

# Unintended Consequences of Holding Dollar Assets\*

Robert Czech  
Bank of England  
robert.czech@bankofengland.co.uk

Shiyang Huang  
Faculty of Business and Economics, University of Hong Kong  
huangsy@hku.hk

Dong Lou  
London School of Economics and CEPR  
d.lou@lse.ac.uk

Tianyu Wang  
Tsinghua University School of Economics and Management  
wangty6@sem.tsinghua.edu.cn

First Draft: November 2021

This Draft: March 2022

---

\*The views expressed in this paper are those of the authors, and not necessarily those of the Bank of England or its committees. We thank Andrew Bailey, Evangelos Benos, Darrell Duffie, Zhiguo He, Mike Joyce, Ralph Koijen, John Lewis, Matt Roberts-Sklar, Zhaogang Song, Misa Tanaka, Sheila Torrance, Nick Vause and seminar and conference participants at CUNEF University, London School of Economics, and the BoE Workshop on Procyclicality in Market-Based Finance for helpful comments. We are also grateful to Josh Lillis and Arjun Mahalingam for their generous help with some of the data used in this paper. All remaining errors are our own.

# Unintended Consequences of Holding Dollar Assets

## Abstract

We propose a novel mechanism through which the US dollar's global dominance can have a large, unexpected impact on foreign safe-asset yields, especially in crisis periods. Non-US institutions hold a substantial amount of dollar assets and hedge their dollar exposures by shorting dollars forward through FX derivatives. In crisis periods, dollars tend to appreciate against all other currencies. To meet margin calls on these short-dollar FX hedging positions, non-US institutions sell their domestic safe assets, thereby contributing to the yield spikes in domestic markets. Consistent with this view, we show that during the recent COVID crisis, UK-based insurance companies and pension funds (ICPFs) with large dollar holdings and FX hedging positions were heavy sellers of UK gilts, and that their selling activity contributed significantly to the observed gilt yield spike in March 2020.

**Keywords:** currency hedging, variation margin, FX derivatives, gilt yields, global reserve currency, COVID crisis

# 1 Introduction

Government bonds issued by developed countries (e.g., US, Germany, UK) are often viewed as the safest and most liquid financial assets. In crisis periods, these high-quality assets traditionally experience large buying demand from investors and appreciate in value – a phenomenon labelled “flight to safety” (e.g., [Vayanos, 2004](#)). In the recent COVID-19 crisis, however, there was an unprecedented global selloff of these liquid, safe financial assets. As shown in Figure 1 (and complemented by Figure 11), the 10-year government bond yields in many developed countries rose substantially in the short 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 ([He et al., 2021](#)). 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 – which 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 holdings 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: e.g., which groups of investors were buying, which were selling, and

the associated price effects. 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 experiences of safe assets in other countries. Consequently, a careful examination of investor trading and bond yield patterns in the UK gilt market during the COVID crisis can provide useful insights on government bonds in other developed countries.

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.<sup>1</sup> Second, this large yield spike was accompanied by heavy selling of three groups of agents: the UK’s Debt Management Office (DMO) auctioned and issued over £4bn of gilts (which was planned and announced months in advance), bond mutual funds sold nearly £4.5bn (driven largely by fund outflows), and insurance companies and pension funds (ICPFs) sold an additional £3.8bn of gilts. Third, this selling of over £12bn of gilts in a short window of seven trading days was entirely absorbed by dealer and non-dealer banks, as well as fixed-income hedge funds. (For reference, the average trading volume between dealers and their clients in the gilt market was roughly £10bn a day in 2019 (Czech et al., 2021a).)

The behavior and price impact of the first two groups of agents are less of a surprise. It is well-documented in 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 a large price impact on securities in the secondary market.<sup>2</sup> Our focus is instead on the trading activity of insurance companies and pension funds, who are typically passive buy-and-hold investors in normal times. We propose that the *abnormal* trading behavior of ICPFs in the COVID crisis was likely due to the US dollar’s global dominance in both financial investment and cross-border transactions.

As the world’s reserve currency, the dollar serves two roles: to facilitate cross-border

---

<sup>1</sup>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.

<sup>2</sup>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.

transactions and to offer investment opportunities in dollar denominated assets. Indeed, many non-US institutions invest large amounts of capital in dollar assets, particularly in 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 (mostly in US 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 insurers in our sample hedged nearly 50 cents for every dollar of exposure to USD assets.

During the COVID crisis, aside from that asset values all over the world dropped precipitously, 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 against all other major currencies; for example, the dollar saw a more than 10% rise against the pound between March 10th and 18th of 2020. As a result of this large exchange rate movement, many UK-based institutions received margin calls on their foreign exchange hedging positions. Insurance companies and pension funds in our data collectively lost £6.4bn in variation margin (VM) on their FX derivatives holdings.

To meet the 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 UK risky holdings, to borrow in the gilt repo market and/or to sell their UK safe assets. As highlighted in [Ma et al. \(2021\)](#), investors tend to follow a pecking order of liquidation – 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 (and increased their repo borrowing by more than £2bn). In the cross-section, a one dollar increase in FX variation margin loss is associated with additional 41 ( $t$ -statistic = 4.23) cents of gilt sales and 22 ( $t$ -statistic = 2.40) cents of repo borrowing.

In our final set of analyses, we connect the selling activity of ICPFs to movements in gilt yields. A simple panel regression shows that a one-standard-deviation increase in ICPFs' selling is associated with a 30bps ( $t$ -statistic = 3.39) increase in long-term gilt yields during

the COVID crisis, or nearly 60% of the total yield spike in this period. This price effect is then completely reversed in the following month.

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

Our proposed mechanism and empirical results have useful implications for investors as well as policymakers in non-US markets, including developed markets. As the costs of investing in foreign assets, especially USD assets, have fallen substantially in recent decades, more investors hold dollar denominated assets today than at any time in history. While investors enjoy the diversification benefit, there is a potential downside to this trend – the reserve currency status of the USD may exacerbate crises in domestic markets through a currency hedging channel. Indeed, as shown in Figure 11, there is a strong parallel between exchange rate movements and yield spikes in many other countries (e.g., Australia, Japan, Switzerland, Germany) during the COVID crisis. Although we do not have detailed bond trading data in these markets, the mechanism discussed in this paper is likely to play an important role in these countries as well.

Against this backdrop, a natural question is whether policymakers could encourage large asset owners to better manage their liquidity in crisis periods by enhancing their liquidity preparedness and by making margin calls more predictable, e.g., through more transparent margin calculations for both centrally and non-centrally cleared derivatives. Such measures

may help prevent a similar liquidity drain in future downturns, and reduce the likelihood of an adverse impact of US dollar appreciations on prices and liquidity in non-US government bond markets.

Our findings also highlight an unexpected consequence of the leverage ratio rule (see also [Duffie and Krishnamurthy, 2016](#); [Duffie, 2018](#); [Andersen et al., 2019](#)). Prior to the new regulation, ICPFs were generally able to post non-cash collateral – such as gilts – to meet their variation margin demands. However, unlike cash collateral, non-cash collateral does not reduce dealers’ derivatives leverage exposure.<sup>3</sup> As a result, dealers found themselves unable to meet their ROE targets on these trades and started adjusting the contracts’ credit support annexes (CSA), often removing the option to post non-cash collateral. Therefore, as ICPFs were unable to post gilts as collateral during the COVID crisis, they had to resort to selling these securities at a discount in the secondary market. This dynamic therefore highlights how the leverage ratio implementation – despite the undoubtedly positive impact on dealers’ capacities to withstand the crisis – may have exacerbated the gilt fire sales by ICPFs during that period.

**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

---

<sup>3</sup>In the treatment of derivative exposures for the purpose of the leverage ratio, the cash portion of variation margin exchanged between counterparties may be viewed as a form of pre-settlement payment. See Basel Committee on Banking Supervision, Leverage Ratio Exposure Measurement, Sections 30.28 and 30.29.

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 effects. 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.<sup>4</sup>

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 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. \(2021b\)](#)

---

<sup>4</sup>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., [Rousová et al., 2020](#); [Alstadheim et al., 2021](#)).

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).

Third, we use the Bank of England's Sterling Money Market data collection, Form SMMD. This transaction-level dataset covers the sterling unsecured and secured (gilt repo) money markets. The data are obtained from dealers in the respective money markets and have been collected since 2016. The data cover 95% of activity where a bank or dealer is a counterparty, but the data do not capture any non-bank to non-bank repo trades. In Figure 10, where we use data on repo amounts outstanding (stocks), the numbers provided account for maturing repo in each period.

Next, we use the EMIR Trade Repository Data on interest rate swaps, forward rate agreements, inflation swaps, and cross-currency basis swaps to estimate the variation margin (VM) calls of individual insurers, pension funds, hedge funds, and mutual funds for each trading day in March 2020. 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. It is important to mention that derivative users are required to settle changes in the market value of the trade at least once a day via the exchange of VM.

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:

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

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 $\times$ 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 $\times$ 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:

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

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.<sup>5</sup>

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

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

where  $USD\ FX\ Holdings_i$  is insurer  $i$ 's USD FX hedging position at the end of 2019. Intuitively,  $\beta_1$  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

---

<sup>5</sup>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.

of  $\beta_1$  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  $\beta_1$  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 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:

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

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. This transformation approximates the natural logarithm of these variables, while enabling us to retain zero-valued and negative observations (see, e.g., [Burbidge et al., 1988](#); [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 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.<sup>6</sup> Importantly, the observed selling pressure may have been further aggravated by ICPFs trying to replenish their liquidity buffers in anticipation of future margin calls.

---

<sup>6</sup>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.

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 a 8% haircut applies to posting non-cash collateral in a currency other than that of the derivative transaction. In our data, more than 80% of insurers' IRS contracts are denominated in pound sterling, compared to only 40% of insurers' FX derivatives. Therefore, these investors have a higher incentive to sell gilts to meet VM calls on FX derivatives to avoid the 8% haircut. Furthermore, ICPFs frequently hold IRS as part of an LDI strategy. Selling gilts to meet VM calls on IRS positions may therefore undermine the duration matching that the IRS was a part of. 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.

### **Gilt Repo Trading**

In addition to selling government bonds directly, an alternative way to meet VM calls is via borrowing through the gilt 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.

By using a variant of the regression model in Equation (4), we now examine whether

VM demands affect ICPF trading in the repo market in a statistically significant manner. More precisely, we again test whether VM demands on FX derivatives, interest rate swaps, or inflation swaps have an impact on both repo (i.e. cash borrowing) as well as reverse repo (i.e. cash lending) trading of ICPFs.

