BANK OF ENGLAND

Staff Working Paper No. 871

Informed trading in government bond markets

Robert Czech, Shiyang Huang, Dong Lou and Tianyu Wang

June 2020

BANK OF ENGLAND

Staff Working Paper No. 871

Informed trading in government bond markets

Robert Czech,[1] Shiyang Huang,[2] Dong Lou[3] and Tianyu Wang[4]

Abstract

Using comprehensive regulatory data, we examine trading by different investor types in government bond markets. Our sample covers virtually all secondary market trading in gilts and contains detailed information on each transaction, including the identities of both counterparties. We find that hedge funds' daily trading positively forecasts gilt returns in the following one to five days, which is then fully reversed in the following month. A part of this short-term return predictability is due to hedge funds' ability to anticipate future demand of other investors. Mutual fund trading also positively predicts gilt returns, but over a longer horizon of one to two months. This return pattern does not revert in the following year and is partly due to mutual funds' ability to forecast changes in short-term interest rates.

Key words: Government bonds, informed trading, return predictability, asset managers.

JEL classification: G11, G12, G14, G23.

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

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 Alina Barnett, Geoff Coppins, John Campbell, Zhi Da, Zhiguo He, Mike Joyce, Christian Julliard, Ralph Koijen, Giang Nguyen, Zhan Shi, Stuart Turnbull, Nick Vause, Quan Wen, and seminar and conference participants at the Bank of England, London School of Economics, Shanghai Advanced Institute of Finance (SAIF), Tsinghua University, University of Hong Kong, the 2019 China International Conference in Finance, the 2020 American Finance Association Annual Meeting, and the 2020 Finance Down Under Conference for helpful comments.

The Bank's working paper series can be found at www.bankofengland.co.uk/working-paper/staff-working-papers

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

ISSN 1749-9135 (on-line)

1. Introduction

Government bond yields serve as a benchmark for virtually all other rates in the financial market. It is thus crucial for academics, investors, and regulators to understand the movements in government bond yields.[1] The traditional view is that the arrival of public information, such as monetary policy announcements, is the main source of variation in the term structure of interest rates. Fleming and Remolona (1997) indeed show that macroeconomic announcements are responsible for many of the largest daily price movements in the US Treasury market.[2] According to this view, trading in government bond markets is mostly due to rebalancing and hedging needs and is unlikely to have a large, persistent effect on bond yields.

An alternative view draws on the premise that investors are unequally informed. Differences in investors' beliefs may stem from their unequal access to information. Moreover, differences in opinions could also be driven by heterogeneity in the ability to relate publicly available economic fundamentals to the term structure of government bond yields. An immediate prediction of this view is that as long as learning is imperfect, trading of the better-informed – those with privileged access to value-relevant information and/or more accurate interpretations of public information – should persistently outperform that of the less-informed.

Our focus in the paper is on the second channel. A priori, it would seem difficult for any investor (or investor type) to acquire an information advantage over other participants in the government bond market given its depth and liquidity. Indeed, a large empirical literature on institutional trading has so far found little evidence that professional money managers are able to earn significant abnormal returns in stock and corporate bond markets (e.g., Wermers, 2000; Cici and Gibson, 2012). More related to our study, prior research on

[1] The literature on the term structure of risk-free rates has primarily focused on the factor structure of yield movements across maturities (see, e.g., Vasicek, 1977; Cox, Ingersoll and Ross, 1985). The consensus so far is that a small number of factors, usually interpreted as the level, slope, and curvature of the term structure, are responsible for nearly all the variation in yield changes (see, e.g., Litterman and Scheinkman, 1991).

[2] Further contributions include, for instance, Fleming and Remolona (1999), Green (2004), Balduzzi, Elton, and Green (2009).

investors' market timing ability has largely concluded that institutions that actively shift their market exposures on average underperform their peers (see, e.g., Huang, Sialm, and Zhang, 2011). It is therefore an intriguing empirical question whether a subset of investors has superior knowledge about future government bond returns.

Prior research on trading in the government bond market has explored a) bond mutual fund holdings data reported at a quarterly frequency (see, e.g., Huang and Wang, 2014), and b) intraday order flow data acquired from one or more dealer banks (see, e.g., Brandt and Kavajecz, 2004). An obvious drawback of the mutual fund holdings data is that researchers only get to observe *quarterly* snapshots of *long* positions held by mutual funds, thus missing all the round trips within a quarter as well as funds' short positions. The high-frequency order flow data do not suffer from this shortcoming, but unfortunately do not include the identities of the counterparties in each transaction. Consequently, researchers have focused on aggregate trading between dealers and non-dealer investors, summed across all reported trades.

We contribute to the debate on informed trading in the government bond market by exploiting comprehensive regulatory data. The ZEN database, which is maintained by the UK's Financial Conduct Authority (FCA), contains all secondary market trades in UK government bonds (gilts) by all FCA-regulated financial institutions. Given that all gilt dealers are UK-domiciled and hence FCA-regulated institutions, the ZEN database effectively covers the entire trading activity in the UK government bond market.

Compared to other datasets used in the prior literature, the ZEN database offers three main advantages. First, like the order flow data from a subset of dealer banks, the ZEN database provides detailed information on all individual transactions (the date and time stamp, transaction price, transaction amount, etc.). Second, unlike the order flow data, we observe the identities of both counterparties in each transaction (for example, a transaction between a dealer bank and a bond fund). Third, the ZEN database covers nearly all investors and transactions; more precisely, the buy and sell transactions in our sample sum up to the total trading volume in the gilt market. The granularity and completeness of our data enable us to systematically analyse the extent to which any investors have a competitive advantage in this market and, furthermore, are able to profit from their information edge.

For ease of comparison, we sort the non-dealer institutions in our sample into four separate groups (that serve different clienteles, have different objectives, and face different regulations): i) hedge funds, ii) mutual funds, iii) non-dealer banks, as well as iv) insurance companies and pension funds (ICPFs). These four groups account for 4%, 14%, 6% and 4% of the aggregate trading volume in the gilt market, respectively.[3] We mainly focus on the first two investor types – hedge funds and mutual funds – as the typical arbitrageurs in financial markets; as a placebo, we also report results for non-dealer banks and ICPFs at the end of the paper.

Our results reveal that both hedge funds and mutual funds have significant information advantages in the gilt market, and that the two groups operate through very different mechanisms. First, there is a strong positive correlation between mutual fund/hedge fund trading and contemporaneous gilt returns. More importantly, their trading positively forecasts future gilt returns, but over different horizons. Specifically, sorting all gilts (with different maturities and vintages) into terciles based on the previous-day net purchases of hedge funds, we find that the tercile of gilts heavily bought outperform the tercile heavily sold by 1.28 *bps* (*t*-statistic = 2.80) on the following day, and 2.88 *bps* (*t*-statistic = 3.16) in the following week, with an annualized Sharpe Ratio of 1.2. This return effect is then completely reversed after two months. Controlling for the level, slope, and curvature factors, which are responsible for most of the variation in gilt yields, has little impact on our result: for example, the five-day three-factor alpha of the long-short bond portfolio remains economically and statistically significant at 2.94 *bps* (*t*-statistic = 3.55). This return result also holds in Fama-MacBeth regressions and exhibits strong persistence in the cross-section of hedge funds.

In stark contrast, mutual fund trading has insignificant return predictive power in the first ten days, but becomes increasingly informative over a longer horizon. For example, the return spread between the top and bottom terciles of gilts, sorted by the previous-day mutual fund order flow, is a statistically insignificant 0.45 *bps* (*t*-statistic = 0.95) on the

[3] The majority of gilt trades (about 68%) takes place in the inter-dealer market. Our four non-dealer investor types plus dealer banks (as well as government entities) are responsible for nearly all gilt transactions.

following day, and an insignificant 1.75 *bps* (t-statistic = 1.63) in the following week. The return spread then grows to 6.47 *bps* (t-statistic = 2.59) by the end of month one, and to 15.61 *bps* (t-statistic = 3.67) by the end of month two. In another exercise, we sort all gilts into quintiles based on the previous-month mutual fund order flow; the return spread between the two extreme quintiles in the following month is 27.52 *bps* (t-statistic = 3.96), with an annualized Sharpe Ratio of 1.5. The three-factor alpha – controlling for the level, slope, and curvature factors – is only modestly reduced to 17.98 *bps* (t-statistic = 3.75) per month. This return pattern again exhibits strong persistence in the cross-section of mutual funds. Moreover, extending the holding period to the following twelve months, we see no evidence of reversal: the cumulative return of the long-short gilt portfolio by the end of month twelve is nearly 1.3%.[4]

We next turn to the sources of the information advantage of hedge funds and mutual funds. Recent theoretical work (see, e.g., Farboodi and Veldkamp, 2019) postulates that arbitrageurs can engage in two types of activities: i) to predict and trade ahead of other investors' demand, and ii) to learn about future asset values in an accurate and efficient manner (more so than the average investor in the market). We examine both mechanisms. To start, we find that hedge funds' daily trading is a strong predictor of future mutual fund trading; a one-standard-deviation increase in hedge funds' net buying in a week forecasts an increase in mutual fund net purchases in the following week by more than 1% (t-statistic = 4.32).[5] We further isolate the part of mutual fund trading that can be relatively easily predicted – capital-flow-induced trading following the definition in Lou (2012) – and find that hedge fund trading is particularly informative about future flow-induced demand of mutual funds.

To analyse the second channel, we repeat our return predictability test of hedge fund trading separately for macro-announcement days and non-announcement days. Our results

[4] As we show later in the paper, we do not find any return predictability for non-dealer banks or ICPFs, potentially due to the fact that those institutions have other objectives (for example ICPFs' liability matching).

[5] Interestingly, hedge fund trading does not significantly forecast future order flows of non-dealer banks and ICPFs. Moreover, order flows of mutual funds, non-dealer banks, and ICPFs do not predict hedge funds' future trading.

show that hedge funds earn nearly twice as much on announcement days (2.50 *bps*) than on non-announcement days (1.28 *bps*). Taken together, our evidence suggests that hedge funds are engaged in both activities described above – a) predicting other investors' future demand (which may be uninformed) and b) learning about value-relevant information.

We conduct a similar set of analyses for the mutual fund sample. First, in contrast to the result for hedge funds, mutual fund trading (measured at the daily or monthly frequency) has no predictive power for future order flows of other investors, consistent with the view that mutual funds are usually not specialised in forecasting the demand of other investors. In our second set of tests, we link mutual funds' abnormal returns to future variations in bond yields. In a time-series regression setting, controlling for known predictors of future interest rates (for example, a set of forward rates plus survey expectations of future interest rates), we find that an aggregate shift in the portfolio duration of mutual funds is a strong predictor of future changes in short-term interest rates. For example, a one-standard-deviation reduction in the aggregate portfolio duration of mutual funds forecasts a 4.49 *bps* (t-statistic = 3.01) increase in the one-year interest rate.[6]

Finally, we analyse mutual funds' abnormal returns around various macroeconomic announcements (which are known to have large impact on short-term interest rates); out of the 17.98 *bps* monthly alpha earned by mutual funds discussed earlier, 7.24 *bps* are earned on just two days: one with monetary policy announcements and the other with inflation and labour statistics announcements. Put differently, mutual funds earn 3.62 *bps*/day on macro-announcement days and only 0.5 *bps*/day on other days.

All in all, our evidence shows that hedge funds and mutual funds have a significant advantage over other market participants in collecting, processing, and trading on information that is relevant for future gilt returns. In particular, our findings highlight the differences in the two groups' approaches to earning abnormal returns in the government bond market. While hedge funds gain from both trading ahead of other investors and quick

[6] Interestingly, mutual fund duration shifts are insignificantly related to future movements in the slope of the term structure. Put differently, mutual funds are able to forecast changes in short-term rates but are unable to forecast changes in long-term rates.

responses to the arrival of macroeconomic news, mutual funds profit from their ability to understand and forecast macroeconomic fundamentals. Through their active trading, these professional managers help to impound value-relevant information into gilt yields and expedite the price discovery process in one of the world's most important financial markets.

2. Related Literature

Our paper is closely related to prior studies on price discovery in the government bond market.[7] Fleming and Remolona (1997) show that macroeconomic announcements are responsible for many of the largest daily price movements in the US Treasury market. Moreover, Brandt and Kavajecz (2004) find that order flows between dealer banks and other investors account for more than a quarter of the daily variation in Treasury yields on days without major macroeconomic announcements. Pasquariello and Vega (2007) further document that the correlation between investor order flows and Treasury yield changes increases with the dispersion of investor beliefs. While most prior studies examine the contemporaneous relation between macro-announcements/order flows and yield changes, we focus squarely on the return predictability of trading by various types of institutions, such as hedge funds and mutual funds.[8] We are able to do so because we observe a) detailed, high-frequency information about virtually all transactions in the gilt market and b) the identities of both counterparties in each transaction.

Our study also contributes to the vast empirical literature on the predictability of the term structure of interest rates. Fama and Bliss (1987) show that forward-spot spreads predict future spot rate changes. Campbell and Shiller (1991) find that larger spreads between long-term and short-term yields forecast rising short-term yields and declining long-term yields. Cochrane and Piazzesi (2005) document that a linear combination of

---

[7] See, for example, Fleming and Remolona (1997, 1999), Balduzzi, Elton, and Green (2001), Green (2004), Brandt and Kavajecz (2004), Andersen, Bollerslev, Diebold, and Vega (2007), Pasquariello and Vega (2007), Valseth (2013).

[8] In a related study, Kondor and Pinter (2019) use the ZEN database to show that institutions outperform in the government bond market when trading with more dealer banks.

forward rates describes the time variation in expected returns of Treasury securities. Piazzesi and Swanson (2008) and Ludvigson and Ng (2009) provide evidence that bond excess returns can be forecasted by macroeconomic factors. Our results reveal that daily/monthly order flows of hedge funds/mutual funds strongly forecast future government bond returns, after controlling for these known predictors of bond returns.

Our work is also related to the literature on the informativeness of investor trading in various financial markets. Chordia, Roll, and Subrahmanyam (2002) show that aggregate order imbalances in the stock market are positively associated with contemporaneous market returns. In the foreign exchange market, Evans and Lyons (2002) show that dealer-client order flows are related to contemporaneous movements in exchange rates. Menkhoff, Sarno, Schmeling, and Schrimpf (2016) further document that dealer-client order flows provide information about future movements in exchange rates. In a similar spirit, this paper shows that trading by hedge funds and mutual funds strongly forecasts subsequent government bond returns. We then provide further evidence for the underlying mechanisms of the documented return pattern: arbitrageurs earn abnormal returns by trading ahead of other investors and/or learning about economic fundamentals.

