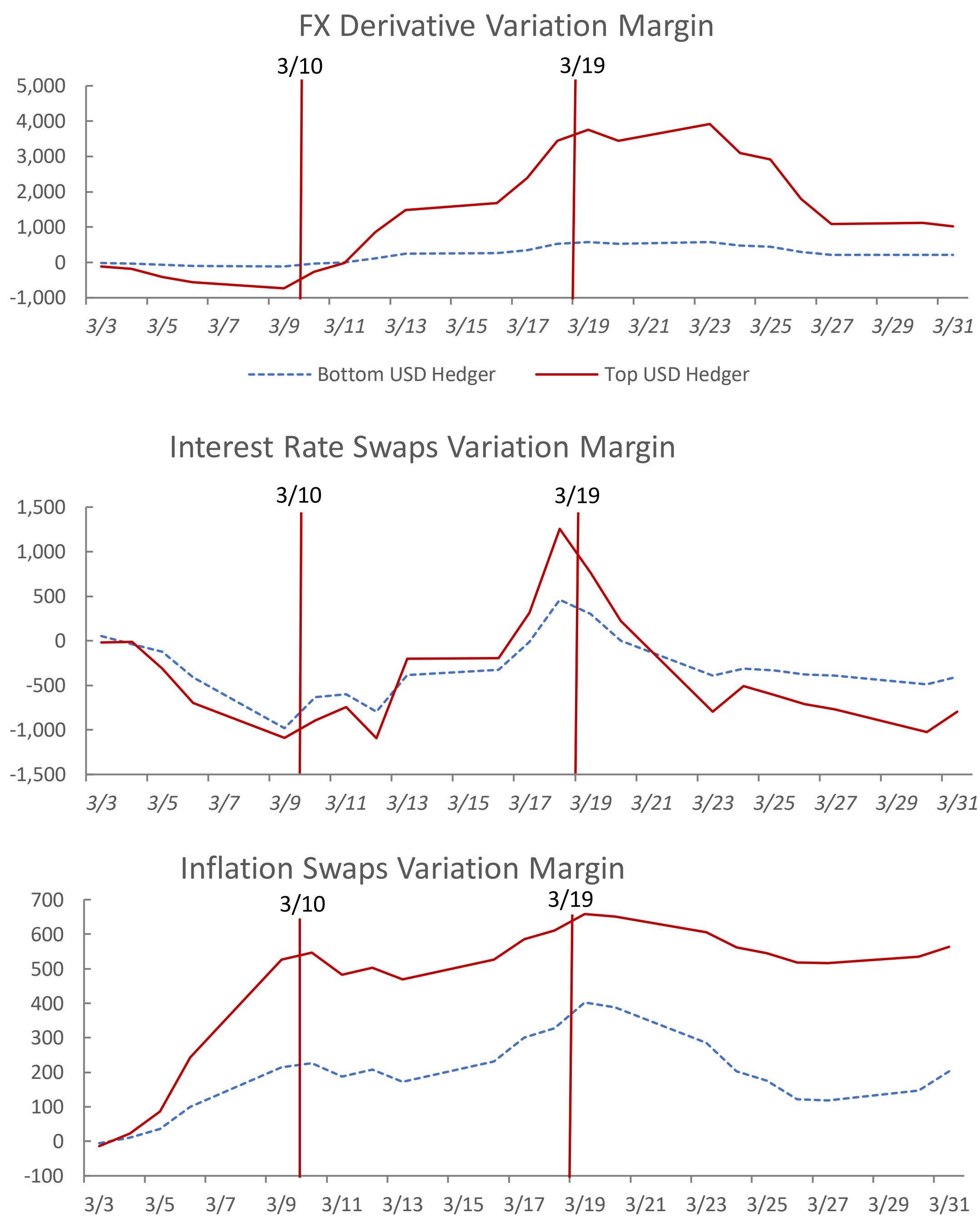


Figure 8: Variation Margin Demands on Top and Bottom USD FX Derivative Hedgers

This figure shows the cumulative variation margin demands on different derivatives of insurance companies from March 1-18 2020. The derivatives include interest rate swaps, FX derivatives, and inflation swaps. We equally allocate insurance companies into two groups based their net USD FX hedging positions at 2019Q4: Top USD FX derivative hedgers (with the above-average net USD exposure) and Bottom USD FX derivative hedgers.