Table 5 reports the results. Panel A shows the results for ICPFs' repo trading. Across all specifications, VM on FX derivatives has a significant positive effect on repo trading volumes in the dash for cash period. In other words, ICPFs increase their borrowing in the gilt repo market when they have to meet VM calls on FX derivatives. For example, as shown in Column 5, the OLS coefficient estimate of VM on FX derivatives is 0.216 and significant at the 5% level. The results remain significant when including time fixed effects.

As shown in Panel B, VM on FX derivatives does not have a significant impact on ICPF's reverse repo trading during the dash for cash. To put it differently, ICPFs do not reduce or extend their repo lending when they have to meet VM calls on FX derivatives. However, ICPFs seem to reduce their repo lending when receiving VM calls on their IRS positions.

### **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:

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

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 6 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 6, 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 6 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:

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

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 7 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:

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

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 7 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 8 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., 2021b](#)). To answer this important

question, we regress future gilt yield changes at different horizons on ICPF order flows:

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

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 9 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.

## 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 7, 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: the DMO 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.

## References

- Alstadheim, Ragna, Kjell Bjorn Nordal, Olav Syrstad, Saskia Ter Ellen, and May-Iren Walstad Wassas**, “Bond market fire sales and turbulence in the Norwegian FX market in March 2020,” *Norges Bank Staff Memo No. 2*, 2021.
- Andersen, Leif, Darrell Duffie, and Yang Song**, “Funding Value Adjustments,” *The Journal of Finance*, 2019, *74* (1), 145–192.
- Anton, Miguel and Christopher Polk**, “Connected Stocks,” *The Journal of Finance*, 2014, *69* (3), 1099–1127.
- Bardoscia, Marco, Gerardo Ferrara, Nicholas Vause, and Michael Yoganayagam**, “Simulating liquidity stress in the derivatives market,” *Journal of Economic Dynamics and Control*, 2021, *133*, 104215.
- Bellemare, Marc F. and Casey J. Wichman**, “Elasticities and the Inverse Hyperbolic Sine Transformation,” *Oxford Bulletin of Economics and Statistics*, 2020, *82* (1), 50–61.
- Burbidge, John B, Lonnie Magee, and A Leslie Robb**, “Alternative transformations to handle extreme values of the dependent variable,” *Journal of the American Statistical Association*, 1988, *83* (401), 123–127.
- Coval, Joshua and Erik Stafford**, “Asset fire sales (and purchases) in equity markets,” *Journal of Financial Economics*, 2007, *86* (2), 479–512.
- Czech, Robert, Bernat Gual-Ricart, Joshua Lillis, and Jack Worlidge**, “The role of non-bank financial intermediaries in the ‘dash for cash’ in sterling markets,” *Bank of England Financial Stability Paper No. 47*, 2021.
- , **Shiyang Huang, Dong Lou, and Tianyu Wang**, “Informed trading in government bond markets,” *Journal of Financial Economics*, 2021, *142* (3), 1253–1274.
- Duffie, Darrell**, “Financial Regulatory Reform After the Crisis: An Assessment,” *Management Science*, 2018, *64* (10), 4835–4857.
- , “Still the World’s Safe Haven? Redesigning the U.S. Treasury Market After the COVID-19 Crisis,” *Hutchins Center Working Paper Number 62*, *Brookings Institution*, 2020.
- **and Arvind Krishnamurthy**, “Passthrough efficiency in the fed’s new monetary policy setting,” *Designing Resilient Monetary Policy Frameworks for the Future. Federal Reserve Bank of Kansas City, Jackson Hole Symposium*, 2016, pp. 1815–1847.
- Edmans, Alex, Itay Goldstein, and Wei Jiang**, “The Real Effects of Financial Markets: The Impact of Prices on Takeovers,” *The Journal of Finance*, 2012, *67* (3), 933–971.
- Greenwood, Robin and David Thesmar**, “Stock price fragility,” *Journal of Financial Economics*, 2011, *102* (3), 471–490.

- Haddad, Valentin, Alan Moreira, and Tyler Muir**, “When Selling Becomes Viral: Disruptions in Debt Markets in the COVID-19 Crisis and the Fed’s Response,” *The Review of Financial Studies*, 01 2021, *34* (11), 5309–5351.
- He, Zhiguo, Stefan Nagel, and Zhaogang Song**, “Treasury inconvenience yields during the COVID-19 crisis,” *Journal of Financial Economics*, 2021.
- Huang, Shiyang, Wenxi Jiang, Xiaoxi Liu, and Xin Liu**, “Does Liquidity Management Induce Fragility in Treasury Prices? Evidence from Bond Mutual Funds,” *Unpublished Working Paper*, 2021.
- , **Yang Song, and Hong Xiang**, “Noise Trading and Asset Pricing Factors,” *Unpublished Working Paper*, 2021.
- Liao, Gordon Y. and Tony Zhang**, “The Hedging Channel of Exchange Rate Determination,” *Unpublished Working Paper*, 2021.
- Lou, Dong**, “A Flow-Based Explanation for Return Predictability,” *The Review of Financial Studies*, 12 2012, *25* (12), 3457–3489.
- , **Hongjun Yan, and Jinfan Zhang**, “Anticipated and Repeated Shocks in Liquid Markets,” *The Review of Financial Studies*, 06 2013, *26* (8), 1891–1912.
- Ma, Yiming, Kairong Xiao, and Yao Zeng**, “Mutual fund liquidity transformation and reverse flight to liquidity,” *Review of Financial Studies*, *forthcoming*, 2021.
- Rousová, Linda Fache, Maddalena Ghio, Simon Kördel, and Dilyara Salakhova**, “Interconnectedness of derivatives markets and money market funds through insurance corporations and pension funds,” *ECB Financial Stability Review*, 2020.
- Schrimpf, Andreas, Hyun Song Shin, and Vladyslav Sushko**, “Leverage and margin spirals in fixed income markets during the Covid-19 crisis,” *BIS Bulletin No. 2*, 2020.
- Vayanos, Dimitri**, “Flight to Quality, Flight to Liquidity, and the Pricing of Risk,” *Unpublished Working Paper*, 2004.

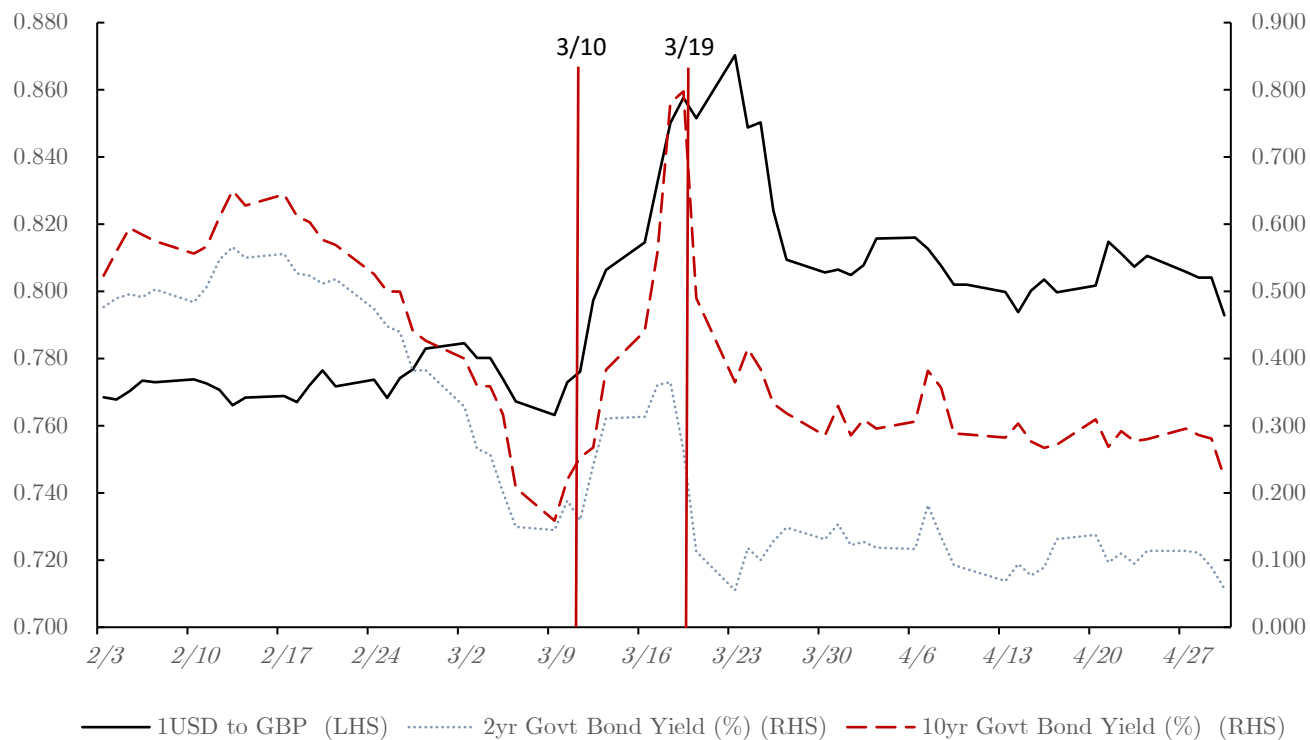


Figure 1: USD/GBP Exchange Rate and UK Government Bond Yields

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.