3. Data

We use the regulatory, transaction-level ZEN database, maintained by the Financial Conduct Authority (FCA). The UK bond market is the fourth largest in the world with a total market value of $6,249bn in the first quarter of 2018 (BIS, 2018). Conventional government bonds (gilts) are nominal fixed-coupon bonds issued by Her Majesty's Treasury (HMT) on behalf of the UK government. Even though gilts are listed on the London Stock Exchange (LSE), the vast majority of trades take place over-the-counter. The Gilt-Edged Market Makers (or GEMMs) are central to the functioning of the gilt market.[9] These financial institutions (mainly large investment banks) are designated primary dealers in the gilt market; endorsed

[9] See the current list of GEMMs at:
https://www.dmo.gov.uk/responsibilities/gilt-market/market-participants/.

by the UK Debt Management Office (DMO), an executive agency of HMT responsible for debt and cash management for the UK Government.

The ZEN database contains details on 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 all trading activity in the gilt market. Each transaction report contains information on the transaction date and time, International Identification Securities Number (ISIN), execution price, transaction size, as well as the identities of the buyer and seller.

The gilt market consists of two tiers: an interdealer market where dealers trade among themselves, and a dealer-client segment where financial and non-financial clients trade with dealers (and in some rare cases with other clients). In Figure 1, we show that the interdealer market accounts for 68% of the total trading volume in the UK government bond market.[10] Our paper focuses on dealer-client trades. The main client sectors are a) mutual funds, b) hedge funds, c) non-dealer banks, d) pension funds and insurance companies (ICPF).[11] We combine pension funds and insurance companies because of the similarities in their investment styles and objectives. For each day/month, we calculate the order flow (or trading activity) of each investor type in each gilt as:

$$OrderFlow_{i,j,t} = \frac{Buy_{i,j,t} - Sell_{i,j,t}}{Buy_{i,j,t} + Sell_{i,j,t}},$$

where $Buy_{i,j,t}$ and $Sell_{i,j,t}$ are the buy volume and sell volume of investor type i in bond j in day/month t. In robustness checks, we use alternative definitions of orders flows (for example, scaled by the total outstanding amount or scaled by the total trading volume of the gilt) and obtain similar results.

[10] The client-client market share is not reported as it is mainly determined by trading between non-dealer banks and/or security firms. Trading volume in this market segment is small compared to the dealer-client market.

[11] The ZEN database captures who executes the trade, but not necessarily who the beneficial owner is. For example, an asset manager could execute a trade on behalf of a pension fund. A further drawback is that some investors could be allocated to different types (e.g. insurance companies with asset manager arms).

Our sample spans the period August 2011 to December 2017. We merge our transaction data with publicly available bond characteristics provided by the UK Debt Management Office and Datastream; this includes the bond issuance size, maturity, coupon, duration, prices, ratings, and accrued interest. Following the prior literature (e.g., Bai, Bali, and Wen, 2019), we only keep bonds with a time-to-maturity longer than one year. This is because a bond is automatically deleted from major bond indices when its time-to-maturity falls below one year. Index-tracking institutions will then mechanically rebalance their holdings, which may cause large price movements. We also exclude inflation-indexed gilts from our sample, given that the coupons/principal payments of these gilts are adjusted in line with movements in inflation.

Regarding macroeconomic news announcements, we focus on public announcements of UK inflation & labour statistics, and the Monetary Policy Committee (MPC) meetings. MPC meeting dates are collected from the Bank of England, and other macro-announcement dates are published by the UK Office for National Statistics. We also obtain information on analysts' forecasts for the UK bank rate, 10-year interest rate, UK GDP growth rate and inflation rate from *Consensus Forecasts*, an international survey of market participants compiled by Consensus Economics.

Finally, to calculate risk-adjusted bond returns, we construct three tradable factors mimicking the level, slope, and curvature factors of the term structure of government bond yields. For the level factor, we use the value-weighted average return of all available gilts. For the slope factor, we use the return differential between the twenty-year gilt and the one-year gilt. The curvature factor is the average return of the twenty-year and one-year gilts, minus that of the ten-year gilt.[12]

Our final sample consists of 55 gilts. Table 1 reports the summary statistics. The average monthly gilt return is 0.45% with a standard deviation of 2.29%. The average issue size is £26bn and the average duration is 10.8 years. Unsurprisingly, order flows of each investor type are on average close to zero, but have substantial cross-sectional and time-

[12] Our results remain robust when using the Bloomberg Barclays Sterling Gilts Total Return index as a proxy for the level factor, or when using the returns of the thirty-year and one-year gilts to construct the slope factor.

series variation. For example, daily order flows of hedge funds (as defined above) have a mean of -1.41% and a standard deviation of 89.85%, and monthly order flows of mutual funds have a mean of 0.59% and a standard deviation of 19.23%.

4. Empirical Results

Our sample includes four main types of non-dealer investors: i) mutual funds, ii) hedge funds, iii) non-dealer banks, and iv) insurance companies and pension funds (ICPFs). These four groups account for 90% of the total trading volume in the dealer-client market. We examine the order flows of each investor type and their relation to both contemporaneous and future bond returns using both a calendar-time portfolio approach and a Fama-MacBeth regression setting. We mainly focus on the order flows of mutual funds and hedge funds as the typical arbitrageurs in financial markets; as a placebo, we also analyse the trading behaviour of non-dealer banks and ICPFs in Section 6.

4.1. Daily Order Flows and Bond Returns

We start by analysing the contemporaneous correlation between investors' daily order flows and bond returns. If a subset of investors is better informed than the rest, their trading should be positively correlated with contemporaneous security returns, as their trading gradually impounds information into prices. Table A1 in the Appendix confirms this prediction. Gilts that are heavily bought by hedge funds on a particular day outperform those that are heavily sold on the same day by 0.92 *bps* (t-statistic = 2.31). If we combine the trades of hedge funds with those of mutual funds, the results are even stronger: gilts heavily collectively bought by hedge funds and mutual funds on a particular day outperform those heavily sold by 1.82 *bps* (t-statistic = 3.91).

To the extent that the market does not immediately and fully respond to the order flows of hedge funds and mutual funds, we expect to see a price drift in the same direction in subsequent periods. To this end, we sort all government bonds in our sample into terciles based on aggregate order flows of either hedge funds or mutual funds on each trading day.[13] We then construct a long-short portfolio that goes long the top tercile and short the bottom tercile of government bonds. Table 2 reports cumulative daily returns of these long-short portfolios.[14] The results show that order flows of hedge funds positively and significantly forecast returns of government bonds in the following one to five days, followed by a complete reversal in the subsequent two months. For example, the return spread between the top and bottom terciles sorted by hedge fund order flows is 1.28 *bps* (*t*-statistic = 2.80) on the following day, which then grows to 2.88 *bps* (*t*-statistic = 3.16) in the following five days. The return spread then becomes a statistically insignificant 1.32 *bps* (*t*-statistic = 0.73) by the end of month one, and -1.28 *bps* (*t*-statistic = -0.31) by the end of month two. This return predictive pattern is virtually unchanged after controlling for known risk factors (i.e. the level, slope, and curvature factors).

Mutual fund trading also positively forecasts bond returns, but over a longer horizon of one to two months. Furthermore, this return predictive pattern does not revert in the following year. For example, as shown in Table 2, as we increase the holding horizon from one day to two months, the return spread between the top and bottom terciles sorted by the daily order flows of mutual funds grows monotonically from 0.45 *bps* (*t*-statistic = 0.95) after one day to 6.47 *bps* (*t*-statistic = 2.59) after one month, to 15.61 *bps* (*t*-statistic = 3.67) after two months. Again, this return predictive pattern is robust to controlling for the level, slope, and curvature factors.

The stark contrast in the return predictive pattern between hedge funds and mutual funds is also apparent in Figure 2, which shows the event-time cumulative returns of the long-short portfolios sorted by daily order flows of the two investor types. The figure reveals that hedge fund trading positively forecasts bond returns in the short run (which peaks after

[13] Since daily trading is relatively sparse, we sort all bonds into terciles to examine the return predictability of daily order flows. The patterns are by and large unchanged if we sort all bonds into quintiles instead.

[14] Appendix Table A2 shows detailed returns (alphas) for each tercile portfolio sorted by daily order flows of hedge funds and mutual funds.

about ten days), followed by a strong reversal in the subsequent month. Mutual fund order flows, on the other hand, positively forecast bond returns in the subsequent two months.

4.2. Monthly Order Flows and Bond Returns

We next analyse investors' monthly order flows and their relation to bond returns in the following year. Specifically, at the end of each month, we sort all government bonds into quintiles based on the order flows of hedge funds or mutual funds in the previous month, and hold the long-short portfolio for the next one to twelve months. These portfolio returns are reported in Table 3.

Consistent with the previous results based on daily order flows, monthly hedge fund order flows have no predictive power for bond returns in the subsequent months. In contrast, monthly mutual fund order flows significantly and positively forecast future bond returns. More specifically, as shown in Panel A, the return spread between the top and bottom quintiles sorted by monthly hedge fund order flows is 6.58 *bps* (*t*-statistic = 0.19) in the first month following portfolio formation. In comparison, the return spread between the top and bottom quintiles sorted by monthly mutual fund order flows is 27.52 *bps* (*t*-statistic = 3.96) in the following month. Controlling for known risk factors (level, slope, and curvature) has virtually no impact on this result. For example, the alpha spread between the top and bottom quintiles sorted by mutual fund order flows is only modestly reduced to 17.98 *bps* (*t*-statistic = 3.75) in the following month.

We again plot the event-time cumulative returns of the long-short portfolios sorted by monthly order flows of hedge funds and mutual funds. Figure 3 reveals that monthly hedge fund trading does not predict future bond returns for any event window, ranging from one month to twelve months. Mutual fund monthly trading, on the other hand, strongly forecasts future bond returns in the following one to twelve months, without any sign of reversal. In other words, the return predictive pattern of mutual fund trading is unlikely to be driven by herding behaviour (Cai, Han, Li, and Li, 2019).

We also plot the cumulative returns of long-short gilt portfolios in *calendar time* in Figure 4. In the left panel, long-short portfolios are sorted by *daily* order flows of hedge funds and mutual funds and are rebalanced every day. In the right panel, long-short portfolios are sorted by *monthly* order flows of mutual funds and hedge funds and held for one month. Consistent with our previous results, hedge funds persistently outperform mutual funds when we consider daily order flows and underperform mutual funds when we consider monthly order flows.

4.3. Fama-MacBeth Regressions

A potential concern with the calendar-time portfolio approach is that the documented return pattern may be driven by omitted variables, such as lagged bond returns (Jostova, Nikolova, Philipov and Stahel, 2013). To address this concern, we conduct Fama-MacBeth regressions of bond returns on order flows of both mutual funds and hedge funds, while controlling for a range of known predictors of government bond returns.

Similar to the portfolio approach, we conduct the regressions at both daily and monthly frequencies. For *daily* order flows, we estimate the following regression:

$$\begin{aligned} RET_{j,d+k} = \beta_0 + \beta_1 Order\ Flow\ of\ Mutual\ Funds_{j,d} + \beta_2 Order\ Flow\ of\ Hedge\ Funds_{j,d} \\ + \gamma Control_{j,d} + \epsilon_{j,d+k}, \qquad (1) \end{aligned}$$

where the dependent variable is bond *j*'s return in the following one or five days. The main independent variables are the daily order flows of mutual funds and hedge funds on day d. The list of control variables includes the issue size, bond maturity, and past bond returns. Analogously, we estimate the following regression at the *monthly* frequency:

$$\begin{aligned} RET_{j,m+1} = \beta_0 + \beta_1 Order\ Flow\ of\ Mutual\ Funds_{j,m} + \beta_2 Order\ Flow\ of\ Hedge\ Funds_{j,m} \\ + \gamma Control_{j,m} + \epsilon_{j,m+1}, \qquad (2) \end{aligned}$$

where the dependent variable is bond *j*'s return in the following month, and the main independent variables are the monthly order flows of mutual funds and hedge funds in month m, plus a similar set of controls as above.

Table 4 reports the results of these Fama-MacBeth regressions. Consistent with the portfolio return results in Tables 2 and 3, daily order flows of hedge funds significantly and positively forecast bond returns in the following one to five days, whereas monthly order flows of hedge funds do not predict future bond returns. In contrast, daily order flows of mutual funds do not forecast future bond returns in the following one to five days, while monthly order flows of mutual funds significantly and positively predict bond returns in the following month.

5. Sources of Return Predictability

Having established the return predictive patterns of hedge funds' and mutual funds' trading activity, we now investigate the sources of such return predictability in the government bond market. Section 5.1 examines the mechanisms behind the return predictability of *daily* hedge fund order flows, and Section 5.2 examines the source of the return predictability of *monthly* mutual fund order flows.

5.1. Sources of Return Predictability: Hedge Funds

Recent theoretical studies (see, e.g., Farboodi and Veldkamp, 2019) argue that arbitrageurs may engage in two types of activities: i) some are able to predict the future demand of other investors and profit from trading ahead of these predictable order flows; ii) some may be more efficient in collecting, processing, and responding to value-relevant information. We test both mechanisms in this section. Our first test explicitly examines whether hedge funds' daily/weekly trading can forecast future order flows of other investors (mutual funds, non-dealer banks, and ICPFs). Our second test examines the return predictability of hedge fund trading around macroeconomic news announcements (monetary policy, inflation, and labour statistics announcements) vs. around non-announcement days.

5.1.1. Predicting Order Flows of Other Investors

We examine the first mechanism by conducting the following panel regression:

$$Order\ Flow\ of\ Others_{j,d+1:d+5} = \beta_0 + \beta_1 Order\ Flow\ of\ Hedge\ Funds_{j,d-4:d} + \\ \beta_2 Order\ Flow\ of\ Others_{j,d-4:d} + \gamma Control_{j,d} + \epsilon_{j,d+1:d+5},$$

where the dependent variable is the aggregate order flow of an investor type (mutual funds, non-dealer banks or ICPFs) in bond j in the next five days. The main independent variable of interest is the order flow of hedge funds in the same bond in the previous week. We control for the bond issue size, maturity, lagged bond returns and lagged order flows of the investor sector. We also include time fixed effects in all specifications to account for market-wide movements.

Table 5 reports the regression results. In Columns (1)-(3) of Panel A, the dependent variable is the following-week order flow of mutual funds; in Panel B, the dependent variable is the following-week order flow of either non-dealer banks or ICPFs. As shown in the first three columns of Panel A, hedge funds' weekly order flows significantly and positively forecast mutual funds' future trading. For example, as shown in Column (1), a one-standard-deviation increase in hedge funds' order flow in a week forecasts an increase in net purchases by mutual funds of 0.81% (=89.85%×0.009, t-statistic = 3.80) in the following week. As shown in Panel B, hedge fund trading is largely unrelated to future order flows of non-dealer banks and ICPFs.[15] Importantly, there is no similar order flow predictive pattern in the opposite direction: as shown in Appendix Table A4, aggregate order flows of other investor types (aside from hedge funds) do not predict future order flows of hedge funds.