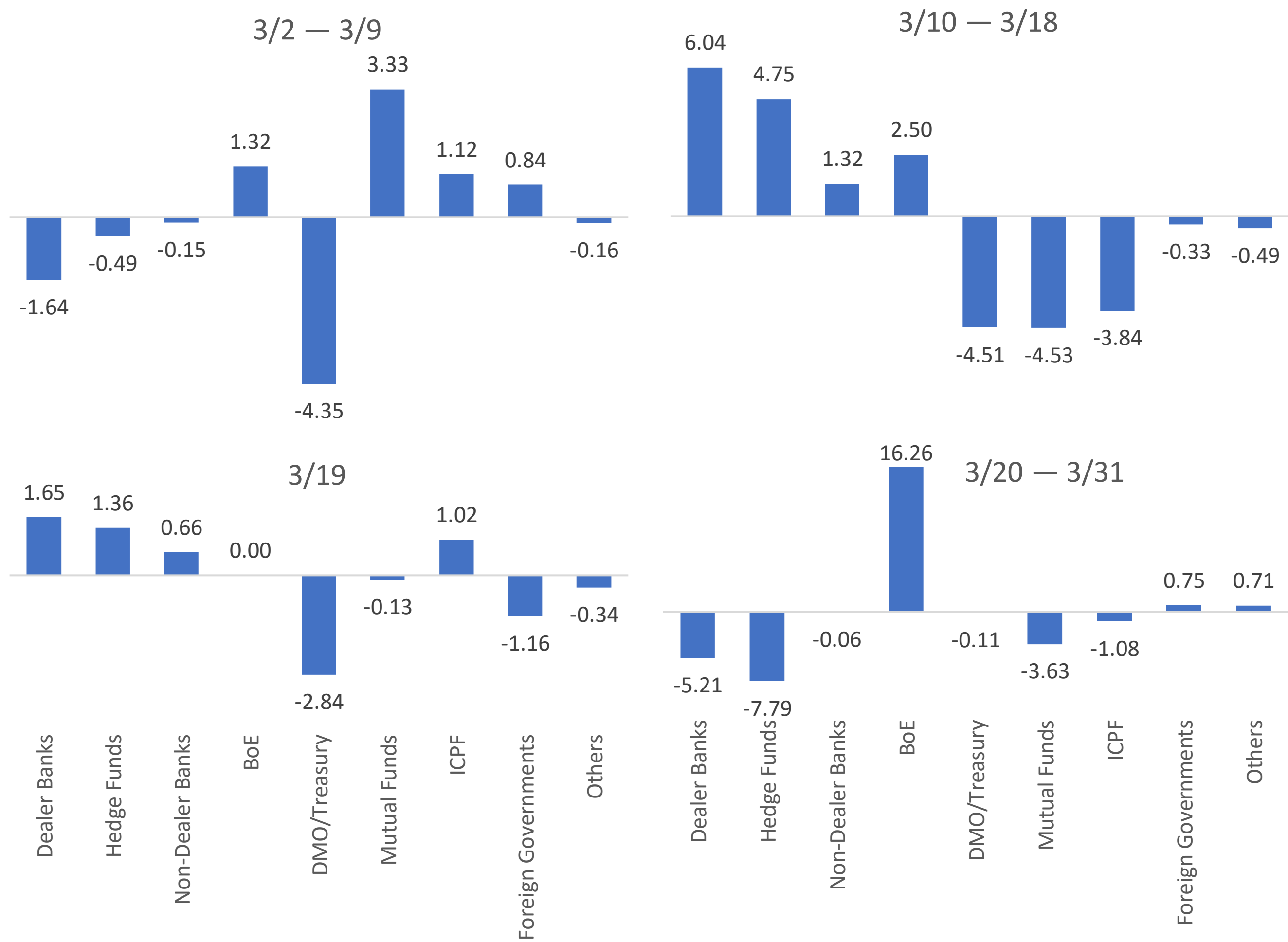


Figure 9: Total Gilt Net Trading Volumes

This figure shows the total gilt net trading volumes of different investor types in March 2020. The investor types include dealer banks, hedge funds, non-dealer banks, Bank of England (BoE), UK Debt Management Office (DMO), mutual funds, insurance companies and pension funds (ICPFs), and foreign governments. The trading volume is in £ billions.