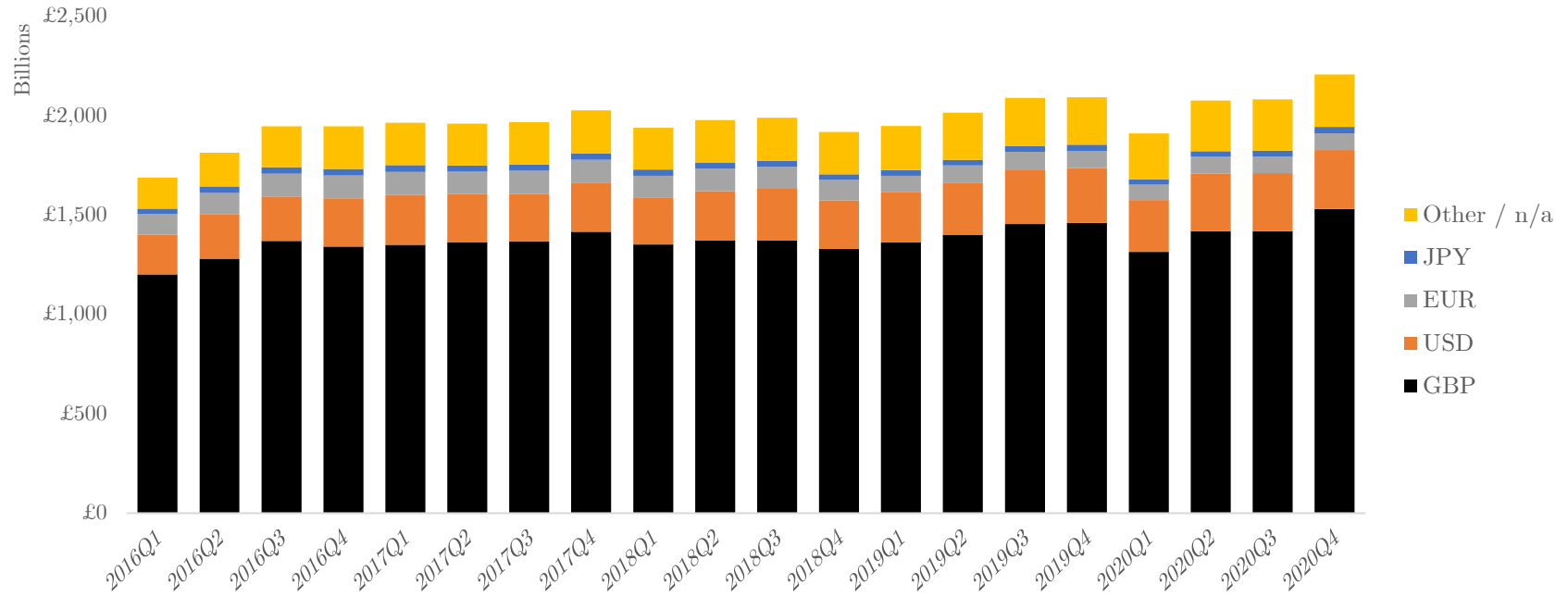


Figure 2: Total Asset Holdings of UK Insurance Companies

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.

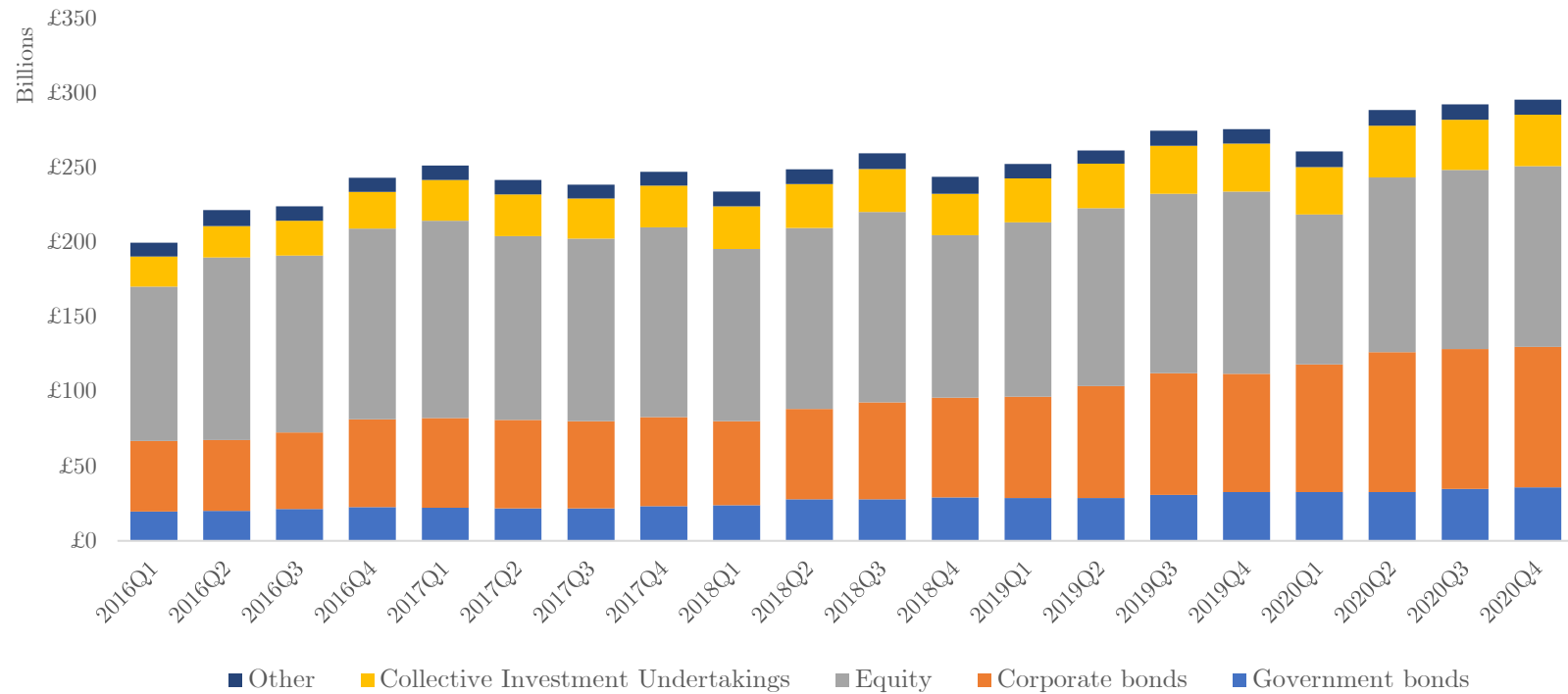


Figure 3: USD Asset Holdings of UK Insurance Companies

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.

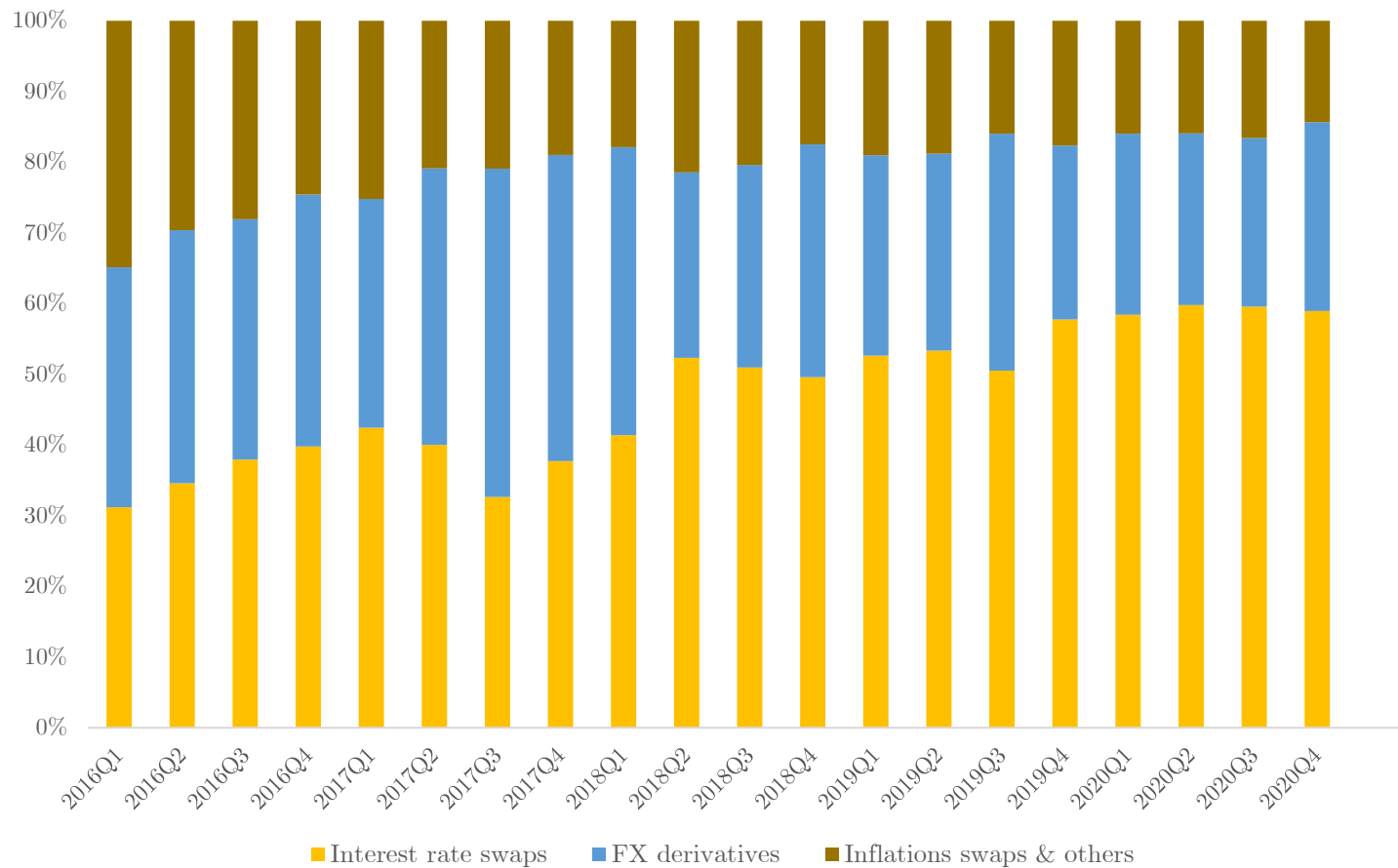


Figure 4: Composition of Derivative Holdings of UK Insurance Companies

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.