We further explore the mechanism through which hedge fund trading can predict mutual fund trading. To this end, we focus on one specific component of mutual fund trading – flow-induced trading (*FIT*). As shown by Coval and Stafford (2007) and Lou (2012), mutual funds tend to scale up and down their existing holdings in response to capital inflows and outflows. Collectively, such flow-induced trading can lead to large price swings in individual securities in the short run, which are then fully reversed in the long run. Since capital flows to mutual funds are predictable based on past fund flows and fund returns, we conjecture that part of hedge funds' ability to forecast future mutual fund trading stems from their ability to forecast mutual fund capital flows.

[15] Instead of using a five-day window to compute order flows, we also run a similar regression of future daily order flows of other investor groups on lagged daily order flows of hedge funds. The results, shown in Appendix Table A3, are qualitatively the same as those reported in Table 5.

To test this hypothesis, we follow Lou (2012) to calculate daily mutual fund flow-induced trading in each government bond as follows. First, using information on daily total net assets (TNA) and fund returns from Morningstar, we compute daily percentage capital flows to fund i as:

$$flow_{i,d} = \frac{TNA_{i,d} - TNA_{i,d-1} * (1 + Ret_{i,d})}{TNA_{i,d-1}}.$$

Next, we calculate fund i's flow-induced trading in bond j by assuming that the fund proportionally scales up or down its holdings in response to capital flows. Since mutual fund holdings information is available only at a monthly frequency (as reported by Morningstar), for each month, we use portfolio weights from the previous month. Mutual fund flow-induced trading (*FIT*) in bond j is then defined as:

$$FIT_{j,d} = \frac{\sum_i flow_{i,d} * w_{i,j,m-1} * TNA_{i,d-1}}{\sum_i w_{i,j,m-1} * TNA_{i,d-1}},$$

where $w_{i,j,m-1}$ is the portfolio weight of fund i in bond j from the previous month-end.[16]

We then examine whether hedge funds can forecast mutual funds' flow-induced trading by conducting the following panel regression:

$$FIT_{j,d+1:d+5} = \beta_0 + \beta_1 HFOrder\ Flow_{j,d-4:d} + \beta_2 FIT_{j,d-4:d} + \gamma Control_{j,d} + \epsilon_{j,d+1:d+5},$$

As shown in Columns (4)-(6) of Panel A in Table 5, weekly hedge fund order flows significantly and positively predict mutual funds' flow-induced trading in the following week. For instance, after controlling for a range of bond characteristics, the coefficients estimate on lagged hedge funds' order flows is 0.056 with a t-statistic of 2.73.[17]

If hedge funds are indeed able to forecast mutual funds' flow-induced trading, an immediate prediction is that hedge fund trading should be more profitable in periods of relatively large mutual fund flow-induced trading in absolute terms. To test this prediction,

[16] Our results remain robust if we instead use total mutual fund holdings in bond j in the previous month in the denominator of the flow-induced trading calculation.

[17] In untabulated results, we find that hedge funds are also able to forecast mutual fund trading that is orthogonal to fund flows.

we repeat the exercise in Table 2 by dividing our sample into two halves based on the aggregate absolute level of mutual fund flow-induced trading. Specifically, on each day, we sum up the *absolute value* of *FIT* across all gilts, and then split all trading days into two subperiods (high- vs. low-*FIT* periods) using the median cut-off of the aggregate absolute *FIT*. As shown in Appendix Table A5, the long-short gilt portfolio sorted by hedge funds' order flows earns significant abnormal returns only in periods with high aggregate absolute *FIT*. Moreover, the difference in the weekly abnormal return spread between high vs. low absolute *FIT* periods, *3.71* bps (*t*-statistic = 3.40) vs. 1.77 *bps* (*t*-statistic = 1.49), is statistically significant.

5.1.2. Macro-News Announcements

In the second test, we examine the possibility that hedge funds process and respond to value-relevant information more efficiently than other market participants and, as a result, earn larger abnormal returns when such information is announced publicly. To test this prediction, we analyse a set of macroeconomic announcements, including monetary policy announcements by the Monetary Policy Committee (MPC), as well as inflation and labour statistics announcements. Specifically, for each macro announcement, we sort all gilts into terciles based on hedge fund order flows on the day *prior* to the announcement. We then track the performance of the long-short portfolio (that goes long the top tercile and short the bottom tercile) on the announcement day.

Table 6 reports the returns of the long-short portfolio sorted by hedge fund trading on macroeconomic announcement days. Panel A examines all types of macro announcements, while Panels B and C report portfolio returns for MPC announcements and inflation/labour statistics announcements, respectively. Across all specifications, the long-short portfolio sorted by hedge fund daily trading earns substantially higher returns on macro-announcement days relative to the unconditional return spread reported in Table 2. For example, as shown in Panel A, the long-short portfolio earns an average 2.50 *bps* (*t*-statistic = 2.26) on days with any macro announcement. For comparison, the unconditional portfolio return reported in Table 2 is 1.28 *bps*. Moreover, controlling for the level, slope and curvature factors has virtually no impact on this result. Interestingly, hedge funds seem to earn higher abnormal returns on labour/inflation statistics announcement days than on monetary policy announcement days: the long-short gilt portfolio sorted by hedge fund trading earns an abnormal return of 1.22 *bps* (*t*-statistic = 2.74) on MPC announcement days vs. 3.53 *bps* (*t*-statistic = 3.16) on inflation/labour statistics announcement days.[18] A potential explanation for this result is that labour/inflation announcements contain less forward-looking information than monetary policy announcements, consistent with the short-lived outperformance of hedge funds.

Taken together, these results indicate that hedge funds, aside from their ability to forecast other investors' future demand, also have superior abilities in processing and responding to macroeconomic information. Both skills likely contribute to the documented return predictive pattern of hedge funds' daily order flows.

5.2. Sources of Return Predictability: Mutual Funds

In this subsection, we turn to the sources of the return predictability of mutual funds' order flows. To start, we examine whether mutual funds are also able to forecast the order flows of other market participants. As shown in Appendix Table A7, mutual funds' monthly order flows have no predictive power for future order flows of other investor groups (the results are similar for daily order flows). In other words, the documented return predictive pattern of mutual fund trading is unlikely due to forecasting other investors' future demand.

We next conduct two related tests to shed more light on the types of value-relevant information that mutual funds trade on. First, we link the trading activity of mutual funds to future movements in the term structure to identify whether mutual funds are able to forecast variations in certain parts of the yield curve. Second, similar to our earlier exercise on hedge fund trading, we decompose the monthly long-short portfolio returns sorted by lagged

[18] In Appendix Table A6, we show that the results are robust to alternative sorting variables or alternative definitions of announcement day returns. For alternative sorting variables, we consider hedge funds' daily order flows in the two or three days prior to the announcement day. For alternative definitions of announcement day returns, we consider the return window (-1,1) around the announcement day.

monthly mutual fund order flows into macro-announcement day returns and non-announcement day returns.

5.2.1. Short-Term and Long-Term Interest Rates

In our first test, we link the trading activity of mutual funds to future movements in short-term and long-term interest rates in a time series regression. Specifically, in each month, we calculate the weighted-average duration change of mutual funds' gilt holdings: specifically, the weighted-average duration of government bonds bought by mutual funds in a month (where the weights are proportional to the trading amount) minus that of government bonds sold by mutual funds. We then examine the relation between this duration change and future variations in the term structure. If mutual funds are indeed able to forecast variations in the shape of the term structure, we expect to see an increase in the portfolio duration shortly before a decrease in short-term interest rates and/or a flattening of the term structure (i.e. a smaller slope); and a decrease in the portfolio duration before an increase in short-term interest rates and/or a steepening of the term structure (i.e. a larger slope).

To test this prediction, we conduct the following time series regression:

$$\Delta Interest\ Rate_{m+k} = \beta_0 + \beta_1\ TradeWeightedDuration_m + \gamma\ Controls_m + \ \epsilon_{m+k},$$

where the dependent variable is either the change in the one-year interest rate or the change in the slope of the term structure (the twenty-year yield minus the one-year yield) from month m to month $m + k$ (where k takes the value of one or three). Other control variables include the forward-spot spread (the difference between the one-year forward rate one or three months ahead and the corresponding spot rate) as in Fama and Bliss (1987) and Cochrane and Piazzesi (2005).[19] We also include changes in analyst forecasts of i) the short-term interest rate, ii) GDP growth rate, and iii) inflation rate to control for information in the public domain which is not captured by the forward rates.

[19] The 13-month and 15-month spot rates are calculated via linear interpolation using the nearest available spot rates in each month.

Table 7 reports the regression results. Panel A shows that mutual funds' active shifts in their weighted-average portfolio duration significantly and negatively forecast changes in short-term interest rates (the one-year rate) one to three months in the future. For example, at the three-month horizon, the coefficient on changes in mutual funds' average duration is a statistically significant -1.73 (t-statistic = -3.01). This estimate implies that a one-standard-deviation reduction in the average portfolio duration of mutual funds forecasts a 4.49 *bps* (= 2.60×1.73) increase in the one-year interest rate.

In Panel B, we show that duration shifts of mutual fund gilt holdings do not forecast future changes in the slope of the term structure. Together, our results suggest that mutual funds are able to forecast changes in short-term rates but are unable to forecast changes in long-term rates.

5.2.2. Macro-News Announcements

Our second test links the return predictability of mutual fund order flows to macroeconomic announcements. If the superior performance of mutual funds is indeed a result of their ability to forecast macroeconomic news before public announcements, these abnormal returns should materialize when such information is made public. Similar to the analysis in Section 5.1.2, we examine mutual funds' trading performance on days with monetary policy announcements as well as inflation and labour statistics announcements vs. days without such announcements. More specifically, we decompose the monthly return of the long-short gilt portfolio sorted by lagged monthly mutual fund order flows into returns realized on macro-announcement days and returns realized on non-announcement days.

The decomposition results are shown in Table 8. Panel A again shows the monthly three-factor alpha of 17.98 *bps* earned by the long-short portfolio sorted by mutual fund order flows (also shown in Table 3). Panel B shows that the same long-short portfolio earns a three-factor alpha of 3.62 *bps* (t-statistic = 3.37) on any macro-news announcement day; Panels C and D further show that the three-factor alpha is 2.87 *bps* (t-statistic = 1.79) on monetary policy announcement days and 4.29 *bps* (t-statistic = 3.61) on inflation and labour statistics announcement days, respectively. These results suggest that about 40% of the total monthly alpha (7.24 *bps* out of 17.98 *bps*) are realized on just two macro-announcement days (there are, on average, one MPC announcement and one inflation/labour statistics announcement each month). Put differently, mutual funds on average earn 3.62 *bps*/day on macro-announcement days and only 0.5 *bps*/day on all other days.

6. Additional Analyses and Robustness Checks

This section provides additional analyses and robustness checks for our main empirical results. In Section 6.1, we use past portfolio returns to rank fund managers into high- vs. low-skilled and examine the persistence in their performance. In Section 6.2, we conduct a series of robustness checks based on various sub-samples and alternative definitions of bond returns. In Section 6.3, we examine the return predictability of order flows of other investor groups: non-dealer banks and ICPFs.

6.1. Persistence of Fund Performance

If our documented return patterns are indeed a reflection of fund managers' ability to collect and process information (be it order flow information or fundamental macroeconomic information) – and to the extent that such abilities are persistent over time – we expect this return pattern to be stronger among hedge funds and/or mutual funds with relatively higher prior performance.[20]

To capture the heterogeneity across hedge funds, on each day we re-estimate regression equation (1) for each individual hedge fund, where the dependent variable is the bond return on day d+1 and the independent variable is the hedge fund's daily order flow in that bond on day d, using daily data from the past three months. Intuitively, the coefficient estimate on the lagged order flow captures the fund's ability to forecast future bond returns.

[20] There is a vast empirical literature on the performance persistence of asset managers (see, e.g., Grinblatt and Titman, 1992; Goetzmann and Ibbotson, 1994; Brown and Goetzmann, 1995; Hendricks, Patel and Zeckhauser, 1993; Carhart, 1997; Bollen and Busse, 2005; Cohen, Coval, and Pastor, 2005). Most of these prior studies focus on equity mutual funds. We instead examine whether hedge funds and mutual funds have persistent skills in predicting government bond returns.

We then divide all hedge funds into two groups on each day: those funds that are above the cross-sectional median are labelled “high-skilled” and those below the median are labelled “low-skilled”. Finally, we repeat the exercise in Table 2 to separately examine the return predictability of daily order flows of high-skilled vs. low-skilled hedge funds.

In a similar vein, in each month we re-estimate equation (2) for each individual mutual fund using monthly bond returns and mutual fund order flow data from the past twelve months. We then divide all mutual funds into “high-skilled” and “low-skilled” groups and repeat the exercise in Table 3 to separately examine the return predictability of the monthly order flows of both groups.

Table 9 reports the long-short gilt portfolio returns for the various subsamples. Panel A contrasts the *daily* return predictability of the order flows of high- vs. low-skilled hedge funds. Panel B examines *monthly* return predictability of the order flows of high- vs. low-skilled mutual funds. As can be seen from Panel A, *daily* order flows of high-skilled hedge funds strongly forecast future gilt returns in the subsequent days while those of low-skilled hedge funds do not. More specifically, the long-short gilt portfolio sorted by daily order flows of high-skilled hedge funds earns a three-factor alpha of 2.98 *bps* (t-statistic = 2.34) in the following five days. In contrast, a similar long-short gilt portfolio sorted by order flows of low-skilled hedge funds produces an insignificant three-factor alpha of 0.93 *bps* (t-statistic = 1.21).

The contrast between high- and low-skilled managers is even more pronounced for mutual funds. As shown in Panel B, the long-short portfolio of government bonds sorted by monthly order flows of high-skilled mutual funds yields a three-factor alpha of 20.1 *bps* (t-statistic = 3.84) in the following month. In comparison, the long-short portfolio sorted by order flows of low-skilled mutual funds generates an insignificant three-factor alpha of -1.91 *bps* (t-statistic = -0.22) in the following month.

In sum, these findings strengthen our interpretation that the return predictability of hedge fund and mutual fund order flows is a result of their ability to efficiently process and trade on information relevant for future bond returns, pointing towards a particular skill of active managers in these two sectors.