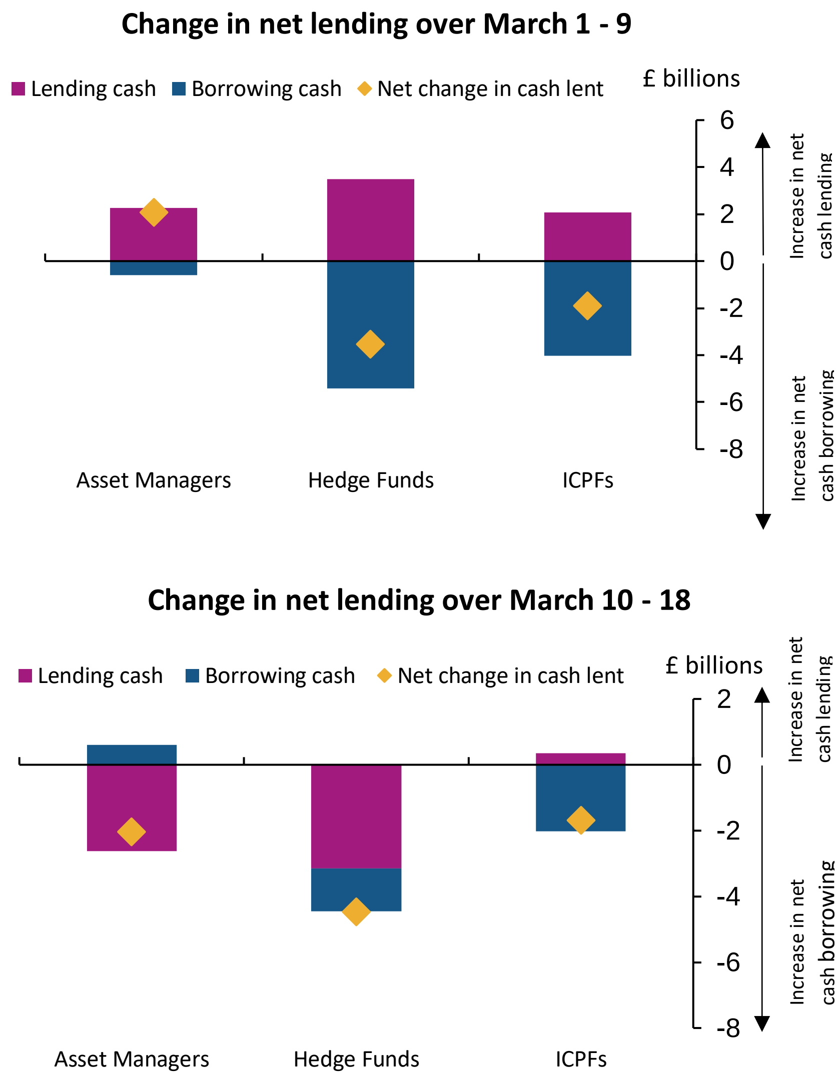


Figure 10: Repo Activity of Mutual Funds, Hedge Funds, and ICPFs

This figure shows the dynamics of the repo trading of mutual funds, hedge funds, and ICPFs from March 1-18 2020. March 10 2020 is the day before the WHO declared COVID-19 as a global pandemic.

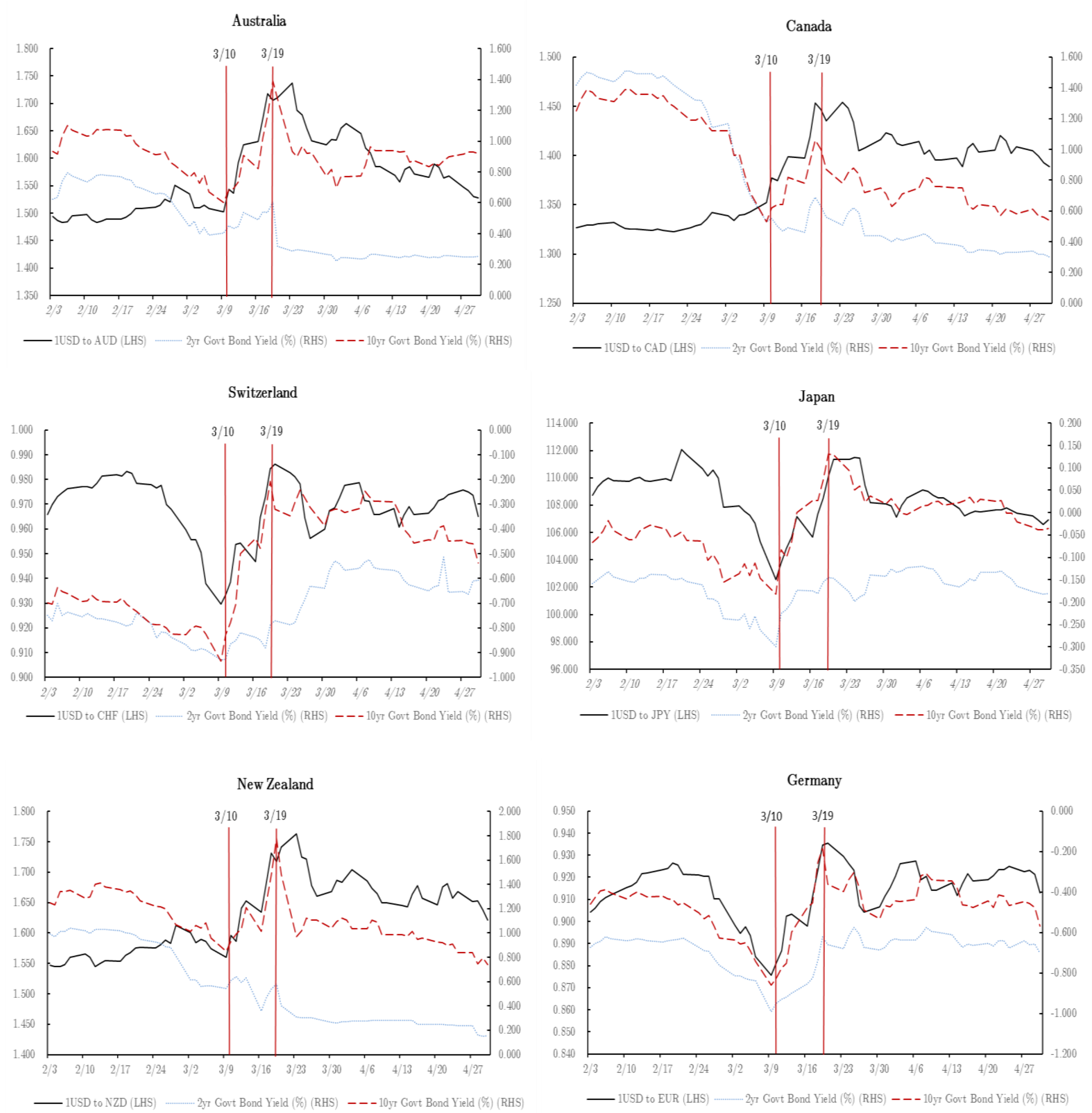


Figure 11: Exchange Rates and Government Bond Yields

This figure shows the dynamics of the exchange rate between different currencies and USD (left-hand-side axis) and government bond yields in different countries (right-hand-side axis) from February to April 2020. March 10 2020 is the day before the WHO declared COVID-19 as a global pandemic. The yield is in percentages.