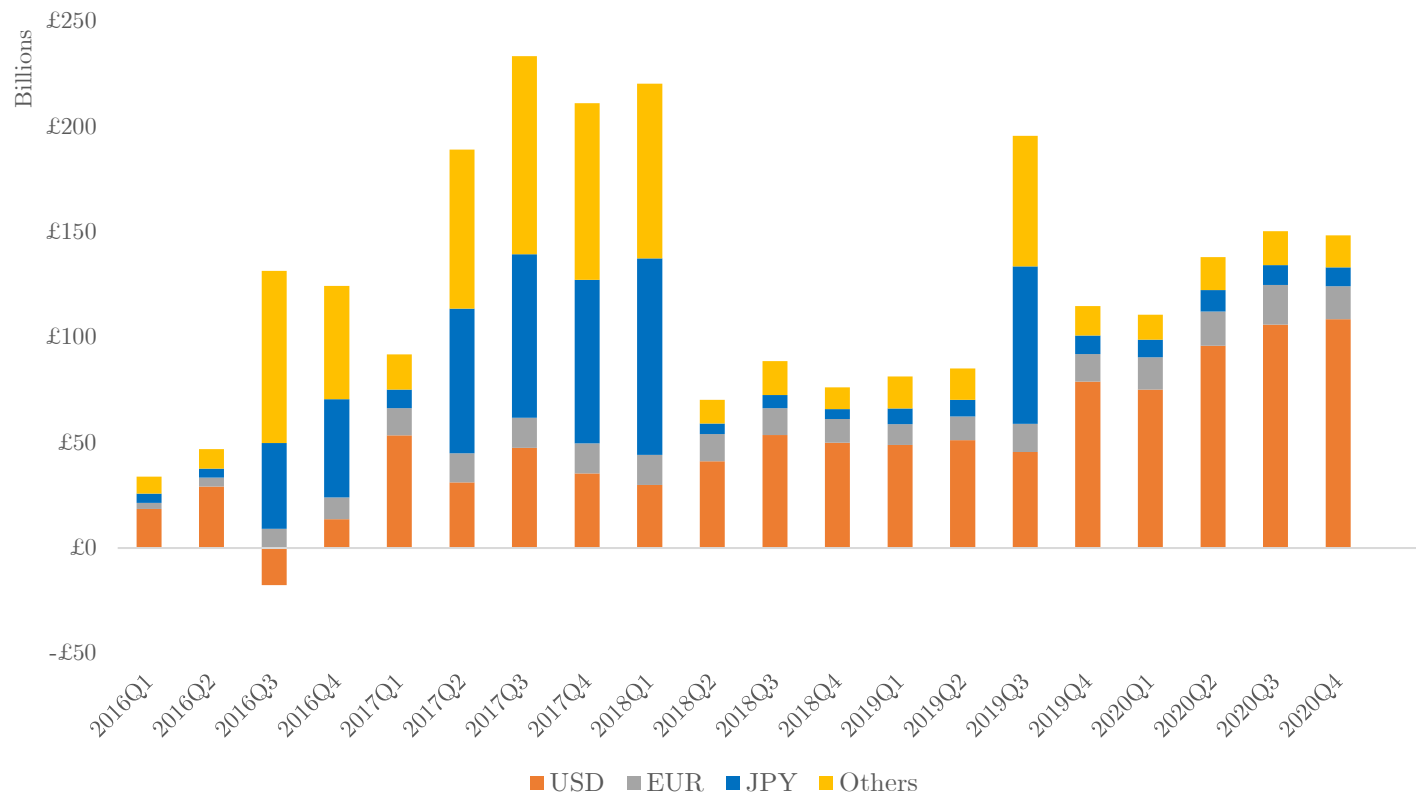


Figure 5: FX Derivative Net Exposure by Currency

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.

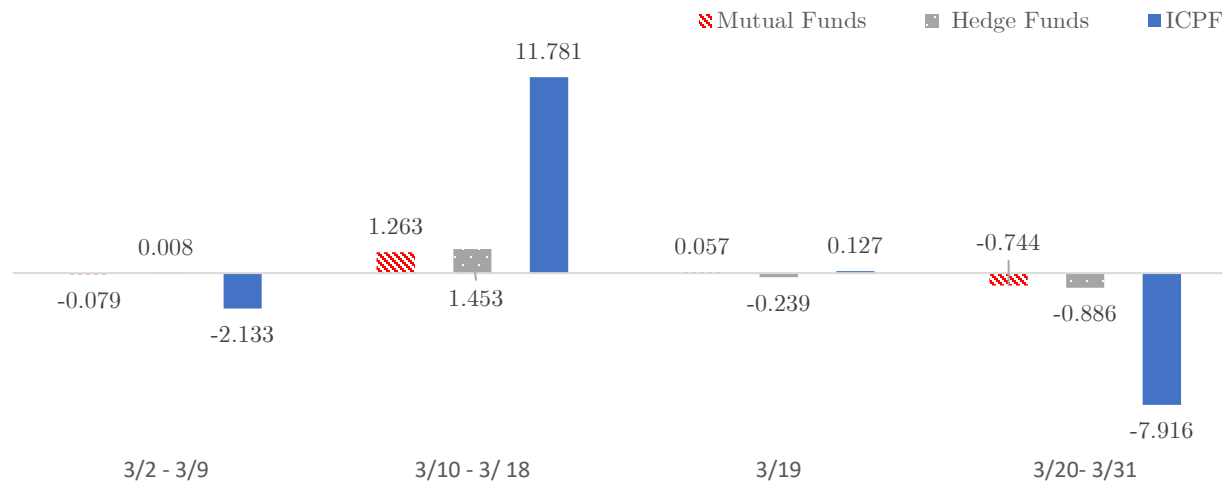


Figure 6: Total Variation Margin Demands on Different Investor Types

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.

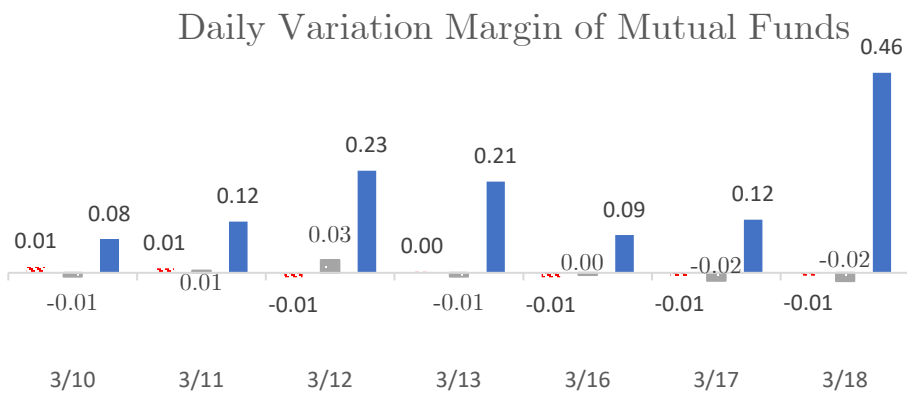
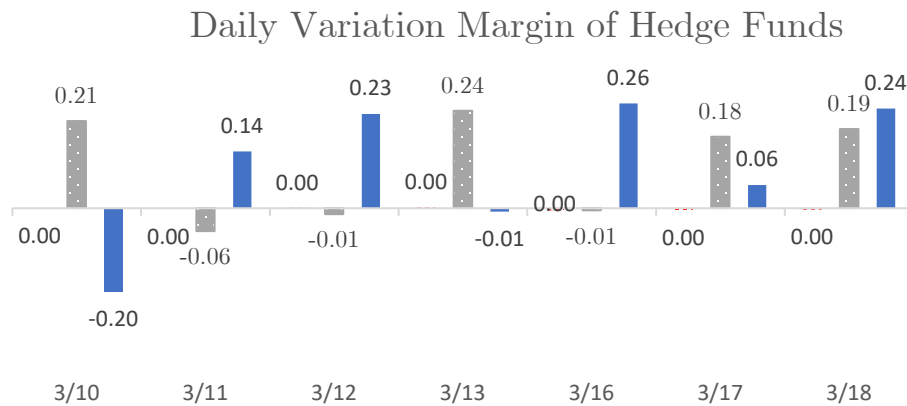
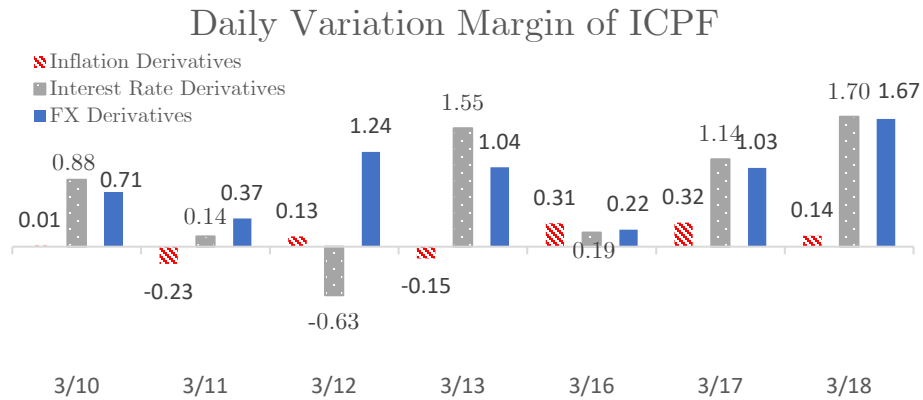


Figure 7: Daily Variation Margin Demands on Different Investor Types

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.

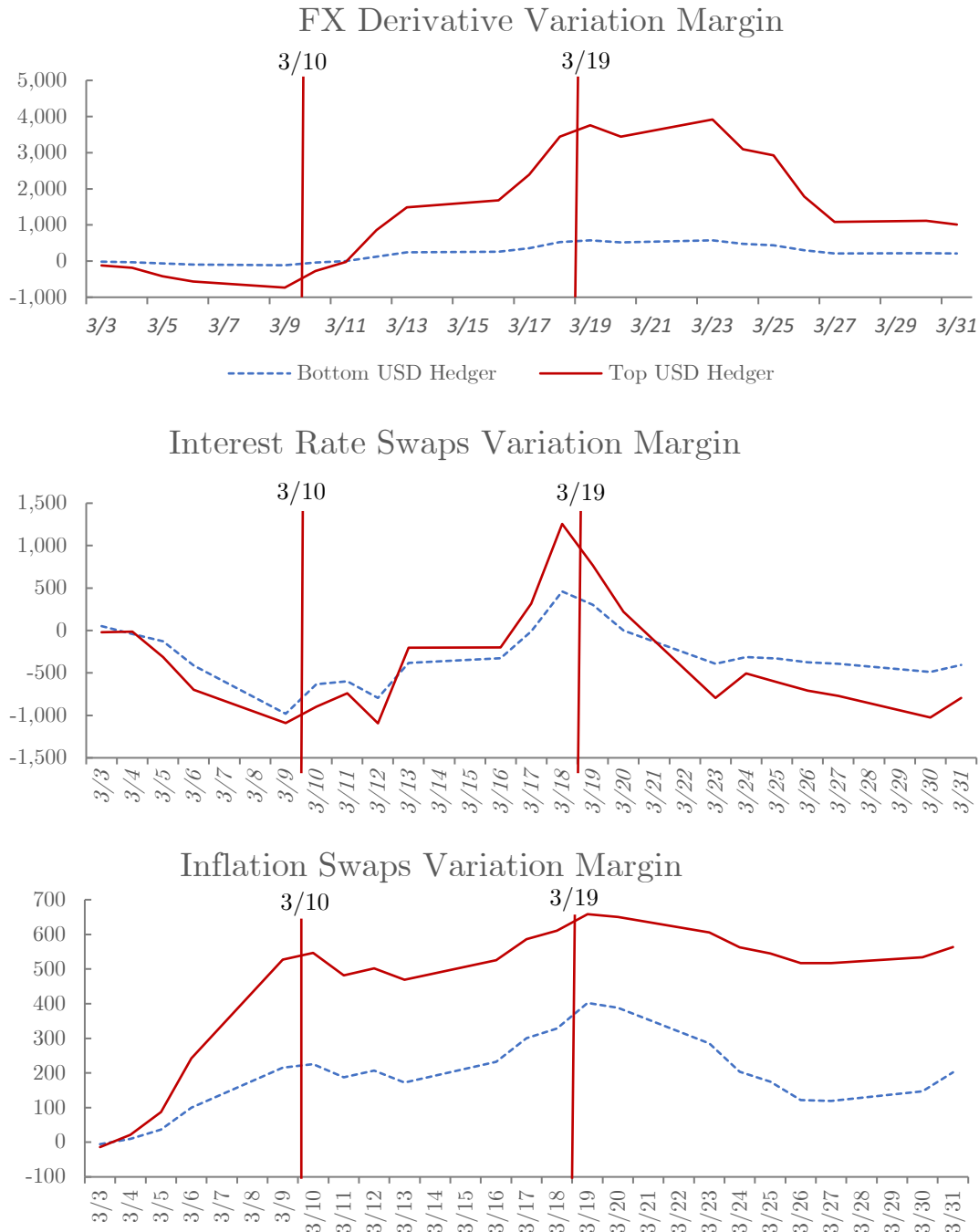


Figure 8: Variation Margin Demands on Top and Bottom USD FX Derivative Hedgers

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.