6.2. Robustness Checks

We also conduct a series of robustness checks of our main result that daily hedge fund order flows and monthly mutual fund order flows help forecast future daily and monthly government bond returns, respectively. Specifically, we consider: a) subperiod analyses of the first vs. second half of our sample; b) alternative definitions of bond returns (only price changes without accrued interest); c) alternative definitions of order flows (buy minus sell scaled by amount outstanding, for example).

As shown in Table 10, our results are robust to all these different tweaks. In Panel A1, for instance, the long-short portfolio sorted by daily hedge fund order flows yields a three-factor alpha of 2.12 *bps* (*t*-statistic = 1.98) and 3.52 *bps* (*t*-statistic = 2.93) in the following five days in the first and second halves of our sample, respectively. The corresponding figures for mutual funds, shown in Panel B1, are 24.53 *bps* (*t*-statistic = 5.06) and 16.09 *bps* (*t*-statistic = 2.00) in the following month in the first and second halves of our sample. Panel A3 shows that the long-short portfolio of government bonds sorted by the alternative definition of daily hedge fund order flows yields a three-factor alpha of 2.41 *bps* ((*t*-statistic = 2.24) in the following five days. Panel B3 shows that the long-short portfolio sorted by the alternative definition of monthly mutual fund order flows produces a three-factor alpha of 27.07 *bps* (*t*-statistic = 2.85) in the following month. These return figures are similar to those reported in Tables 2 and 3.

6.3. Return Predictability of Order Flows of Non-Dealer Banks and ICPFs

Thus far, we have focused on the typical arbitrageurs in financial markets – hedge funds and mutual funds – and have provided strong evidence that both groups have superior skills in forecasting future government bond returns. In this section, we examine the behaviour of two other important investor types in the gilt market: non-dealer banks and insurance companies and pension funds (ICPFs).

Specifically, we conduct the same analyses as in Tables 2 and 3, but we now focus on the order flows of non-dealer banks and ICPFs. Panel A of Appendix Table A8 shows the next-day return of the long-short portfolios of government bonds sorted by *daily* order flows of non-dealer banks and ICPFs; Panel B reports the next-month return of the long-short portfolios sorted by *monthly* order flows of non-dealer banks and ICPFs.

As can be seen from the table, in contrast to what we find for hedge funds and mutual funds, order flows of non-dealer banks and ICPFs do not have any predictive power for future gilt returns at either the daily or monthly frequency. Across all specifications, the returns of the long-short gilt portfolio sorted by order flows of either investor group is economically small and statistically insignificant, and in some cases even negative. These results are consistent with the view that hedge funds and mutual funds tend to be the more skilled investors in financial markets.

7. Conclusion

We examine the role of institutional investors, such as hedge funds and mutual funds, in the government bond market. Our regulatory data cover virtually all secondary-market transactions in gilts and provide detailed information on each individual transaction – including the identities of both counterparties. The granularity and completeness of our data enable us to analyse the extent to which any group (or groups) of investors have a competitive advantage in collecting, processing, and trading on information relevant for future gilt returns.

Our results reveal that both hedge funds and mutual funds tend to be informed investors in the gilt market, but the two groups operate at very different horizons and through different mechanisms. On the one hand, hedge funds' daily order flows positively forecast gilt returns in the following one to five days, which is then fully reversed in the following two months. A part of this short-term return predictive pattern can be attributed to hedge funds trading ahead of other investors' predictable order flow, especially mutual funds' flow induced trading. Mutual fund order flows, on the other hand, also positively predict bond returns, but over a longer horizon of one to two months. Importantly, this return pattern does not revert in the following year. Additional analyses reveal that the superior performance of mutual funds is partly due to their ability to forecast future movements in short-term interest rates.

Taken together, our findings provide the first, detailed evidence for the types of arbitrage activity that hedge funds and mutual funds are engaged in. In particular, our study highlights the differences in the two groups' approaches to earning abnormal returns in the government bond market. Hedge funds appear to be more nimble (given their shorter-term return predictability) and are able to forecast and trade ahead of other investors' future demand. (There is also some evidence that hedge funds tend to be better informed before public announcements of macroeconomic news, possibly due to their faster responses to the arrival of information.) Mutual funds, on the other hand, seem to focus more on understanding the economic fundamentals; for instance, their trading is a strong predictor of future movements in short-term interest rates. A potentially interesting direction for future research is to link our documented trading-return relation (and the associated information-acquisition decisions) of hedge funds and mutual funds to differences in contractual incentives and constraints – for example, the fact that mutual funds, unlike hedge funds, do not charge a performance fee and must allow for daily inflows and outflows.

References

Andersen, Torben G., Tim Bollerslev, Francis X. Diebold, and Clara Vega, 2007, “Real-time price discovery in global stock, bond and foreign exchange markets.” *Journal of International Economics* 73.2, 251-277.

Bai, Jennie, Turan G. Bali and Quan Wen, 2019, “Common risk factors in the cross-section of corporate bond returns.” *Journal of Financial Economics* 131.3, 619-642.

Balduzzi, Pierluigi, Edwin J. Elton, and T. Clifton Green, 2009, “Economic News and Bond Prices: Evidence from the U.S. Treasury Market.” *Journal of Financial and Quantitative Analysis* 36.4, 523-543.

BIS, 2018, “2018 Q1 Debt Securities Statistics”, *Bank for International Settlements Report*.

Bollen, Nicolas P. B., and Jeffrey A. Busse, 2005, “Short-Term Persistence in Mutual Fund Performance.” *Review of Financial Studies* 18.2, 569–597.

Brandt, Michael W., and Kenneth A. Kavajecz, 2004, “Price discovery in the US Treasury market: The impact of order flow and liquidity on the yield curve.” *Journal of Finance* 59.6, 2623-2654.

Brown, Stephen J., and William N. Goetzmann, 1995, “Performance Persistence.” *Journal of Finance* 50.2, 679-698.

Cai, Fang, Song Han, Dan Li, and Yi Li, 2019, “Institutional herding and its price impact: Evidence from the corporate bond market.” *Journal of Financial Economics* 131.1, 139-167.

Campbell, John Y, and Robert Y. Shiller, 1991, “Yield Spreads and Interest Rate Movements: A Bird’s Eye View.” *Review of Economic Studies* 58, 495-514.

Carhart, Mark M., 1997, “On Persistence in Mutual Fund Performance.” *Journal of Finance* 52.1, 57-82.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2002, "Order imbalance, liquidity, and market returns." *Journal of Financial Economics* 65.1, 111-130.

Cici, Gjergji, and Scott Gibson, 2012, "The performance of corporate bond mutual funds: Evidence based on security-level holdings." *Journal of Financial and Quantitative Analysis* 47.1, 159-178.

Cochrane, John and Monika Piazzesi, 2005, “Bond risk premia.” *American Economic Review* 95, 138–160.

Cohen, Randolph B., Joshua D. Coval, and Luboš Pástor, 2005, “Judging fund managers by the company they keep.” *Journal of Finance* 60.3, 1057–1096.

Coval, Joshua, and Erik Stafford, 2007, "Asset fire sales (and purchases) in equity markets." *Journal of Financial Economics* 86.2, 479-512.

Cox, John C, Jonathan E. Ingersoll, Jr., and Stephen A. Ross, 1985, "A Theory of the Term Structure of Interest Rates." *Econometrica* 53.2, 385-407.

Diebold, Francis X., and Canlin Li, 2006, "Forecasting the term structure of government bond yields." *Journal of Econometrics* 130.2, 337-364.

Evans, Martin DD, and Richard K. Lyons, 2002, "Order flow and exchange rate dynamics." *Journal of Political Economy* 110.1, 170-180.

Fama, Eugene F. and Bliss, Robert R, 1987. "The Information in Long-Maturity Forward Rates." *American Economic Review,* 77.4, 680-692.

Farboodi, Maryam, and Laura Veldkamp, 2019, "Long Run Growth of Financial Technology." forthcoming at *American Economic Review*.

Fleming, Michael J., and Eli M. Remolona, 1997, "What moves the bond market?" *Economic Policy Review*, 3(4), 31-50.

Fleming, Michael J., and Eli M. Remolona, 1999, "Price formation and liquidity in the US Treasury market: The response to public information." *Journal of Finance* 54.5, 1901-1915.

Green, T. Clifton, 2004, "Economic news and the impact of trading on bond prices." *Journal of Finance* 59.3, 1201-1233.

Grinblatt, Mark, and S. Titman, 1992, "The Persistence of Mutual Fund Performance." *Journal of Finance* 47.5, 1977-1984.

Goetzmann, William N., and Roger G. Ibbotson, 1994, "Do Winners Repeat?" J*ournal of Portfolio Management* 20.2, 9-18.

Hendricks, Darryll, Jayendu Patel, and Richard Zeckhauser, 1993, "Hot Hands in Mutual Funds: Short-Run Persistence of Relative Performance, 1974–1988." *Journal of Finance* 48.1, 93-130.

Huang, Jennifer, Clemens Sialm, and Hanjiang Zhang, 2011, "Risk Shifting and Mutual Fund Performance." *Review of Financial Studies* 24.8, 2575-2616.

Huang, Jinzhi, and Ying Wang, 2014, "Timing Ability of Government Bond Fund Managers: Evidence from Portfolio Holdings." *Management Science* 60.8, 2019-2109.

Jostova, Gergana, Stanislava Nikolova, Alexander Philipov, and Christof W. Stahel, 2013, "Momentum in Corporate Bond Returns." *Review of Financial Studies* 26.7, 1649-1693.

Kondor, Peter, and Pinter, Gabor, 2019, “Clients' Connections: Measuring the Role of Private Information in Decentralised Markets.” *CEPR Discussion Paper No. DP13880*.

Litterman, Robert, and Scheinkman, Jose, 1991, “Common Factors Affecting Bond Returns.” *Journal of Fixed Income* 1, 54-61.

Lou, Dong, 2012, "A flow-based explanation for return predictability." *Review of Financial Studies* 25.12, 3457-3489.

Lucca, David O., and Emanuel Moench, 2015, “The Pre-FOMC Announcement Drift.” *Journal of Finance* 70.1, 329-371.

Ludvigson, Sydney, and Serena Ng, 2009, “Macro Factors in Bond Risk Premia.” *Review of Financial Studies* 22, 5027-5067.

Menkhoff, Lukas, Lucio Sarno, Maik Schmeling, and Andreas Schrimpf, 2016, "Information flows in foreign exchange markets: Dissecting customer currency trades." *Journal of Finance* 71.2, 601-634.

Pasquariello, Paolo, and Clara Vega, 2007, "Informed and strategic order flow in the bond markets." *Review of Financial Studies* 20.6, 1975-2019.

Piazzesi, Monika, and Eric T. Swanson, 2008, “Futures Prices as Risk-adjusted Forecasts of Monetary Policy.” *Journal of Monetary Economics* 55, 677-691.

Savor, Pavel, and Mungo Wilson, 2014, “Asset pricing: A tale of two days.” *Journal of Financial Economics* 113.2, 171-201.

Vasicek, Oldrich, 1977, “An equilibrium characterization of the term structure.” *Journal of Financial Economics* 5.2, 177-188.

Wermers, Russ, 2000, "Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses." *Journal of Finance* 55.4, 1655-1695.

Table 1: Summary Statistics

This table reports the summary statistics for our sample, which covers the period August 2011 to December 2017. Information on government bond returns, total market capitalizations (£ billions), maturity, duration, and bond yields is provided by DataStream and the UK Debt Management Office. Investors' order flows are from the ZEN database maintained by the Financial Conduct Authority (FCA). For each group of investors, on each day and/or each month, we calculate the order flow as the buy volume minus sell volume scaled by the total trading volume of the group. Our sample includes four groups of investors: a) mutual funds, b) hedge funds, c) non-dealer banks, and d) pension funds and insurance companies (ICPF). The table reports the mean, median, standard deviation (SD), 5th/25th/75th/95th percentiles, and the number of observations.

Frequency	Variable	Mean	SD	5th	25th	50th	75th	95th	No. Obs.
Monthly	Bond Return (%)	0.45	2.29	-3.25	-0.43	0.26	1.25	4.49	2,923
	Order Flow — Mutual Funds (%)	0.59	19.23	-35.50	-11.29	0.45	13.01	36.41	2,923
	Order Flow — Hedge Fund (%)	-1.50	57.15	-100.00	-42.05	-1.21	37.74	100.00	2,814
	Order Flow — Bank (%)	0.24	31.19	-56.40	-19.49	-0.17	21.26	58.91	2,923
	Order Flow — ICPF (%)	-1.44	42.03	-73.69	-30.99	-1.54	28.40	70.39	2,923
Daily	Bond Return (%)	0.02	0.53	-0.81	-0.16	0.01	0.21	0.86	59,753
	Order Flow — Mutual Funds (%)	0.15	60.16	-98.90	-44.70	0.08	45.62	98.73	59,753
	Order Flow — Hedge Fund (%)	-1.41	89.85	-100.00	-100.00	0.00	100.00	100.00	23,870
	Order Flow — Bank (%)	0.14	74.93	-100.00	-79.97	0.00	79.96	100.00	50,367
	Order Flow — ICPF (%)	-1.22	75.87	-100.00	-84.79	-0.05	80.46	100.00	47,345
Monthly	Amount Outstanding (£B)	25.73	7.59	10.21	21.31	26.64	31.69	35.96	2,923
	Time to maturity (Year)	16.16	13.82	1.81	4.69	10.02	26.26	43.76	2,923
	Duration (Year)	10.80	7.48	1.70	4.29	8.65	16.83	23.79	2,923
	Yield (%)	1.75	1.00	0.26	0.91	1.72	2.51	3.42	2,923

Table 2: Daily Order Flows and Future Bond Returns: Portfolio Sorting

This table reports the returns of calendar-time long-short gilt portfolios sorted by daily order flows of hedge funds and mutual funds. For each bond on each day, we calculate the daily order flow of hedge funds (mutual funds) as the net buy volume scaled by the total trading volume of hedge funds (mutual funds). We then sort all gilts into three groups based on the daily order flows of hedge funds (mutual funds) and weight the bonds equally within each group. We report the return (alpha) spreads between the top and bottom terciles ("High minus Low": H-L) on the following trading day (Panel A), five trading days (Panel B), ten trading days (Panel C), one month (Panel D), and two months (Panel E). We report the raw returns, alphas adjusted by the market factor (1F Alpha), and alphas adjusted by the market, slope, and curvature factors (3F Alpha). All returns and alphas are reported in basis points. *T*-statistics are computed based on standard errors with Newey-West correction and are reported in parentheses. Long-short portfolio returns significant at the 5% level are indicated in bold.