Table A1: Derivative Hedging Positions and Variation Margin on Interest Rate/Inflation Swaps

This table reports the results of regressions of a given insurer's estimated variation margin (VM) demands on USD FX hedging positions. The sample period is March 1-18 2020. The observations are at the investor-day level. The dependent variable in columns (1)-(3) is the insurer's variation margin on interest rate swaps on each day, and the dependent variable in columns (4)-(6) is the insurer's variation margin on inflation swaps on each day. Positive (negative) values mean that the investor was a net payer (receiver) of VM. The key independent variable is $Indicator\_Top$, which is an indicator variable equal to one if the insurer's USD FX hedging position is above the sample median at the end of 2019Q4, and zero otherwise. $Dash\_for\_Cash$ is an indicator variable, which is equal to one if the date of the observation is between March 10-18 2020, and zero otherwise. *T*-statistics are based on robust standard errors and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	VM Interest Rate Swaps			VM Inflation Swaps		
	March 1-9	March 10-18	March 1-18	March 1-9	March 10-18	March 1-18
	(1)	(2)	(3)	(4)	(5)	(6)
DepVar:	Variation Margin (VM)					
$Indicator\_Top$	-3.622	21.530	-3.622	6.808	-2.029	6.808
	(-0.062)	(0.503)	(-0.062)	(0.711)	(-0.531)	(0.713)
$Indicator\_Top \times$			25.152			-8.837
$Dash\_for\_Cash$			(0.348)			(-0.859)
$Dash\_for\_Cash$			67.009***			-6.721
			(3.345)			(-1.016)
No. of Obs.	60	84	144	50	70	120
Adj. R^2	0.000	0.000	0.016	0.000	0.000	0.034

Table A2: Variation Margin and Mutual Fund & Hedge Fund Trading

This table reports the results of panel regressions of the gilt net trading volume of mutual funds and hedge funds on their estimated variation margin (VM) demands. The sample period is March 1-18 2020, and the observations are at the investor-day level. The dependent variable is the daily gilt net trading volume of a given mutual fund or hedge fund. In columns (1)-(2), the main independent variable is the daily variation margin of the given mutual fund, and this variable is denoted as VM. In column (3), the main independent variables include the mutual fund's daily variation margin on FX derivatives, interest rate swaps, and inflation swaps. In columns (4)-(5), the main independent variable is the daily variation margin of the given hedge fund. In column (6), the main independent variables include the hedge fund's daily variation margin on FX derivatives, interest rate swaps, and inflation swaps. Positive (negative) values mean that the investor was a net payer (receiver) of VM. The dependent variable and the variation margins are adjusted using the inverse hyperbolic sine method. We also control for time fixed effects. *T*-statistics are based on robust standard errors and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Mutual Funds			Hedge Funds		
	(1)	(2)	(3)	(4)	(5)	(6)
DepVar:	Net Gilt Trading Volume			Net Gilt Trading Volume		
VM	-0.047	-0.056		0.009	-0.019	
	(-1.091)	(-1.228)		(0.217)	(-0.416)	
VM on FX Derivatives			-0.044			0.004
			(-0.522)			(0.078)
VM on Interest Rate Swaps			-0.064			-0.060
			(-0.774)			(-0.654)
VM on Inflation Swaps			0.157			0.112
			(1.268)			(0.391)
Time FE	No	Yes	Yes	No	Yes	Yes
Bond FE	No	Yes	Yes	No	Yes	Yes
No. of Obs.	545	539	539	958	954	954
Adj. R^2	0.005	0.117	0.131	0.000	0.123	0.124

Table A3: Order Flows and Gilt Yields: Value-Weighted Approach and Comparison with 2019

This table reports the results of panel regressions of bond yield changes on contemporaneous order flows of ICPFs, mutual funds, non-dealer banks and hedge funds. The sample period in Panel A is from March 1-18 2020; the sample period in Panel B is from January 1 - December 31 2019, and March 1-18 2020. The observations are at the bond maturity bucket-day level. The dependent variable is the yield change from the previous trading day to the current trading day. The main independent variables are order flows of insurance companies and pension funds (ICPF Trading$_{j,t}$), mutual funds (Mutual Fund Trading$_{j,t}$), non-dealer banks (Non-Dealer Bank Trading$_{j,t}$), and hedge funds (Hedge Fund Trading$_{j,t}$). We calculate the order flow of a particular investor type as the total net trading volume (buy volume minus sell volume) of this investor type scaled by the total trading volume across all types of investors. We then calculate the value-weighted average yield change and order flows within each maturity bucket (1-3 years, 3-5 years, 5-7 years, 7-10 years, 10-15 years, 15+ years, and index-linked). In Panel B, $COVID\ Period_t$ is an indicator variable, which equals one if the day is between March 1-18 2020, and zero otherwise. Control variables include the logarithm of total client volume and gilts' time-to-maturity. *T*-statistics are based on robust standard errors and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