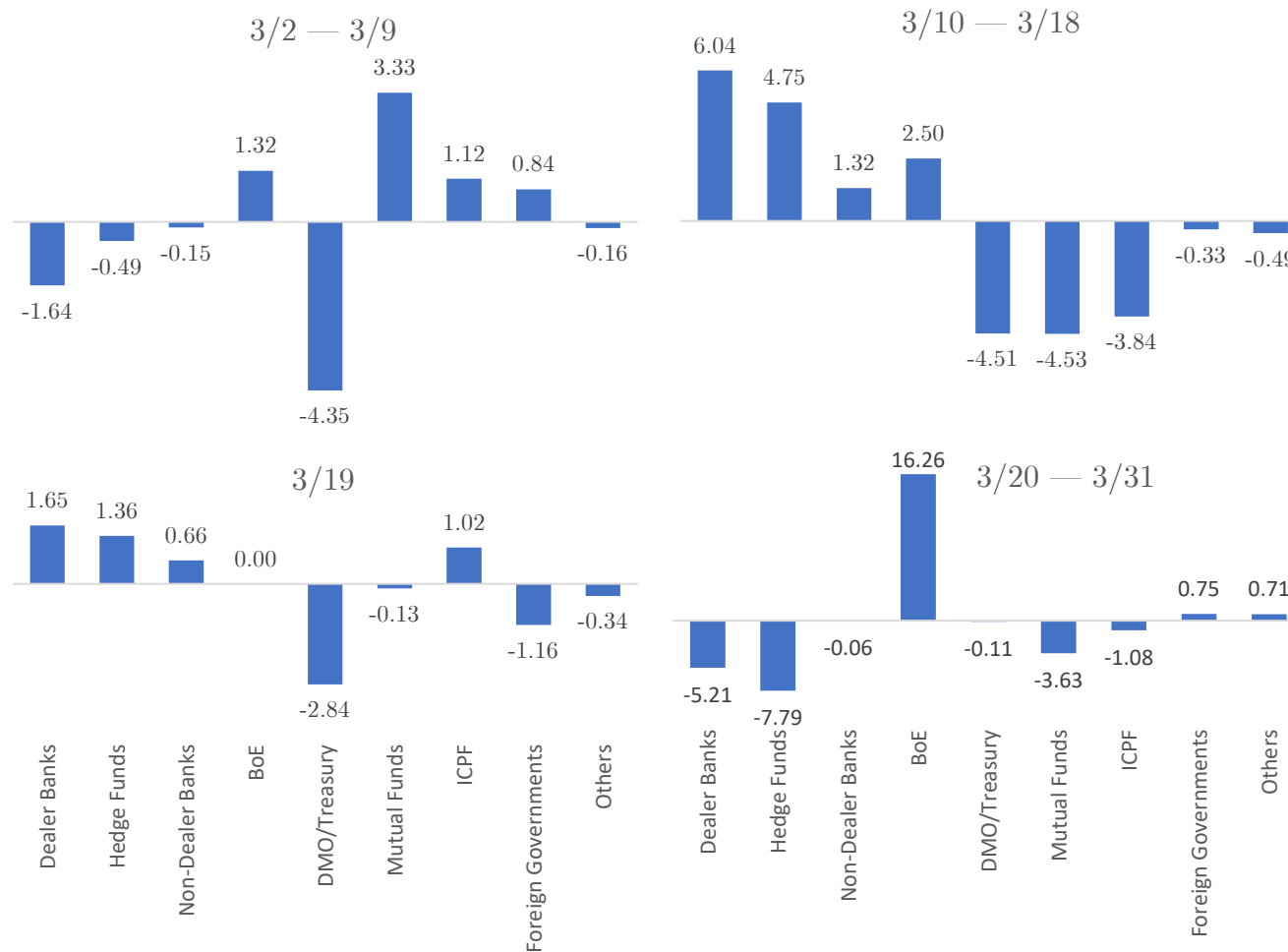


Figure 9: Total Gilt Net Trading Volumes

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.

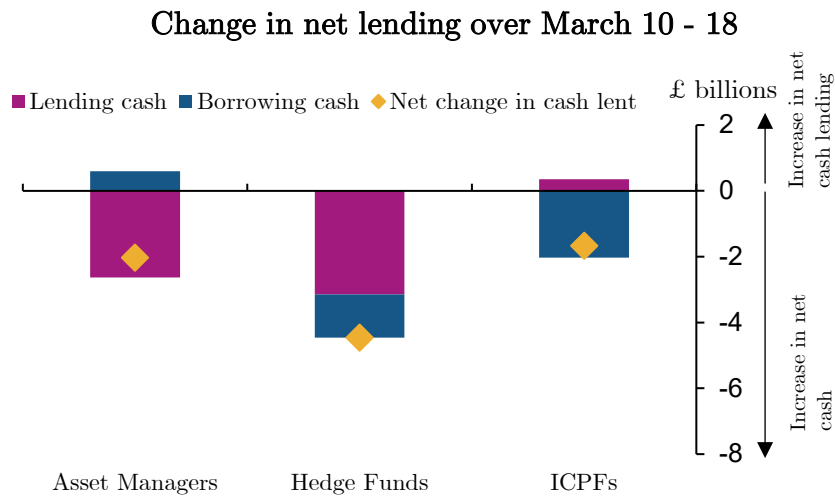
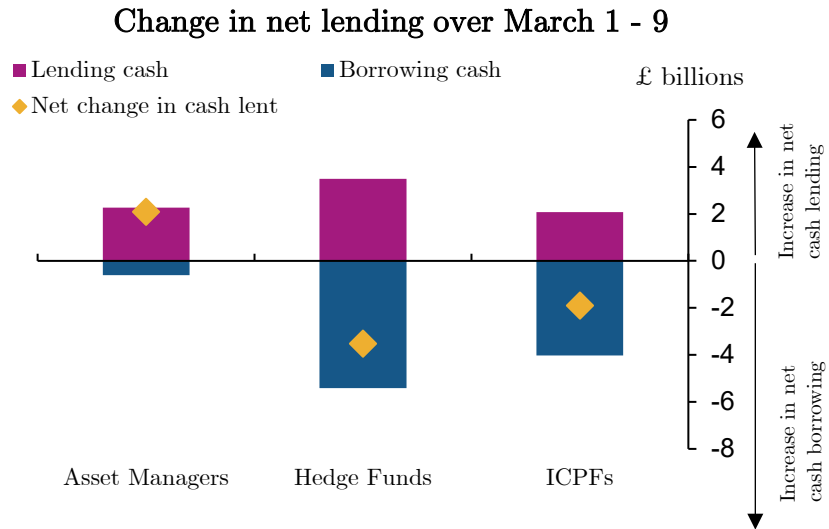


Figure 10: Repo Activity of Mutual Funds, Hedge Funds, and ICPFs

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.