Panel A: Holding Period = 1 Day						
	Hedge Funds			Mutual Funds		
	Return	Alpha (1F)	Alpha (3F)	Return	Alpha (1F)	Alpha (3F)
H-L	**1.28**	**1.38**	**1.39**	0.45	0.34	0.34
	(2.80)	**(3.16)**	**(3.20)**	(0.95)	(0.72)	(0.71)

Panel B: Holding Period = 5 Days						
	Hedge Funds			Mutual Funds		
	Return	Alpha (1F)	Alpha (3F)	Return	Alpha (1F)	Alpha (3F)
H-L	**2.88**	**2.94**	**2.94**	1.75	1.43	1.50
	(3.16)	**(3.32)**	**(3.55)**	(1.63)	(1.41)	(1.49)

Panel C: Holding Period = 10 Days						
	Hedge Funds			Mutual Funds		
	Return	Alpha (1F)	Alpha (3F)	Return	Alpha (1F)	Alpha (3F)
H-L	**2.64**	**2.89**	**2.74**	2.54	1.18	1.40
	(2.33)	**(2.62)**	**(2.49)**	(1.70)	(0.85)	(0.98)

Panel D: Holding Period = 1 Month						
	Hedge Funds			Mutual Funds		
	Return	Alpha (1F)	Alpha (3F)	Return	Alpha (1F)	Alpha (3F)
H-L	1.32	2.46	2.39	**6.47**	4.00	4.81
	(0.73)	(1.45)	(1.37)	**(2.59)**	(1.66)	(1.83)

Panel E: Holding Period = 2 Months						
	Hedge Funds			Mutual Funds		
	Return	Alpha (1F)	Alpha (3F)	Return	Alpha (1F)	Alpha (3F)
H-L	-1.28	-0.34	-1.57	**15.61**	**6.35**	**5.55**
	(-0.31)	(-0.19)	(-0.85)	**(3.67)**	**(3.49)**	**(3.03)**

Table 3: Monthly Order Flows and Future Bond Returns: Portfolio Sorting

This table reports the returns of calendar-time long-short gilt portfolios sorted by monthly order flows of hedge funds and mutual funds. In Panel A, the sorting variable is monthly order flows of hedge funds. In Panel B, the sorting variable is monthly order flows of mutual funds. For each bond in each month, we calculate the monthly order flow of hedge funds (mutual funds) as the net buy volume scaled by the total trading volume of hedge funds (mutual funds). We then sort all gilts into five groups based on the monthly order flows of hedge funds (mutual funds) and weight the bonds equally within each group. These portfolios are held for one month. We report the raw returns, alphas adjusted by the market factor (1F Alpha), and alphas adjusted by the market, slope, and curvature factors (3F Alpha). All returns and alphas are reported in basis points. *T*-statistics are computed based on standard errors with Newey-West correction and are reported in parentheses. Long-short portfolio returns significant at the 5% level are indicated in bold.

Panel A: Hedge Funds						
Order Flows	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
1 (Low)	39.68	(2.32)	1.45	(0.38)	1.15	(0.27)
2	39.47	(2.13)	-4.60	(-1.06)	-4.67	(-1.06)
3	46.66	(2.43)	4.99	(0.96)	5.50	(1.17)
4	46.01	(2.74)	5.32	(1.01)	5.06	(0.88)
5 (High)	46.26	(2.83)	4.31	(0.69)	4.35	(0.70)
H-L	6.58	(0.19)	2.82	(0.31)	3.21	(0.32)

Panel B: Mutual Funds						
Order Flows	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
1 (Low)	29.53	(2.41)	-3.98	(-1.01)	-3.82	(-0.92)
2	42.91	(2.52)	-0.61	(-0.15)	-1.03	(-0.31)
3	44.70	(2.19)	-1.20	(-0.26)	-1.34	(-0.27)
4	50.10	(2.66)	3.79	(0.75)	3.45	(0.64)
5 (High)	57.05	(3.38)	13.60	(3.85)	14.16	(3.20)
H-L	**27.52**	(**3.96**)	**17.59**	(**3.56**)	**17.98**	(**3.75**)

Table 4: Order Flows and Future Bond Returns: Fama-MacBeth Regressions

This table reports the results of Fama-MacBeth regressions of bond returns on order flows of hedge funds and mutual funds. In Panel A, the main independent variables are the daily order flows of hedge funds and mutual funds, and the dependent variable is the next day (five-day) bond returns (in percentage). In Panel B, the main independent variable is the monthly order flows of hedge funds and mutual funds, and the dependent variable is the next month bond returns (in percentage). We also control for lagged bond returns, size (the logarithm of the bond's total market capitalization), and maturity (the logarithm of the time-to-maturity). *T*-statistics are computed based on standard errors with Newey-West correction and are reported in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Daily Order Flows and Future Bond Returns

	Ret_{d+1}			$Ret_{d+1:d+5}$		
$Order\ Flow\ Hedge\ Funds_d$	0.003***		0.004***	0.006**		0.006**
	(2.734)		(3.204)	(2.187)		(2.050)
$Order\ Flow\ Mutual\ Funds_d$		0.001	0.002		0.001	-0.001
		(1.120)	(1.480)		(0.201)	(-0.155)
$Bond\ Ret_d$	-0.291**	-0.321**	-0.292**	-0.152	-0.135	-0.175
	(-2.390)	(-2.530)	(-2.238)	(-0.871)	(-0.776)	(-1.067)
$Size_d$	0.000	-0.002	-0.005	0.025	0.026	0.037
	(-0.041)	(-0.316)	(-0.774)	(1.506)	(1.475)	(1.785)
$Maturity_d$	0.021	0.034	0.032	0.510*	0.361	0.500*
	(0.341)	(0.527)	(0.493)	(1.945)	(1.374)	(1.939)
No. Obs.	23,325	23,325	23,325	23,325	23,325	23,325
Adj. R^2	0.791	0.789	0.787	0.793	0.792	0.795

Panel B: Monthly Order Flows and Future Bond Returns

		R_{m+1}	
$Order\ Flow\ Mutual\ Funds_m$	0.183***		0.185***
	(2.826)		(2.771)
$Order\ Flow\ Hedge\ Funds_m$		-0.001	-0.001
		(-0.012)	(-0.089)
$Bond\ Ret_m$	-0.113	-0.105	-0.112
	(-1.164)	(-1.105)	(-1.135)
$Size_m$	-0.086**	-0.087**	-0.083**
	(-2.395)	(-2.362)	(-2.291)
$Maturity_m$	0.389***	0.385***	0.392***
	(3.830)	(3.852)	(3.848)
No. Obs.	2,804	2,804	2,804
Adj. R^2	0.798	0.796	0.798

Table 5: Hedge Fund Order Flows and Future Non-Dealer Order Flows

This table reports results of panel regressions of trading by mutual funds (or non-dealer banks / insurance companies and pension funds (ICPFs)) on lagged hedge fund order flow. For each bond on day d, we calculate the order flow of each group of investors (e.g., hedge funds) as the net buy volume scaled by the total trading volume of this group of investors. Panel A reports the results of hedge fund order flows predicting future mutual fund trading. In columns (1)-(3), the dependent variable is the mutual fund order flow on days d+1 to d+5. In columns (4)-(6), the dependent variable is flow-induced trading of mutual funds (*FIT*) on days d+1 to d+5. Panel B reports the results of hedge fund order flows predicting other investors' trading. In columns (1)-(3), the dependent variable is order flows of ICPFs on days d+1 to d+5. In columns (4)-(6), the dependent variable is order flows of non-dealer banks on days d+1 to d+5. Other control variables include the bond size (the logarithm of the bond's total market capitalization), maturity (the logarithm of time-to-maturity), trading volume, lagged bond returns, lagged order flows, as well as time fixed effects. *T*-statistics, based on standard errors clustered at both the time and bond level, are reported in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Predicting Mutual Fund Trading						
	(1)	(2)	(3)	(4)	(5)	(6)
	$Order\ Flow\ of\ Mutual\ Funds_{d+1:d+5}$			$MF\ Flow\ Induced\ Trade_{d+1:d+5}$		
$Order\ Flow\ of\ Hedge\ Funds_{d-4:d}$	0.009***	0.009***	0.010***	0.054***	0.054***	0.056***
	(3.798)	(3.911)	(4.320)	(2.684)	(2.705)	(2.726)
$Order\ Flow\ of\ MF(or\ FIT)_{d-4:d}$		0.061***	0.058***		0.033***	0.033***
		(10.589)	(9.769)		(2.711)	(2.691)
$Size_d$		-6.549***	-6.292***		91.260***	95.795***
		(-5.181)	(-4.914)		(3.225)	(3.307)
$Maturity_d$		-0.121***	-0.104***		0.124	0.149
		(-22.759)	(-16.725)		(0.740)	(0.804)
$Volume_{d-4:d}$		0.000	0.000**		0.002	0.002
		(1.464)	(2.093)		(0.785)	(0.827)
$Return_{d-4:d}$		0.013***	0.012***		0.041**	0.042**
		(7.778)	(6.872)		(2.180)	(2.186)
$Order\ Flow\ of\ MF(or\ FIT)_{d-9:d-5}$			0.038***			0.003
			(6.216)			(0.249)
$Order\ Flow\ of\ MF(or\ FIT)_{d-14:d-10}$			0.013**			-0.002
			(2.251)			(-0.219)
$Order\ Flow\ of\ MF(or\ FIT)_{d-19:d-15}$			0.011*			0.000
			(1.792)			(0.017)
$Order\ Flow\ of\ MF(or\ FIT)_{d-24:d-20}$			0.004			-0.028***
			(0.687)			(-2.924)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	46,939	46,815	45,755	22,848	22,719	22,144
Adj. R^2	0.046	0.071	0.068	0.555	0.562	0.564

Panel B: Predicting Other Investors' Trading						
	ICPFs			Non-Dealer Banks		
	(1)	(2)	(3)	(4)	(5)	(6)
	$Order\ Flow\ _{d+1:d+5}$			$Order\ Flow_{d+1:d+5}$		
$Order\ Flow\ of\ Hedge\ Funds_{d-4:d}$	0.007	0.007	0.007	-0.005	-0.006	-0.007
	(1.007)	(0.970)	(0.927)	(-0.691)	(-0.785)	(-0.961)
$Order\ Flow\ _{d-4:d}$		0.046***	0.040***		0.021*	0.020*
		(4.329)	(3.875)		(1.822)	(1.715)
$Size_d$		2.246	2.495		-0.813	0.322
		(0.660)	(0.728)		(-0.322)	(0.124)
$Maturity_d$		-0.230***	-0.178***		-0.182***	-0.165***
		(-7.429)	(-5.738)		(-7.311)	(-6.163)
$Volume_{d-4:d}$		-0.001	-0.001		-0.001*	-0.001*
		(-1.431)	(-0.832)		(-1.901)	(-1.686)
$Return_{d-4:d}$		0.034***	0.027***		0.021***	0.018***
		(5.059)	(4.419)		(3.972)	(3.794)
$Order\ Flow_{d-9:d-5}$			0.020**			-0.007
			(2.627)			(-0.700)
$Order\ Flow_{d-14:d-10}$			0.014*			0.002
			(1.867)			(0.276)
$Order\ Flow_{d-19:d-15}$			0.018*			0.009
			(1.873)			(0.953)
$Order\ Flow_{d-24:d-20}$			0.026***			0.018**
			(3.242)			(2.232)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	43,011	42,863	41,673	43,011	42,863	41,673
Adj. R^2	0.057	0.081	0.074	0.057	0.081	0.074

Table 6: Hedge Fund Order Flows and Macro-News Announcements

This table reports the returns of the long-short gilt portfolio sorted by daily hedge fund order flows on macroeconomic news announcement days. Macroeconomic news includes Monetary Policy Committee (MPC) meetings and announcements of inflation and labour statistics. On the day before each macroeconomic news announcement, we calculate the daily hedge fund order flow as the net buy volume scaled by the total trading volume of hedge funds. We then sort bonds into three groups and weight the bonds equally within each group. Panel A reports the returns of the long-short gilt portfolio on any macroeconomic news announcement days. Panel B reports the returns of the long-short portfolio on MPC meeting days, and finally Panel C reports the returns of the long-short portfolio on inflation and labour statistics announcement days. We report the raw returns, alphas adjusted by the market factor (1F Alpha), and alphas adjusted by the market, slope, and curvature factors (3F Alpha). All returns and alphas are reported in basis points. *T*-statistics are computed based on standard errors with Newey-West correction and are reported in parentheses. Long-short portfolio returns significant at the 5% level are indicated in bold.

Panel A: All Macro-News Announcements						
	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
H-L	**2.50**	(**2.26**)	**2.52**	(**2.41**)	**2.52**	(**2.62**)

Panel B: Monetary Policy Committee (MPC) Meetings						
	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
H-L	0.90	(1.74)	**1.00**	(**1.97**)	**1.22**	(**2.74**)

Panel C: Inflation and Labour Statistics Announcements						
	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
H-L	**3.42**	(**2.96**)	**3.54**	(**3.17**)	**3.53**	(**3.16**)

Table 7: Mutual Fund Order Flows and Interest Rate Changes

This table reports the predictability of mutual fund trading for future variation in the term structure of interest rates. In each month, we measure mutual fund trading activity as the weighted average duration change of mutual funds' government bond holdings: specifically, the weighted average duration of government bonds bought by mutual funds minus the weighted average duration of government bonds sold by mutual funds, dubbed $Trade\ Weighted\ Duration$. In Panel A, the dependent variables are changes in the short-term interest rate (one-year rate) one or three months ahead. In Panel B, the dependent variables are the changes in the slope of the term structure of interest rates, i.e. the difference between the twenty-year bond yield and one-year bond yield. Other control variables include the forward spread, changes in analyst forecasts of interest rates, changes in analyst forecasts of the GDP growth rate, changes in analyst forecasts of the inflation rate, and a time trend. All dependent variables are in basis points. T-statistics are computed based on standard errors with Newey-West correction and are reported in parentheses. *, **, *** indicate statistically significant at the 10%, 5%, and 1% level, respectively.