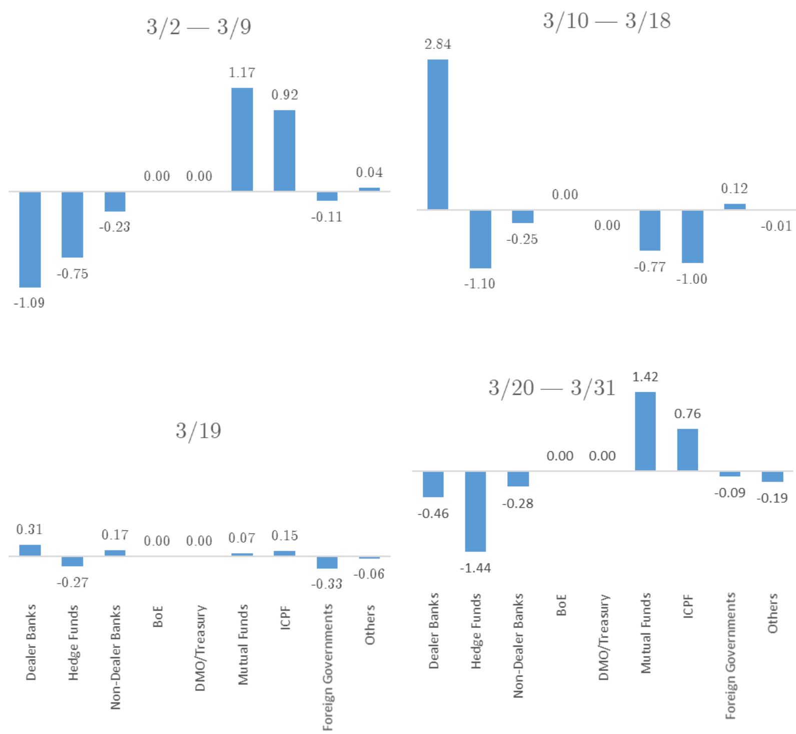
Panel A: March 1 - 18				
	(1)	(2)	(3)	(4)
DepVar:		△Yield(t-1,t)		
ICPF Trading$_{j,t}$	-0.370***			
	(-3.481)			
Mutual Fund Trading$_{j,t}$		-0.258***		
		(-3.400)		
Non-Dealer Bank Trading$_{j,t}$			0.601***	
			(2.949)	
Hedge Fund Trading$_{j,t}$				0.120**
				(2.138)
Log(volume)$_{j,t}$	-0.027	-0.016	-0.013	-0.013
	(-1.391)	(-0.830)	(-0.638)	(-0.643)
Maturity$_{j,t}$	0.003*	0.002	0.002	0.002
	(1.666)	(1.160)	(1.218)	(1.268)
Constant	0.565	0.347	0.278	0.281
	(1.398)	(0.852)	(0.656)	(0.657)
No. of Obs.	91	91	91	91
Adj. R^2	0.124	0.082	0.078	0.049

Panel B: Compared to Jan - Dec 2019				
	(1)	(2)	(3)	(4)
ICPF Trading$_{j,t}$	-0.011			
	(-0.980)			
Mutual Fund Trading$_{j,t}$		-0.006		
		(-0.737)		
Non-Dealer Bank Trading$_{j,t}$			0.010	
			(0.614)	
Hedge Fund Trading$_{j,t}$				-0.015**
				(-2.253)
ICPF Trading$_{j,t}$	-0.311***			
$\times$ $COVID\ Period_t$	(-3.444)			
Mutual Fund Trading$_{j,t}$		-0.209***		
$\times$ $COVID\ Period_t$		(-2.721)		
Non-Dealer Bank Trading$_{j,t}$			0.526***	
$\times$ $COVID\ Period_t$			(2.583)	
Hedge Fund Trading$_{j,t}$				0.125**
$\times$ $COVID\ Period_t$				(2.216)
$COVID\ Period_t$	0.020**	0.022**	0.024***	0.024**
	(2.345)	(2.419)	(2.638)	(2.497)
Controls	Yes	Yes	Yes	Yes
No. of Obs.	1,862	1,862	1,862	1,862
Adj. R^2	0.038	0.029	0.029	0.026