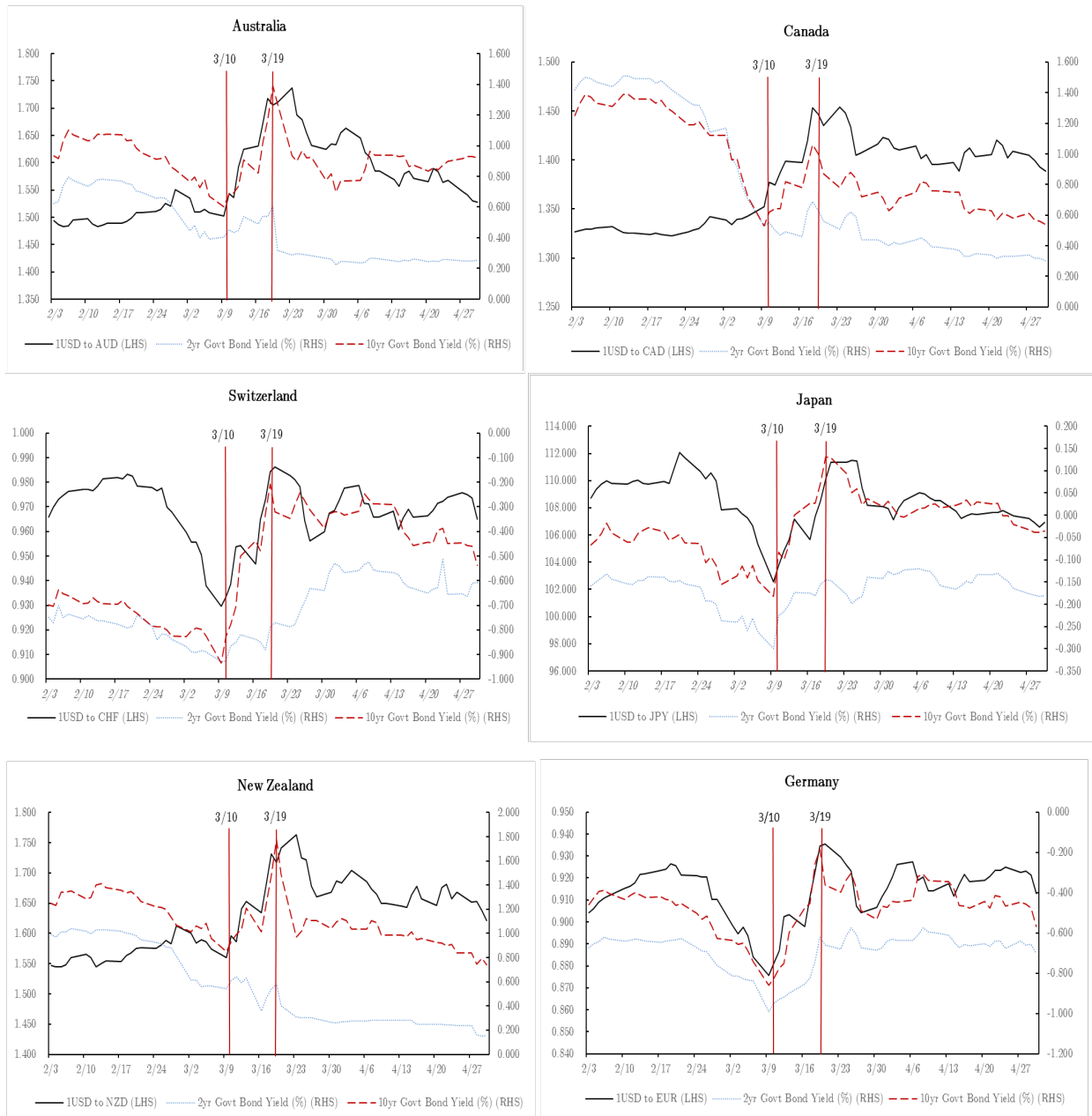


Figure 11: Exchange Rates and Government Bond Yields

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 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.

<b>Panel A: Insurers' Holdings and Hedging Positions</b>						
	Mean	Std.Dev	Q25	Q50	Q75	
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	

<b>Panel B: Gilt Yield Change</b>						
$\Delta$ Yield (March 1–18) (bps)	2.43	8.82	-3.47	-0.40	7.62	
$\Delta$ Yield (March 1–9) (bps)	-4.34	4.00	-5.22	-3.66	-1.90	
$\Delta$ Yield (March 10–18) (bps)	8.23	7.60	3.37	7.20	11.72	

<b>Panel C: Estimated Daily Variation Margin per Investor</b>						
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

<b>Panel D: Gilt Trading</b>						
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.

<b>Panel A: Foreign Asset Holdings and Hedging Positions</b>			
	(1)	(2)	(3)
DepVar:	Derivative Hedging Positions		
Foreign Asset Holdings	0.262*** (9.811)	0.262*** (9.805)	0.262*** (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 <sup>2</sup>	0.191	0.191	0.139

<b>Panel B: Comparison between Hedging Position for USD Assets and Assets in Other Currencies</b>					
	Excluding USD Assets			USD Assets Only	
	(1)	(2)	(3)	(4)	(5)
DepVar:	Derivative Hedging Positions				
Foreign Asset Holdings	0.202*** (9.572)	0.202*** (9.609)	0.201*** (9.710)	0.542*** (3.446)	0.507*** (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 <sup>2</sup>	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 1<sup>st</sup> to 18<sup>th</sup> 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.

<b>Panel A: Comparison of Variation Margin Between Top and Bottom USD Hedgers</b>			
	Flight to safety period (March 1 - 9)	Dash for cash period (March 10 - 18)	March 1 - 18
	(1)	(2)	(3)
DepVar:	VM	VM	VM
<i>Indicator_Top</i>	-14.975** (-2.599)	61.512*** (3.085)	-14.975*** (-2.605)
<i>Dash_for_Cash</i>			76.487*** (3.680)
<i>Indicator_Top</i> × <i>Dash_for_Cash</i>			16.453*** (2.859)
No. of Obs.	74	105	179
Adj. R <sup>2</sup>	0.062	0.067	0.150

<b>Panel B: USD FX Derivative Holdings and Variation Margin</b>			
	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*** (-4.969)	0.005*** (4.574)	-0.001*** (-4.981)
<i>Dash_for_Cash</i>			0.006*** (5.604)
USD FX Derivative Holdings × <i>Dash_for_Cash</i>			26.855*** (3.710)
No. of Obs.	74	105	179
Adj. R <sup>2</sup>	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 1<sup>st</sup> to 18<sup>th</sup> 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 (-0.855)	0.130 (1.547)	-0.142** (-2.138)	-0.163** (-2.278)	0.131 (1.551)	0.11 (1.261)	0.268 (1.239)	0.095 (0.651)
VM × <i>Dash_for_Cash</i>					-0.273*** (-2.544)	-0.273** (-2.412)		
VM(>0) × <i>Dash_for_Cash</i>							-0.742*** (-3.041)	
VM(<0) × <i>Dash_for_Cash</i>								0.215 (1.020)
<i>Dash_for_Cash</i>					-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 <sup>2</sup>	0.002	0.021	0.025	0.046	0.024	0.047	0.127	0.118

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

**Table 5: Variation Margin and Repo Trading Volume**

This table reports the results of panel regressions of the repo (cash borrowing) and reverse repo (cash lending) trading volume of insurance companies and pension funds (ICPFs) on estimated daily variation margins. The sample period is from March 10<sup>th</sup> to 18<sup>th</sup> 2020, and the observations are at the investor-day level. In Panel A, the dependent variable is the daily repo trading volume (in £ million) of a particular ICPF. In Panel B, the dependent variable is the ICPF's daily reverse repo trading volume (in £ million). 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 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.

<b>Panel A: Repo Trading</b>					
	(1)	(2)	(3)	(4)	(5)
	Dash for cash period (March 10 - 18)				
VM on FX Derivatives	0.177** (2.292)			0.170** (1.973)	0.216** (2.398)
VM on Interest Rate Swaps		-0.094 (-1.581)		-0.074 (-1.221)	-0.093 (-1.407)
VM on Inflation Swaps			-0.110 (-0.593)	-0.182 (-0.912)	-0.103 (-0.524)
Time FE	No	No	No	No	Yes
No. of Obs.	146	146	146	146	146
Adj. R <sup>2</sup>	0.0159	0.0106	-0.0038	0.0204	0.0403

<b>Panel B: Reverse Repo Trading</b>					
	(1)	(2)	(3)	(4)	(5)
	Dash for cash period (March 10 - 18)				
VM on FX Derivatives	-0.014 (-0.154)			-0.059 (-0.545)	0.013 (0.139)
VM on Interest Rate Swaps		-0.146** (-2.336)		-0.165** (-2.479)	-0.251*** (-3.958)
VM on Inflation Swaps			0.027 (0.293)	-0.083 (-0.734)	-0.149 (-1.187)
Time FE	No	No	No	No	Yes
No. of Obs.	34	34	34	34	33
Adj. R <sup>2</sup>	-0.0308	0.0841	-0.0296	0.0351	0.1861

**Table 6: 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 turnover ratio 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.

<b>Panel A: Variation Margin (VM) and Net Gilt Trading Volume</b>						
	(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*** (-4.457)	0.003 (0.238)	-0.055*** (-5.131)	-0.058*** (-5.041)	-0.037*** (-3.250)	-0.036*** (-2.899)
$VM \times Liquid\_Bond$					-0.042* (-1.862)	-0.049** (-2.186)
<i>Liquid_Bond</i>					-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 <sup>2</sup>	0.007	0.000	0.017	0.112	0.019	0.115

<b>Panel B: Variation Margin (VM) on Different Derivative Groups and Net Gilt Trading Volume</b>				
	(1)	(2)	(3)	(4)
	Dash for cash period (March 10 - 18)			
DepVar:	Net Gilt Trading Volume			
VM on FX Derivatives	-0.102*** (-5.153)	-0.094*** (-4.233)	-0.043* (-1.828)	-0.037 (-1.408)
VM on Interest Rate Swaps	-0.045*** (-4.096)	-0.047*** (-4.080)	-0.020* (-1.712)	-0.019 (-1.552)
VM on Inflation Swaps	0.031 (1.068)	0.056 (1.242)	-0.015 (-0.464)	0.016 (0.336)
VM on FX Derivatives × <i>Liquid_Bond</i>			-0.150*** (-3.650)	-0.141*** (-3.325)
VM on Interest Rate Swaps × <i>Liquid_Bond</i>			-0.063*** (-2.691)	-0.069*** (-2.912)
VM on Inflation Swaps × <i>Liquid_Bond</i>			0.102* (1.712)	0.091 (1.527)
<i>Liquid_Bond</i>			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 <sup>2</sup>	0.026	0.117	0.041	0.130

**Table 7: 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 Trading<sub>j,t</sub>), mutual funds (Mutual Fund Trading<sub>j,t</sub>), non-dealer banks (Non-Dealer Bank Trading<sub>j,t</sub>), and hedge funds (Hedge Fund Trading<sub>j,t</sub>). 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<sub>t</sub>* 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.

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

<b>Panel B: January - March 18</b>				
	(1)	(2)	(3)	(4)
ICPF Trading <sub>i,t</sub>	-0.019 (-0.806)			
Mutual Fund Trading <sub>i,t</sub>		-0.019 (-0.960)		
Non-Dealer Bank Trading <sub>i,t</sub>			-0.021 (-0.376)	
Hedge Fund Trading <sub>i,t</sub>				-0.019 (-1.347)
ICPF Trading <sub>i,t</sub> × <i>COVID_Period</i> <sub>t</sub>	-0.308*** (-3.292)			
Mutual Fund Trading <sub>i,t</sub> × <i>COVID_Period</i> <sub>t</sub>		-0.197** (-2.551)		
Non-Dealer Bank Trading <sub>i,t</sub> × <i>COVID_Period</i> <sub>t</sub>			0.560*** (2.672)	
Hedge Fund Trading <sub>i,t</sub> × <i>COVID_Period</i> <sub>t</sub>				0.132** (2.299)
<i>COVID_Period</i> <sub>t</sub>	0.025*** (2.892)	0.027*** (2.884)	0.029*** (3.105)	0.029*** (2.947)
Controls	Yes	Yes	Yes	Yes
No. of Obs.	378	378	378	378
Adj. R <sup>2</sup>	<b>0.133</b>	0.103	0.102	0.089

**Table 8: 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<sub>j,t</sub>), mutual funds (Mutual Fund Trading<sub>j,t</sub>), non-dealer banks (Non-Dealer Bank Trading<sub>j,t</sub>), and hedge funds (Hedge Fund Trading<sub>j,t</sub>). 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.