Panel A: Predicting Changes in Short-term Interest Rates				
	ΔIR_{m+1}		ΔIR_{m+3}	
$Trade\ Weighted\ Duration_m$	-0.526*	-0.513*	-1.728***	-1.654***
	(-1.86)	(-1.72)	(-3.01)	(-2.80)
$Forward\ Spread_{\mathrm{m}}$		-0.605		-0.944
		(-1.59)		(-0.89)
$\Delta IR\ Forecast_m$		-0.012		0.097***
		(-0.16)		(2.79)
$\Delta GDP\ Forecast_m$		0.025		0.002
		(0.56)		(0.02)
$\Delta Inflation\ Forecast_m$		0.011		0.005
		(0.18)		(0.06)
Time Trend	Yes	Yes	Yes	Yes
No. Obs.	77	77	77	77
Adj. R^2	0.019	-0.020	0.160	0.135

Panel B: Predicting Changes in Term Spreads				
	$\Delta Slope_{m+1}$		$\Delta Slope_{m+3}$	
$Trade\ Weighted\ Duration_m$	-0.278	-0.698	-1.774	-0.913
	(-0.62)	(-1.24)	(-1.51)	(-0.47)
$\Delta Slope\ Forecast_m$		0.028		-0.195
		(0.16)		(-1.06)
$\Delta GDP\ Forecast_m$		0.182		-0.059
		(1.47)		(-0.26)
$\Delta Inflation\ Forecast_m$		0.036		0.139
		(0.32)		(0.50)
Time Trend	Yes	Yes	Yes	Yes
No. Obs.	77	77	77	77
Adj. R^2	-0.025	-0.026	0.001	-0.009

Table 8: Mutual Fund Order Flows and Macro-News Announcements

This table reports the returns of the long-short gilt portfolio sorted by monthly mutual fund order flows on macroeconomic news announcement days. Macroeconomic news includes the Monetary Policy Committee (MPC) meetings and announcements of inflation and labour statistics. For each bond in each month, we calculate the monthly mutual fund order flow as the net buy volume scaled by the total trading volume of mutual funds. We then sort bonds into five groups and weight the bonds equally within each group. The long-short portfolios are held for one month. Panel A repeats the result of Panel B of Table 3. Panel B reports returns to the long-short gilt portfolio on any macroeconomic news announcement days. Panel C reports the returns of the long-short portfolio on MPC meeting days, and finally Panel D reports the returns of the long-short portfolio on inflation and labour statistics announcement days. We report the raw returns, alphas adjusted by the market factor (1F Alpha), and alphas adjusted by the market, slope, and curvature factors (3F Alpha). All returns and alphas are reported in basis points. *T*-statistics are computed based on standard errors with Newey-West correction and are reported in parentheses. Long-short portfolio returns significant at the 5% level are indicated in bold.

Panel A: Portfolio Returns in the Following Month						
	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
H-L	**27.52**	(**3.96**)	**17.59**	(**3.56**)	**17.98**	(**3.75**)

Panel B: Returns on Macro-News Announcements Days						
	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
H-L	**3.03**	(**2.72**)	**3.09**	(**3.21**)	**3.62**	(**3.37**)

Panel C: Returns on Monetary Policy Committee (MPC) Ann. Days						
	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
H-L	2.72	(1.74)	**2.85**	(**2.05**)	2.87	(1.79)

Panel D: Returns on Inflation and Labour Statistics Ann. Days						
	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
H-L	**3.50**	(**2.87**)	**3.49**	(**3.01**)	**4.29**	(**3.61**)

Table 9: Persistence in Return Predictability

This table examines the persistence in gilt return predictability of hedge fund and mutual fund trading. In Panel A, we classify hedge funds into high-skilled and low-skilled based on the return predictability of their daily order flows in the past three months. We then repeat the portfolio sorting exercise as in Table 2 for both groups of hedge funds. In Panel B, we classify mutual funds into high-skilled and low-skilled based on the return predictability of their monthly order flows using data from the past 12 months. We then repeat the portfolio sorting exercise as in Table 3 for both groups of mutual funds. We report the raw returns, alphas adjusted by the market factor (1F Alpha), and alphas adjusted by the market, slope, and curvature factors (3F Alpha). All returns and alphas are reported in basis points. *T*-statistics are computed based on standard errors with Newey-West correction and are reported in parentheses. Long-short portfolio returns significant at the 5% level are indicated in bold.

Panel A: Daily Order Flows of Hedge Funds and Next Five-Day Bond Returns

	High Skilled Hedge Funds			Low Skilled Hedge Funds		
	Return	Alpha (1F)	Alpha (3F)	Return	Alpha (1F)	Alpha (3F)
Low	7.55	-1.29	-1.00	9.35	0.53	0.58
	(1.34)	(-1.21)	(-0.97)	(1.58)	(-0.21)	(-0.11)
High	10.47	1.95	1.98	9.92	1.09	1.51
	(1.89)	(1.59)	(1.65)	(1.76)	(1.02)	(1.27)
H-L	**2.93**	**3.24**	**2.98**	0.56	0.56	0.93
	(2.25)	**(2.53)**	**(2.34)**	(1.21)	(1.08)	(1.21)

Panel B: Monthly Order Flows of Mutual Funds and Next-Month Bond Returns

	High Skilled Hedge Funds			Low Skilled Mutual Funds		
	Return	Alpha (1F)	Alpha (3F)	Return	Alpha (1F)	Alpha (3F)
Low	15.04	-8.71	-7.61	27.01	3.24	2.64
	(0.98)	(-2.26)	(-2.83)	(1.65)	(0.55)	(0.47)
High	40.05	11.59	12.49	28.05	0.94	0.73
	(2.42)	(2.69)	(2.89)	(1.70)	(0.25)	(0.19)
H-L	**25.02**	**20.29**	**20.10**	1.04	-2.30	-1.91
	(4.18)	**(3.24)**	**(3.84)**	(0.13)	(-0.28)	(-0.22)

Table 10: Order Flows and Future Bond Returns (Robustness Checks)

This table reports robustness checks for the portfolio sorting exercise reported in Tables 2 and 3. In Panel A, the sorting variable is daily hedge fund order flows and the holding period is one day. We conduct subsample analyses in Panel A1, consider an alternative measure of bond returns based on the clean price in Panel A2, and use an alternative definition of order flows (net buy volume scaled by the amount outstanding) in Panel A3. In Panel B, the sorting variable is monthly mutual fund order flows and the holding period is one month. Again, we conduct subsample analyses in Panel B1, consider an alternative measure of bond returns based on the clean price in Panel B2, and use an alternative definition of order flows in Panel B3. We report the raw returns, alphas adjusted by the market factor (1F Alpha), and alphas adjusted by the market, slope, and curvature factors (3F Alpha). All returns and alphas are reported in basis points. T-statistics are computed based on standard errors with Newey-West correction and are reported in parentheses. Long-short portfolio returns significant at the 5% level are indicated in bold.

Panel A: Return Predictability of Daily Hedge Fund Order Flows						
Panel A1: August 2011 – October 2014						
	Return	T-stat	Alpha (1F)	T-stat	Alpha (3F)	T-stat
1 (Low)	12.35	(2.01)	0.02	(0.02)	0.30	(0.30)
3 (High)	14.54	(2.50)	2.16	(2.47)	2.42	(2.78)
H-L	**2.19**	**(1.99)**	**2.14**	**(2.01)**	**2.12**	(1.98)
November 2014 – December 2017						
1 (Low)	4.92	(0.64)	-2.59	(-2.69)	-2.16	(-2.25)
3 (High)	8.57	(1.11)	1.18	(1.24)	1.36	(1.48)
H-L	**3.65**	**(2.87)**	**3.77**	**(2.99)**	**3.52**	**(2.93)**

Panel A2: Predicting Bond Price Changes						
	Return	T-stat	Alpha (1F)	T-stat	Alpha (3F)	T-stat
1 (Low)	3.53	(0.68)	-0.22	(-0.30)	-1.45	(-1.21)
3 (High)	6.59	(1.28)	2.85	(4.23)	1.90	(1.78)
H-L	**3.05**	**(3.56)**	**3.07**	**(3.62)**	**3.35**	**(2.28)**

Panel A3: Alternative Measure of Order Flows						
	Return	T-stat	Alpha (1F)	T-stat	Alpha (3F)	T-stat
1 (Low)	8.55	(1.95)	-1.02	(-1.15)	-0.50	(-0.60)
3 (High)	11.42	(2.58)	1.46	(1.61)	1.91	(2.26)
H-L	**2.87**	**(2.60)**	**2.48**	**(2.28)**	**2.41**	**(2.24)**

Panel B: Return Predictability of Monthly Mutual Fund Order Flows

Panel B1: August 2011 – October 2014

	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
1 (Low)	32.67	(1.34)	-10.82	(-2.50)	-12.63	(-4.06)
5 (High)	53.83	(2.27)	11.48	(2.56)	11.90	(4.17)
H-L	**21.16**	**(2.98)**	**22.30**	**(3.34)**	**24.53**	**(5.06)**
November 2014 – December 2017						
1 (Low)	18.00	(1.49)	-5.88	(-0.98)	-5.63	(-1.05)
5 (High)	44.84	(2.75)	11.76	(2.28)	10.46	(2.28)
H-L	**26.84**	**(2.23)**	17.64	(1.90)	**16.09**	**(2.00)**

Panel B2: Predicting Bond Price Changes

	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
1 (Low)	-2.32	(-0.18)	-36.96	(-7.79)	-36.97	(-8.22)
5 (High)	20.49	(1.33)	-18.69	(-5.75)	-18.17	(-6.21)
H-L	**22.81**	**(3.61)**	**18.27**	**(3.20)**	**18.80**	**(3.86)**

Panel B3: Alternative Measure of Order Flows

	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
1 (Low)	33.72	(2.43)	29.40	(1.06)	32.52	(1.24)
5 (High)	59.50	(3.13)	56.23	(1.65)	59.60	(1.87)
H-L	**25.79**	**(3.28)**	**26.84**	**(2.57)**	**27.07**	**(2.85)**

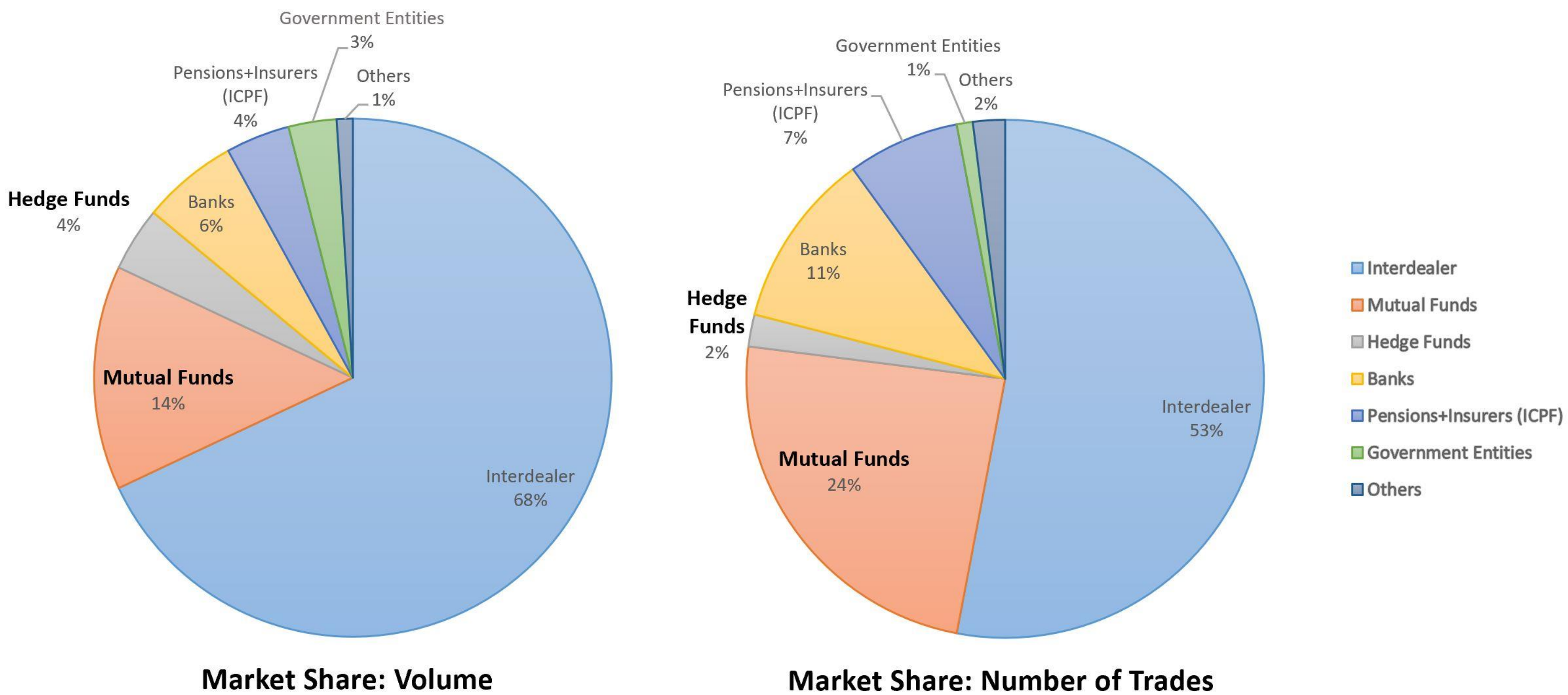

Figure 1: UK Government Bond Market Shares by Investor Type
This figure shows the breakdown of the total trading volume and number of trades in the UK government bond market. Trading volume and the number of trades are constructed using the ZEN database maintained by the Financial Conduct Authority (FCA). The sample period is August 2011 to December 2017.