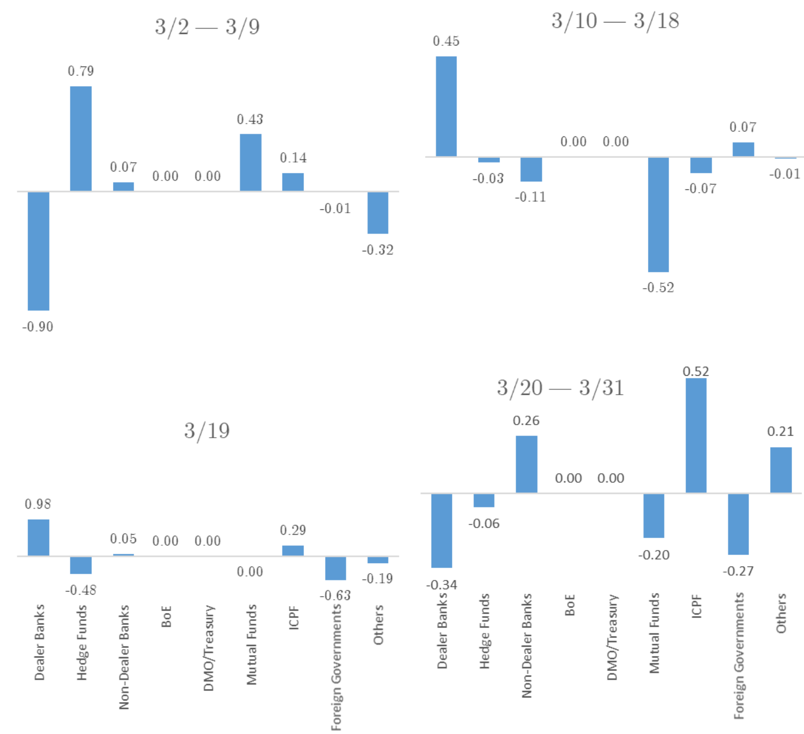
Table A4: Mutual Fund Flows and Mutual Fund Trading

This table reports the results of regressions of gilt net trading volumes of mutual funds on their fund flows. The sample period is from March 1-18 2020, and the observations are at the investor-day level. The dependent variable is the gilt net trading volume (buy volume minus sell volume) of a particular mutual fund on day t, and independent variables are the fund flows of this given mutual fund at day t and lagged fund flows from day t-1 to day t-3. Both dependent and independent variables are transformed using the inverse hyperbolic sine transformation method. In column (1)-(2), the sample includes observations from March 1-18. In columns (3)-(4), the sample includes observations from March 1-9. In columns (5)-(6), the sample includes observations from March 10-18. *T*-statistics are based on bootstrapped standard errors and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	March 1 - 18		Flight to Safety March 1 - 9		Dash for Cash March 10 - 18	
	(1)	(2)	(3)	(4)	(5)	(6)
	$DepVar\text{:}\ Net\ Gilt\ Trading\ Volume_t$					
$Flow_t$	0.253***	0.220***	0.152***	0.119**	0.311***	0.293***
	(9.039)	(6.959)	(3.498)	(2.464)	(8.927)	(6.695)
$Flow_{t-1}$		0.083**		0.083*		0.060
		(2.441)		(1.717)		(1.201)
$Flow_{t-2}$		-0.051		-0.022		-0.086*
		(-1.521)		(-0.461)		(-1.825)
$Flow_{t-3}$		0.030		0.002		0.078*
		(0.978)		(0.040)		(1.879)
Constant	-0.428***	-0.394***	0.057	0.051	-0.418***	-0.405***
	(-3.840)	(-3.472)	(0.342)	(0.303)	(-3.804)	(-3.778)
No. of Obs.	4,026	4,003	1,752	1,745	2,274	2,258
Adj-R^2	0.070	0.074	0.023	0.025	0.091	0.098