<b>Panel A: Short-Term Bonds</b>				
DepVar:	(1)	(2)	(3)	(4)
		$\Delta\text{Yield}_{j,t}$		
ICPF Trading <sub>j,t</sub>	-0.187** (-2.169)			
Mutual Fund Trading <sub>j,t</sub>		-0.081 (-1.045)		
Non-Dealer Bank Trading <sub>j,t</sub>			0.168 (0.716)	
Hedge Fund Trading <sub>j,t</sub>				0.185* (1.849)
Controls	Yes	Yes	Yes	Yes
No. of Obs.	26	26	26	26
Adj. R <sup>2</sup>	0.244	0.166	0.151	0.236
<b>Panel B: Long-Term Bonds</b>				
ICPF Trading <sub>j,t</sub>	-0.547*** (-3.387)			
Mutual Fund Trading <sub>j,t</sub>		-0.473*** (-3.564)		
Non-Dealer Bank Trading <sub>j,t</sub>			0.914*** (2.915)	
Hedge Fund Trading <sub>j,t</sub>				0.105 (1.583)
Controls	Yes	Yes	Yes	Yes
No. of Obs.	65	65	65	65
Adj. R <sup>2</sup>	0.155	0.119	0.087	0.028

**Table 9: 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,  $\Delta \text{Yield}(t-1, t+k)$ , 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 $_{i,t}$ ). 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.

<b>Panel A: All Bonds</b>				
	(1)	(2)	(3)	(4)
DepVar:	$\Delta \text{Yield}(t-1, t+1)$	$\Delta \text{Yield}(t-1, t+5)$	$\Delta \text{Yield}(t-1, t+15)$	$\Delta \text{Yield}(t-1, t+21)$
ICPF Trading $_{i,t}$	-0.515*** (-2.965)	-0.211 (-0.576)	0.110 (0.733)	0.206 (1.496)
No. of Obs.	91	91	91	91
Adj. R <sup>2</sup>	0.111	0.097	0.114	0.101
<b>Panel B: Short-term Bonds</b>				
ICPF Trading $_{i,t}$	-0.186 (-1.116)	-0.405 (-1.472)	-0.203 (-1.067)	-0.022 (-0.135)
No. of Obs.	26	26	26	26
Adj. R <sup>2</sup>	0.106	0.089	0.074	0.013
<b>Panel C: Long-term Bonds</b>				
ICPF Trading $_{i,t}$	-0.783** (-2.540)	0.036 (0.059)	0.347* (1.941)	0.398** (2.030)
No. of Obs.	65	65	65	65
Adj. R <sup>2</sup>	0.135	0.116	0.075	0.100

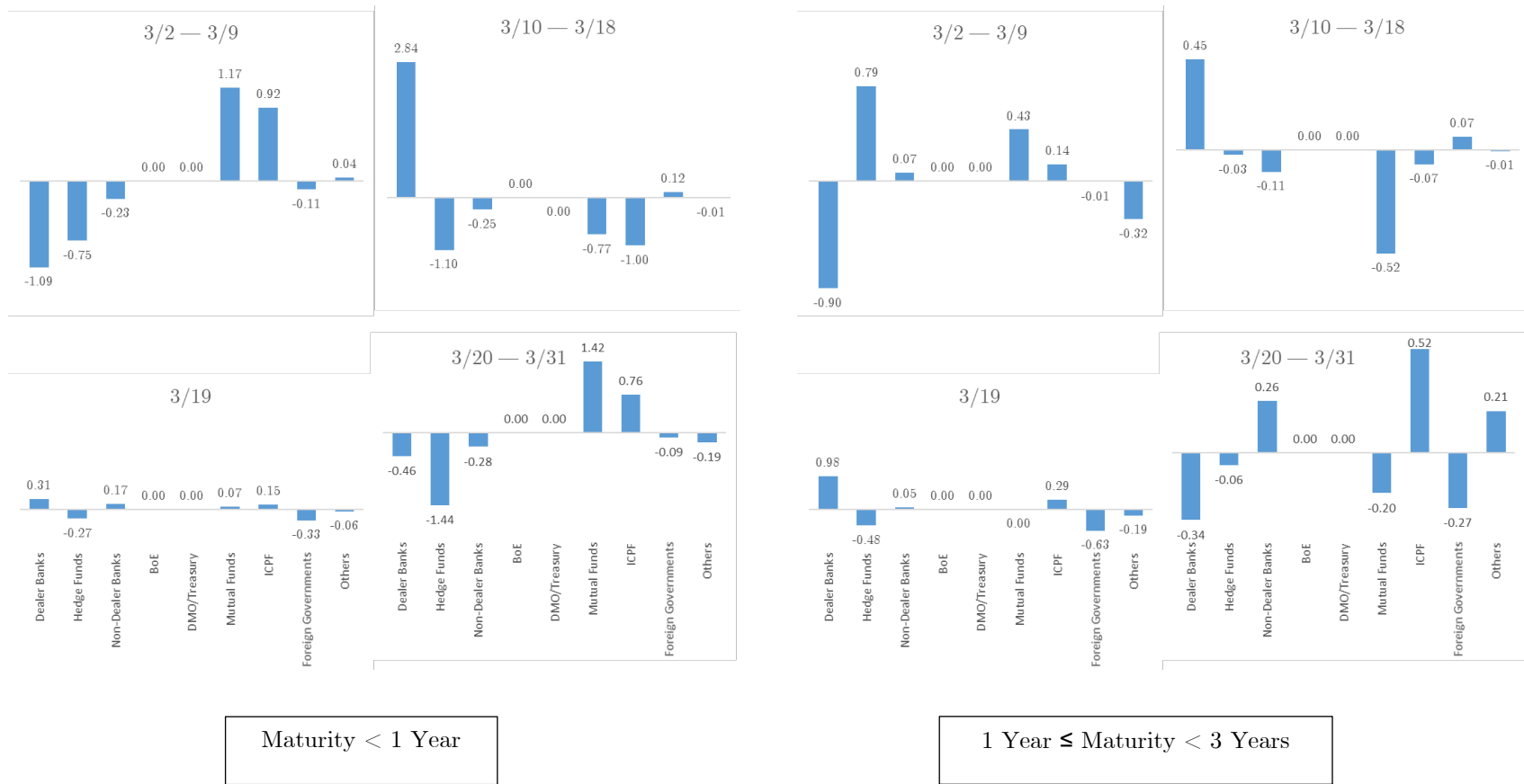
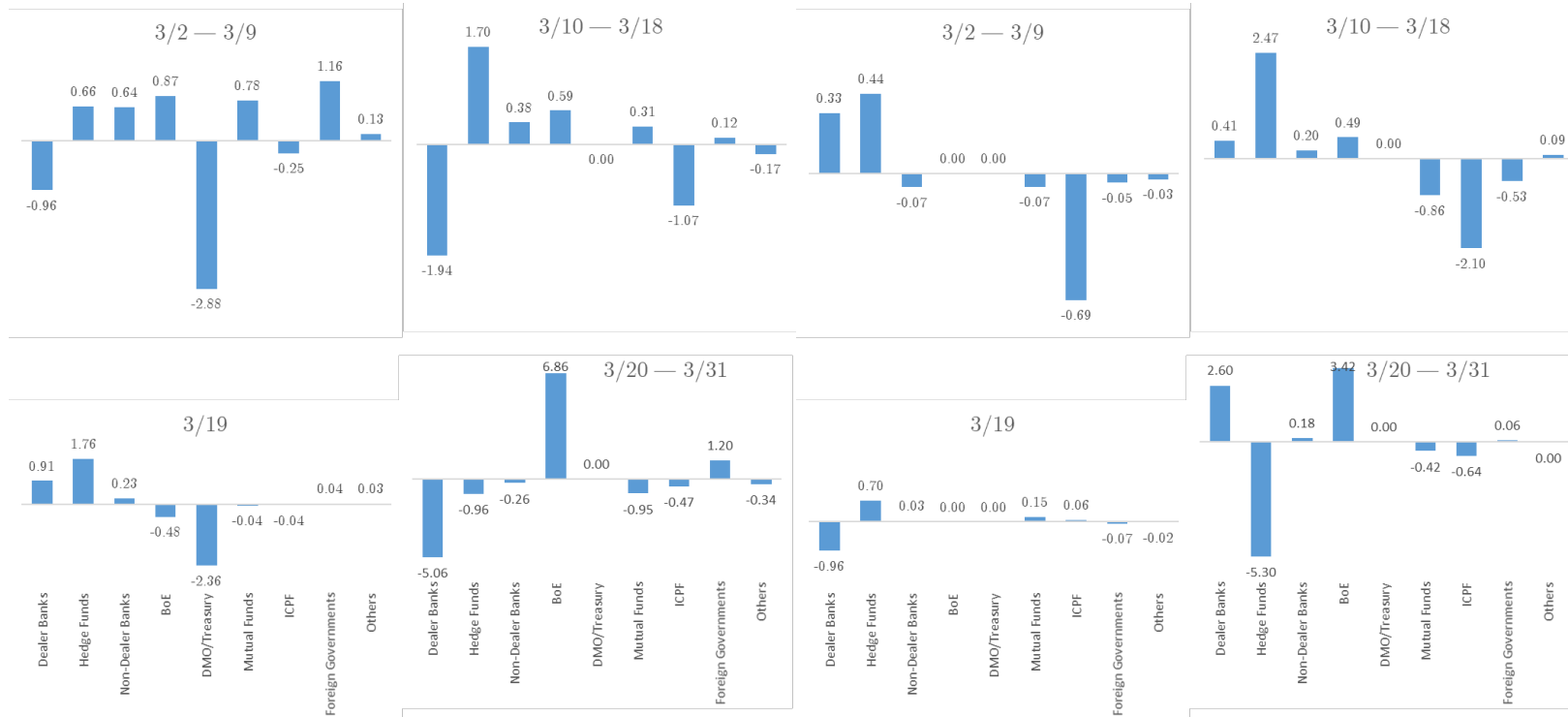


Figure A1: Total Gilt Net Trading Volumes

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.