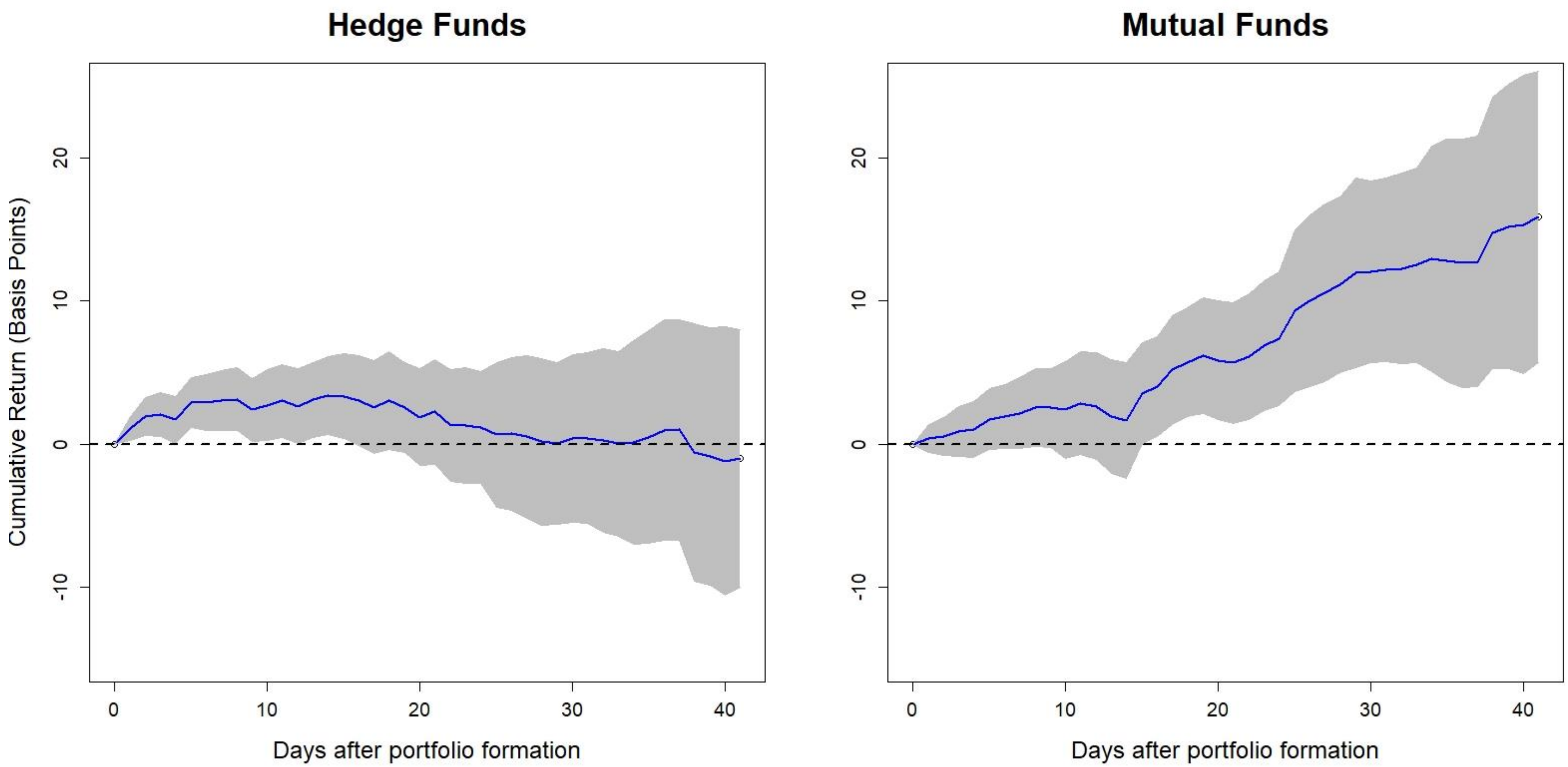

Figure 2: Event-Time Long-Short Portfolio Returns – Sorted by Daily Order Flows
This figure shows event-time returns of the long-short portfolio sorted by daily order flows of hedge funds and mutual funds. On each day, we sort all gilts into three groups based on hedge fund/mutual fund order flows and construct a long-short portfolio that goes long the top group and short the bottom group. The 95% confidence interval (in grey) is calculated based on block-bootstrapped standard errors.

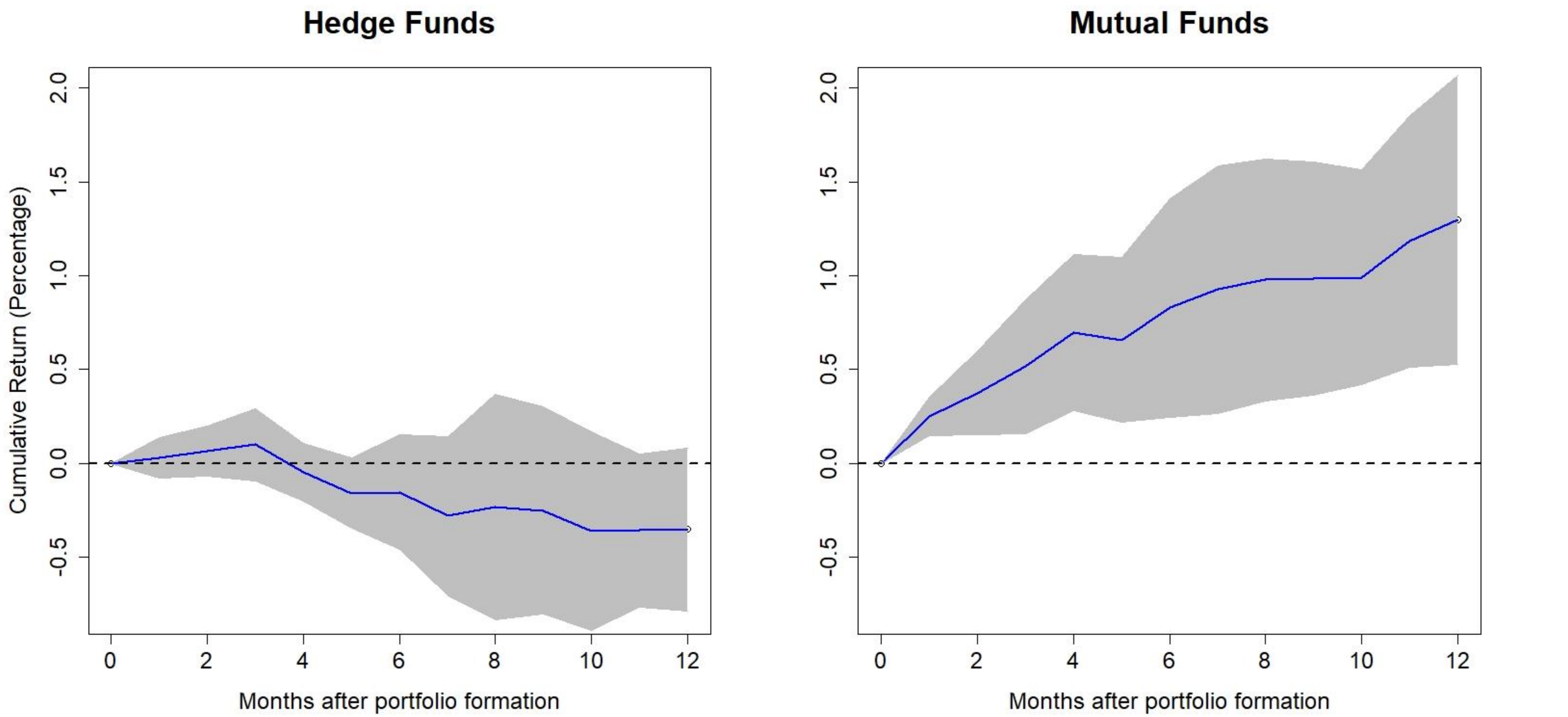

Figure 3: Event-Time Long-Short Portfolio Returns – Sorted by Monthly Order Flows

This figure shows event-time returns of the long-short portfolio sorted by monthly order flows of hedge funds and mutual funds. In each month, we sort all gilts into five groups based on hedge fund/mutual fund order flows and construct a long-short portfolio that goes long the top group and short the bottom group. The 95% confidence interval (in grey) is calculated based on block-bootstrapped standard errors.

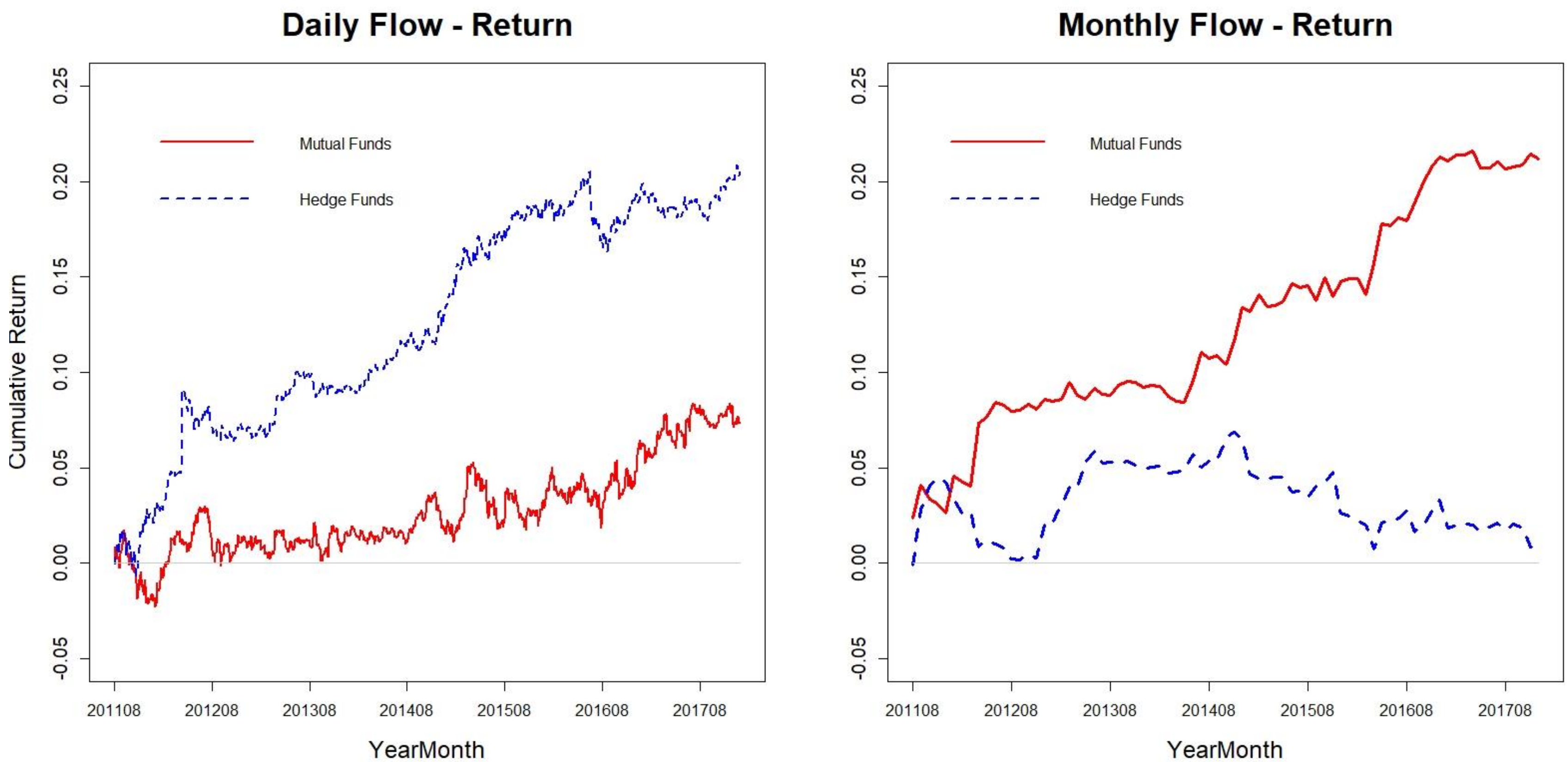

Figure 4: Calendar-Time Cumulative Portfolio Returns

This figure shows the cumulative return of the long-short portfolio sorted by hedge fund and mutual fund order flows. In the left panel, on each day, we sort gilts into three groups based on daily order flows of hedge funds/mutual funds and construct a long-short portfolio that goes long the top group and short the bottom group. In the right panel, in each month, we sort gilts into five groups based on monthly order flows of hedge funds/mutual funds and construct a long-short portfolio that goes long the top group and short the bottom group.

Appendix

Table A1: Daily Order Flows and Contemporaneous Bond Returns – Portfolio Sorting

This table reports the contemporaneous returns of calendar-time long-short gilt portfolios sorted by daily order flows of hedge funds and mutual funds. In Panel A, the sorting variable is daily order flows of hedge funds. In Panel B, the sorting variable is daily order flows of mutual funds. In Panel C, the sorting variable is daily order flows of hedge and mutual funds combined. For each bond on each day, we calculate the daily order flow of hedge funds (mutual funds) as the net buy volume scaled by the total trading volume of hedge funds (mutual funds). We then sort all gilts into three groups based on the daily order flows of hedge funds (mutual funds) and weight the bonds equally within each group. We report the raw returns, alphas adjusted by the market factor (1F Alpha), and alphas adjusted by the market, slope, and curvature factors (3F Alpha). All returns and alphas are reported in basis points. *T*-statistics are computed based on standard errors with Newey-West correction and are reported in parentheses. Long-short portfolio returns significant at the 5% level are indicated in bold.

Panel A (Daily Level): Hedge Funds						
	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
1 (Low)	1.46	(1.44)	-0.72	(-2.58)	-0.58	(-1.95)
2	2.10	(2.02)	-0.14	(-0.51)	-0.13	(-0.49)
3 (High)	2.39	(2.43)	0.29	(1.01)	0.31	(1.09)
H-L	**0.92**	**(2.31)**	**1.10**	**(2.56)**	**0.89**	**(2.16)**

Panel B (Daily Level): Mutual Funds						
	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
1 (Low)	1.18	(1.23)	-0.84	(-2.20)	-0.85	(-2.24)
2	2.63	(2.26)	0.18	(0.55)	0.38	(1.12)
3 (High)	2.15	(2.13)	-0.01	(-0.04)	-0.01	(-0.02)
H-L	0.97	(1.74)	0.83	(1.51)	0.84	(1.55)

Panel C: Hedge Funds and Mutual Funds						
	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
1 (Low)	1.15	(1.30)	-0.81	(-2.61)	-0.84	(-2.89)
2	2.25	(2.04)	-0.25	(-0.99)	-0.15	(-0.64)
3 (High)	2.96	(3.20)	0.86	(3.82)	0.82	(3.60)
H-L	**1.82**	(**3.91**)	**1.67**	(**3.70**)	**1.66**	(**3.80**)

Table A2: Daily Order Flows and Future Bond Returns – Portfolio Sorting

This table reports detailed results of calendar-time long-short gilt portfolios sorted by daily order flows of hedge funds and mutual funds (Table 2). For each bond on each day, we calculate the daily order flow of hedge funds (mutual funds) as the net buy volume scaled by the total trading volume of hedge funds (mutual funds). We then sort all gilts into three groups based on the daily order flows of hedge funds (mutual funds) and weight the bonds equally within each group. We report the return (alpha) spreads between the top and bottom terciles ("High minus Low": H-L) on the following trading day (Panel A), five trading days (Panel B), ten trading days (Panel C), one month (Panel D), and two months (Panel E). We report the raw returns, alphas adjusted by the market factor (1F Alpha), and alphas adjusted by the market, slope, and curvature factors (3F Alpha). All returns and alphas are reported in basis points. *T*-statistics are computed based on standard errors with Newey-West correction and are reported in parentheses. Long-short portfolio returns significant at the 5% level are indicated in bold.