Maturity < 1 Year

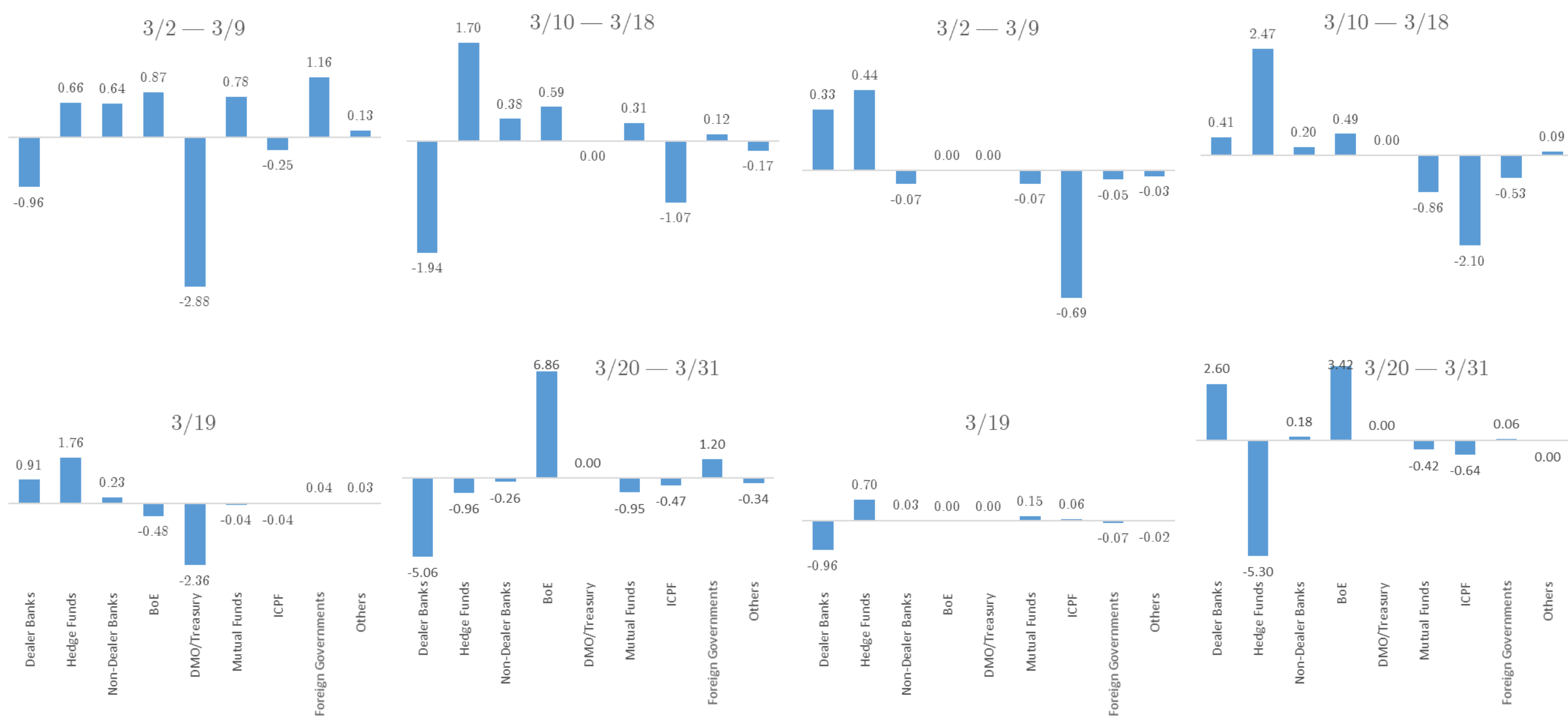


1 Year ≤ Maturity < 3 Years

Figure A1: Total Gilt Net Trading Volumes

This figure shows the total gilt net trading volume of different investor types in March 2020. The investor types include dealer banks, hedge funds, non-dealer banks, Bank of England (BoE), UK Debt Management Office (DMO), mutual funds, insurance companies and pension funds (ICPFs), and foreign governments. We allocate gilts to different groups based on the residual maturities. The trading volume is in £ billions.

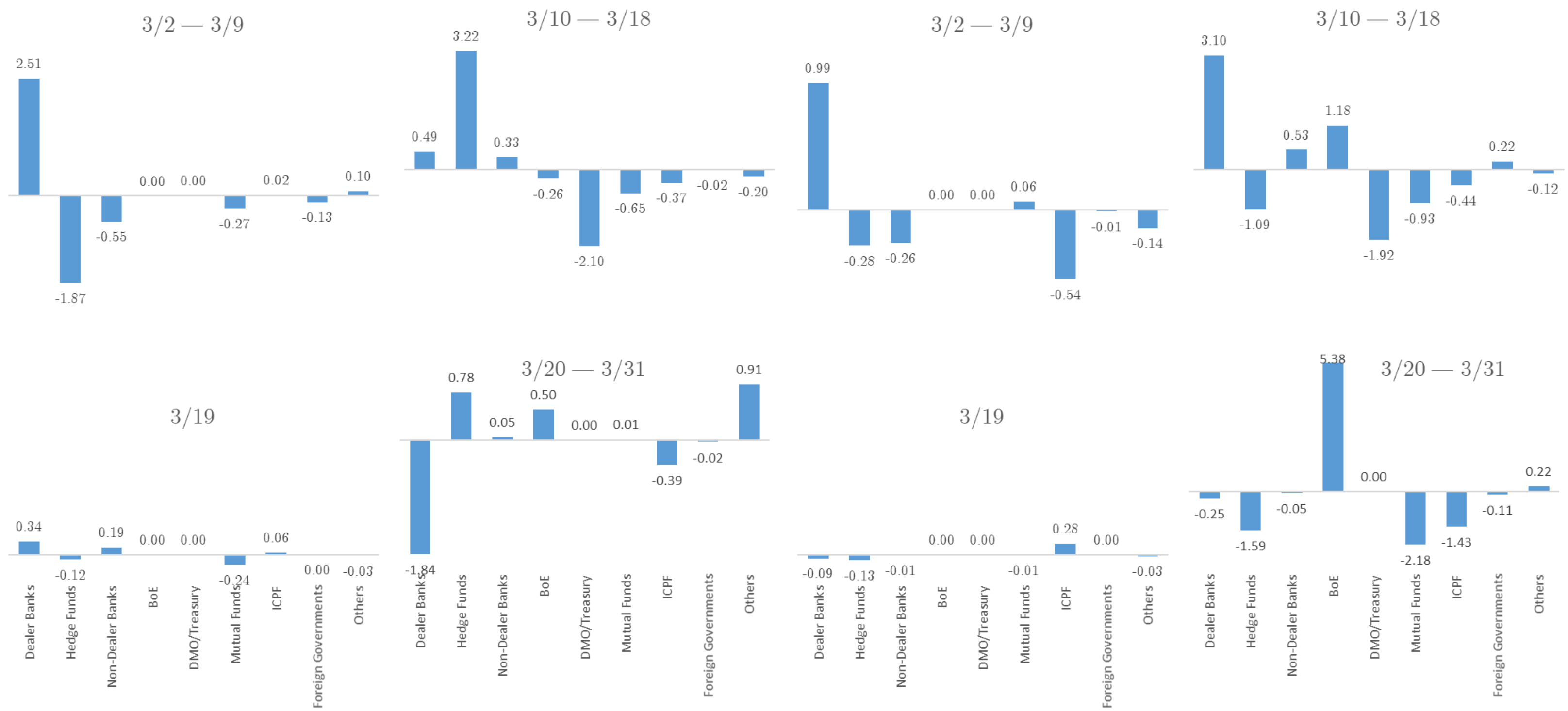
Figure A1 (Continued)