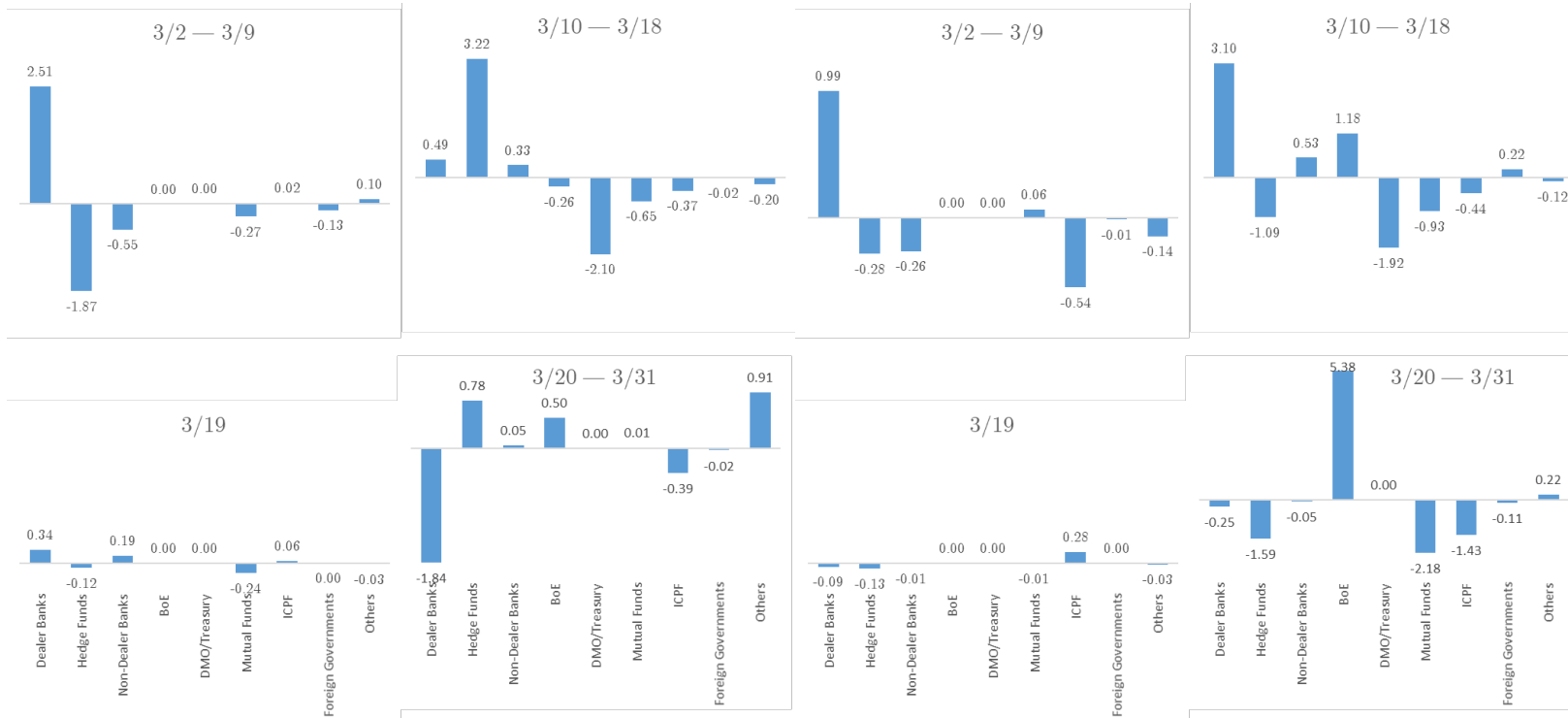
Figure A1 (Continued)



3 Years ≤ Maturity < 7 Years

7 Years ≤ Maturity < 10 Years

Figure A1 (Continued)



10 Years ≤ Maturity < 15 Years

Maturity ≥ 15 Years

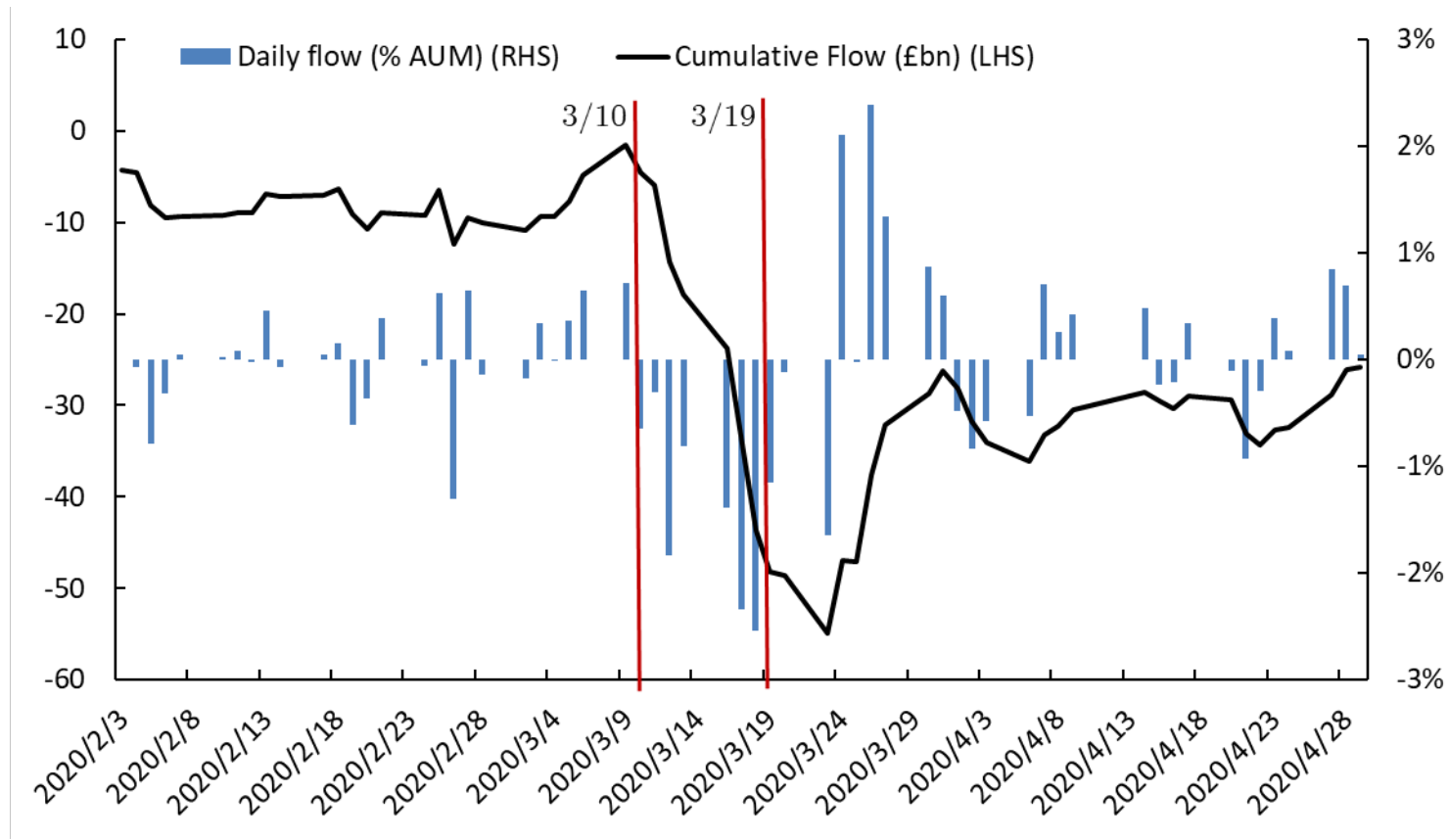


Figure A2: Mutual Fund Flows

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.

**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)					
<i>Indicator_Top</i>	-3.622 (-0.062)	21.530 (0.503)	-3.622 (-0.062)	6.808 (0.711)	-2.029 (-0.531)	6.808 (0.713)
<i>Indicator_Top</i> ×			25.152 (0.348)			-8.837 (-0.859)
<i>Dash_for_Cash</i>			67.009*** (3.345)			-6.721 (-1.016)
No. of Obs.	60	84	144	50	70	120
Adj. R <sup>2</sup>	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.

DepVar:	Mutual Funds			Hedge Funds		
	(1)	(2)	(3)	(4)	(5)	(6)
	Net Gilt Trading Volume			Net Gilt Trading Volume		
VM	-0.047 (-1.091)	-0.056 (-1.228)		0.009 (0.217)	-0.019 (-0.416)	
VM on FX Derivatives			-0.044 (-0.522)			0.004 (0.078)
VM on Interest Rate Swaps			-0.064 (-0.774)			-0.060 (-0.654)
VM on Inflation Swaps			0.157 (1.268)			0.112 (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 <sup>2</sup>	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<sub>j,t</sub>), mutual funds (Mutual Fund Trading<sub>j,t</sub>), non-dealer banks (Non-Dealer Bank Trading<sub>j,t</sub>), and hedge funds (Hedge Fund Trading<sub>j,t</sub>). 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*<sub>t</sub> 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.

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

Panel B: Compared to Jan - Dec 2019				
	(1)	(2)	(3)	(4)
ICPF Trading <sub>j,t</sub>	-0.011 (-0.980)			
Mutual Fund Trading <sub>j,t</sub>		-0.006 (-0.737)		
Non-Dealer Bank Trading <sub>j,t</sub>			0.010 (0.614)	
Hedge Fund Trading <sub>j,t</sub>				-0.015** (-2.253)
ICPF Trading <sub>j,t</sub> × COVID Period <sub>t</sub>	-0.311*** (-3.444)			
Mutual Fund Trading <sub>j,t</sub> × COVID Period <sub>t</sub>		-0.209*** (-2.721)		
Non-Dealer Bank Trading <sub>j,t</sub> × COVID Period <sub>t</sub>			0.526*** (2.583)	
Hedge Fund Trading <sub>j,t</sub> × COVID Period <sub>t</sub>				0.125** (2.216)
COVID Period <sub>t</sub>	0.020** (2.345)	0.022** (2.419)	0.024*** (2.638)	0.024** (2.497)
Controls	Yes	Yes	Yes	Yes
No. of Obs.	1,862	1,862	1,862	1,862
Adj. R <sup>2</sup>	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)
<i>DepVar: Net Gilt Trading Volume<sub>t</sub></i>						
$Flow_t$	0.253*** (9.039)	0.220*** (6.959)	0.152*** (3.498)	0.119** (2.464)	0.311*** (8.927)	0.293*** (6.695)
$Flow_{t-1}$		0.083** (2.441)		0.083* (1.717)		0.060 (1.201)
$Flow_{t-2}$		-0.051 (-1.521)		-0.022 (-0.461)		-0.086* (-1.825)
$Flow_{t-3}$		0.030 (0.978)		0.002 (0.040)		0.078* (1.879)
Constant	-0.428*** (-3.840)	-0.394*** (-3.472)	0.057 (0.342)	0.051 (0.303)	-0.418*** (-3.804)	-0.405*** (-3.778)
No. of Obs.	4,026	4,003	1,752	1,745	2,274	2,258
Adj-R <sup>2</sup>	0.070	0.074	0.023	0.025	0.091	0.098