3 Years ≤ Maturity < 7 Years

7 Years ≤ Maturity < 10 Years

Figure A1 (Continued)



10 Years ≤ Maturity < 15 Years

Maturity ≥ 15Years

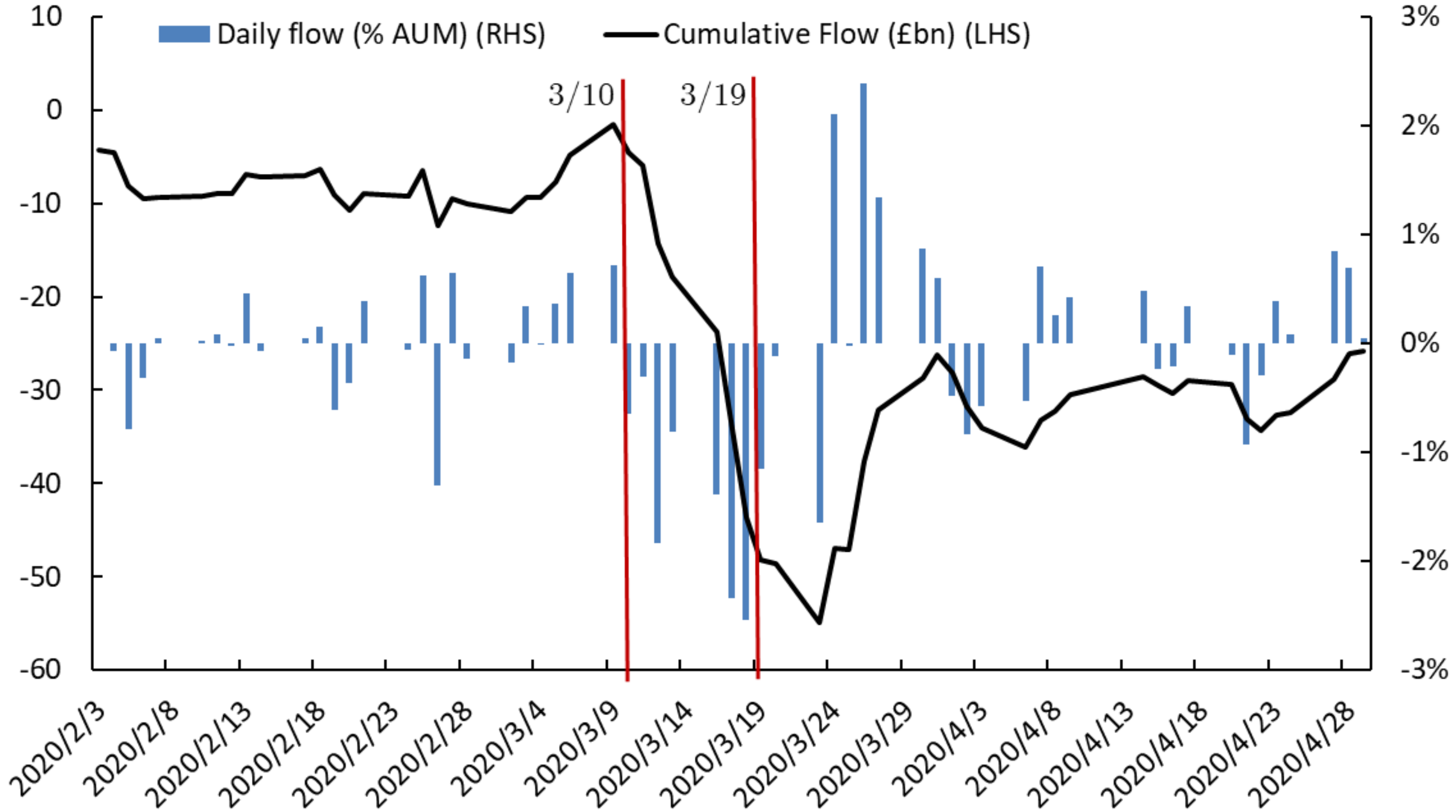


Figure A2: Mutual Fund Flows

This figure shows the dynamics of mutual fund flows from February 3 to April 30 2020. The solid line represents the cumulative mutual fund flows in £ billions, and the bars represent the daily percentage fund flows. The sample of mutual funds includes all funds that trade in the gilt market.