Panel A: Holding Period = 1 day

	Hedge Funds						Mutual Funds					
	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
1 (Low)	1.26	(1.20)	-0.76	(-2.07)	-0.75	(-2.04)	1.52	(1.55)	-0.33	(-0.90)	-0.34	(-0.92)
2	1.72	(1.76)	-0.34	(-1.18)	-0.32	(-1.13)	2.20	(1.97)	-0.03	(-0.09)	0.04	(0.11)
3 (High)	2.54	(2.65)	0.62	(2.23)	0.64	(2.26)	1.97	(2.02)	0.01	(0.03)	-0.00	(-0.01)
H-L	**1.28**	**(2.80)**	**1.38**	**(3.16)**	**1.39**	**(3.20)**	0.45	(0.95)	0.34	(0.72)	0.34	(0.71)

Panel B: Holding Period = 5 days

	Hedge Funds						Mutual Funds					
	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
1 (Low)	8.86	(1.98)	-1.33	(-1.79)	-1.08	(-1.49)	8.60	(2.05)	-1.01	(-1.29)	-0.80	(-1.01)
2	9.92	(2.06)	-0.90	(-1.16)	-0.53	(-0.68)	11.72	(2.30)	0.50	(0.52)	0.79	(0.86)
3 (High)	11.74	(2.66)	1.61	(2.15)	1.85	(2.72)	10.35	(2.35)	0.41	(0.50)	0.70	(0.85)
H-L	**2.88**	**(3.16)**	**2.94**	**(3.32)**	**2.94**	**(3.55)**	1.75	(1.63)	1.43	(1.41)	1.50	(1.49)

Panel C: Holding Period = 10 Days												
	Hedge Funds						Mutual Funds					
	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
1 (Low)	18.42	(2.40)	-2.22	(-2.51)	-1.46	(-1.70)	17.22	(2.62)	-1.90	(-1.75)	-1.23	(-1.09)
2	19.71	(2.24)	-1.70	(-1.81)	-0.66	(-0.69)	22.92	(2.62)	0.19	(0.17)	0.76	(0.73)
3 (High)	21.06	(2.72)	0.67	(0.75)	1.28	(1.41)	19.76	(2.63)	-0.72	(-0.68)	0.17	(0.16)
H-L	**2.64**	(**2.33**)	**2.89**	(**2.62**)	**2.74**	(**2.49**)	2.54	(1.70)	1.18	(0.85)	1.40	(0.98)

Panel D: Holding Period = 1 Month												
	Hedge Funds						Mutual Funds					
	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
1 (Low)	40.62	(2.89)	-3.12	(-2.33)	-2.07	(-1.46)	37.61	(3.26)	-3.34	(-1.96)	-2.86	(-1.59)
2	44.04	(2.81)	-1.20	(-0.83)	-0.05	(-0.03)	45.37	(3.01)	-1.82	(-1.11)	-0.37	(-0.22)
3 (High)	41.94	(3.01)	-0.67	(-0.51)	0.32	(0.24)	44.08	(3.16)	0.66	(0.39)	1.95	(1.10)
H-L	1.32	(0.73)	2.46	(1.45)	2.39	(1.37)	**6.47**	(**2.59**)	4.00	(1.66)	4.81	(1.83)

Panel E: Holding Period = 2 Months												
	Hedge Funds						Mutual Funds					
	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
1 (Low)	74.75	(2.87)	0.03	(0.03)	2.54	(2.22)	65.28	(2.64)	-4.11	(-3.84)	-2.69	(-2.65)
2	77.28	(2.83)	-4.47	(-3.47)	-1.12	(-0.83)	88.84	(2.60)	-0.72	(-0.64)	1.18	(1.10)
3 (High)	73.47	(2.92)	-0.31	(-0.24)	0.97	(0.76)	80.89	(2.82)	2.24	(1.98)	2.86	(2.55)
H-L	-1.28	(-0.31)	-0.34	(-0.19)	-1.57	(-0.85)	**15.61**	(**3.67**)	**6.35**	(**3.49**)	**5.55**	(**3.03**)

Table A3: Hedge Fund Order Flows and Future Non-Dealer Order Flows

This table reports the results of panel regressions of order flows by mutual funds (or non-dealer banks / insurance companies and pension funds (ICPFs)) on lagged hedge fund order flow. For each bond on day d, we calculate the order flow of each group of investors (e.g. mutual funds) as the net buy volume scaled by the total trading volume of this group of investors. Columns (1)-(2) report the results of hedge fund order flows predicting mutual fund order flows on the following day. Columns (3)-(4) report the results of hedge fund order flows predicting ICPF order flows on the following day. Columns (5)-(6) report the results of hedge fund order flows predicting non-dealer bank order flows on the following day. Other control variables include the bond size (the logarithm of the bond's total market capitalization), maturity (the logarithm of time-to-maturity), trading volume, lagged bond returns, lagged order flows, as well as time fixed effects. T-statistics, based on standard errors clustered at both the time and bond level, are reported in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Mutual Funds		ICPFs		Non-Dealer Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
$Order\ Flow\ of\ Hedge\ Funds_d$	0.016***	0.015***	0.016**	0.010	0.013**	0.007
	(3.786)	(3.423)	(2.515)	(1.204)	(2.259)	(1.039)
$Order\ Flow_d$		0.075***		0.047***		0.052***
		(9.498)		(4.718)		(5.765)
$Size_d$		3.396***		7.987***		3.702
		(2.676)		(2.889)		(1.579)
$Maturity_d$		-0.141***		-0.243***		-0.187***
		(-11.039)		(-8.098)		(-8.998)
$Volume_d$		0.000		-0.001*		-0.003***
		(0.394)		(-1.941)		(-4.121)
$Return_d$		0.015***		0.020***		0.011***
		(5.763)		(3.889)		(3.032)
$Order\ Flow_{d-1}$		0.035***		0.030***		0.021**
		(4.616)		(2.975)		(2.468)
$Order\ Flow_{d-2}$		0.014*		0.050***		0.007
		(1.805)		(5.147)		(0.825)
$Order\ Flow_{d-3}$		0.015*		0.046***		0.009
		(1.951)		(4.664)		(1.021)
$Order\ Flow_{d-4}$		0.015**		0.017*		0.023***
		(1.982)		(1.776)		(0.007)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	23,504	22,856	20,945	11,920	22,011	16,129
Adj. R^2	0.076	0.098	0.140	0.199	0.080	0.113

Table A4: Non-Dealer Order Flows and Future Hedge Fund Order Flows

This table reports the results of panel regressions of hedge fund order flows on lagged aggregate market order flows (excluding hedge funds). For each bond on day *d*, we calculate the aggregate market order flow as the net buy volume scaled by the total trading volume in the market excluding hedge funds. In columns (1)-(3), the dependent variable is the hedge fund order flow on day *d*+1. In columns (4)-(6), the dependent variable is the hedge fund order flow on days *d*+1 to *d*+5. Other control variables include the bond size (the logarithm of the bond's total market capitalization), maturity (the logarithm of time-to-maturity), trading volume, lagged bond returns, lagged order flows, as well as time fixed effects. *T*-statistics, based on standard errors clustered at both the time and bond level, are reported in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

	$Order\ Flow\ of\ Hedge\ Funds_{d+1}$			$Order\ Flow\ of\ Hedge\ Funds_{d+1:d+5}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$Order\ Flow\ of\ Hedge\ Funds_d$	0.176***	0.175***	0.126***	0.075***	0.075***	0.033***
	(15.387)	(15.322)	(6.311)	(9.533)	(9.603)	(2.714)
$Order\ Flow\ of\ Others_d$	-0.011	-0.011	0.015	-0.012	-0.011	0.018
	(-0.552)	(-0.541)	(0.372)	(-1.044)	(-0.930)	(0.814)
$Size_d$		-0.041	0.093*		-0.010	0.127**
		(-1.414)	(1.707)		(-0.423)	(2.453)
$Maturity_d$		-0.003***	0.001		-0.002***	0.003***
		(-3.766)	(0.702)		(-2.836)	(3.106)
$Volume_d$		-0.029***	-0.010		-0.011**	-0.014
		(-2.913)	(-0.644)		(-2.164)	(-1.317)
$Return_d$		1.377**	0.369		-6.746***	-5.701*
		(2.422)	(0.241)		(-3.597)	(-1.833)
$Order\ Flow\ of\ Hedge\ Funds_{d-1}$			0.041**			0.011
			(2.242)			(0.980)
$Order\ Flow\ of\ Hedge\ Funds_{d-2}$			0.024			-0.000
			(1.152)			(-0.024)
$Order\ Flow\ of\ Hedge\ Funds_{d-3}$			0.014			0.007
			(0.834)			(0.597)
$Order\ Flow\ of\ Hedge\ Funds_{d-4}$			0.025			0.020
			(1.408)			(1.640)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	13,267	13,267	3,656	20,422	20,422	4,537
Adj. R^2	0.136	0.138	0.311	0.086	0.088	0.273

Table A5: Daily Hedge Fund Order Flows and Future Bond Returns – Double Sorting

This table reports the return predictability of daily hedge fund order flows for periods with high and low mutual fund flow-induced trading (*FIT*). We follow Lou (2012) to calculate *FIT* for each bond on each day. We then aggregate the absolute value of *FIT* across all bonds and use this aggregate *FIT* measure to divide our sample period into high-*FIT* and low-*FIT* days. For each subperiod, we repeat the portfolio sorting exercise of Table 2. We report the return (alpha) spreads between the top and bottom terciles ("High minus Low": H-L) on the following trading day (Panel A), and the following five trading days (Panel B). We report the raw returns, alphas adjusted by the market factor (1F Alpha), and alphas adjusted by the market, slope, and curvature factors (3F Alpha). All returns and alphas are reported in basis points. *T*-statistics are computed based on standard errors with Newey-West correction and are reported in parentheses. Long-short portfolio returns significant at the 5% level are indicated in bold.

Panel A: Holding Period = 1 day

	High Flow-Induced Trade						Low Flow-Induced Trade					
	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
1 (Low)	1.25	(0.80)	-1.25	(-2.13)	-1.26	(-2.19)	1.28	(0.82)	-0.25	(-0.53)	-0.28	(-0.59)
2	2.14	(1.60)	-0.31	(-0.85)	-0.31	(-0.85)	1.27	(0.82)	-0.32	(-0.75)	-0.33	(-0.77)
3 (High)	3.52	(2.65)	1.20	(3.07)	1.21	(3.12)	1.52	(1.05)	0.04	(0.11)	0.04	(0.09)
H-L	**2.27**	(**2.93**)	**2.46**	(**3.37**)	**2.47**	(**3.50**)	0.24	(0.44)	0.29	(0.54)	0.32	(0.59)

Panel B: Holding Period = 5 days

	High Flow-Induced Trade						Low Flow-Induced Trade					
	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
1 (Low)	11.09	(1.88)	-1.20	(-1.10)	-1.16	(-1.07)	6.54	(0.93)	-1.32	(-1.37)	-0.93	(-1.00)
2	12.47	(1.96)	-0.63	(-0.55)	-0.34	(-0.31)	7.27	(0.93)	-1.03	(-0.95)	-0.80	(-0.73)
3 (High)	15.10	(2.51)	2.78	(2.60)	2.55	(2.70)	8.25	(1.20)	0.49	(0.54)	0.84	(0.95)
H-L	**4.01**	(**3.10**)	**3.98**	(**3.30**)	**3.71**	(**3.40**)	1.70	(1.32)	1.81	(1.46)	1.77	(1.49)

Table A6: Hedge Fund Order Flows and Macro-News Announcements

This table reports robustness checks for the portfolio returns of the long-short gilt portfolio sorted by daily hedge fund order flows on (or around) macroeconomics news announcement days (Table 6). Macroeconomic news includes Monetary Policy Committee (MPC) meetings and announcements of inflation and labour statistics. In Panel A, we consider alternative windows to calculate order flows (one, two, or three days prior to each announcement). In Panel B, we also consider alternative windows to calculate the returns around macroeconomic announcement days (from the day before to the day after each announcement). We report the raw returns, alphas adjusted by the market factor (1F Alpha), and alphas adjusted by the market, slope, and curvature factors (3F Alpha). All returns and alphas are reported in basis points. *T*-statistics are computed based on standard errors with Newey-West correction and are reported in parentheses. Long-short portfolio returns significant at the 5% level are indicated in bold.

Panel A: Predicting returns on announcement days						
Sorting Variable	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
	All Macro News					
Past 1 day's order flow	**2.50**	**(2.26)**	**2.52**	**(2.41)**	**2.52**	**(2.62)**
Past 2 days' order flow	**4.12**	**(3.36)**	**4.30**	**(3.31)**	**4.10**	**(3.64)**
Past 3 days' order flow	**3.43**	**(3.16)**	**3.53**	**(3.35)**	**3.36**	**(3.75)**
	Monetary Policy Committee (MPC) Meetings					
Past 1 day's order flow	0.90	(1.74)	**1.00**	**(1.97)**	**1.22**	**(2.74)**
Past 2 days' order flow	**4.69**	**(2.56)**	**5.03**	**(2.49)**	3.99	(1.91)
Past 3 days' order flow	**3.24**	**(2.35)**	**3.33**	**(2.32)**	**2.34**	(1.28)
	Inflation and Labour Announcements					
Past 1 day's order flow	**3.42**	**(2.96)**	**3.54**	**(3.17)**	**3.53**	**(3.16)**
Past 2 days' order flow	**3.42**	**(2.96)**	**3.54**	**(3.17)**	**3.53**	**(3.16)**
Past 3 days' order flow	**2.98**	**(2.87)**	**2.98**	**(2.86)**	**2.98**	**(2.87)**

Panel B: Predicting returns in the (-1,1) window around announcement days						
	All Macro News					
Past 1 day's order flow	**8.72**	**(4.26)**	**8.69**	**(4.19)**	**8.51**	**(4.29)**
Past 2 days' order flow	**5.30**	**(2.74)**	**5.28**	**(2.69)**	**5.14**	**(2.75)**
Past 3 days' order flow	**4.54**	**(2.51)**	**4.49**	**(2.47)**	**4.38**	**(2.46)**
	Monetary Policy Committee (MPC) Meetings					
Past 1 day's order flow	**8.50**	**(2.93)**	**8.50**	**(3.01)**	**7.46**	**(2.86)**
Past 2 days' order flow	**7.62**	**(2.58)**	**7.63**	**(2.57)**	**6.79**	**(2.56)**
Past 3 days' order flow	**7.13**	**(2.86)**	**7.13**	**(2.84)**	**6.21**	**(2.80)**
	Inflation and Labour Announcements					
Past 1 day's order flow	**9.11**	**(3.31)**	**9.00**	**(3.62)**	**9.01**	**(3.79)**
Past 2 days' order flow	**3.20**	**(2.08)**	**3.17**	**(2.13)**	**3.33**	**(2.46)**
Past 3 days' order flow	1.58	(0.87)	1.39	(0.91)	2.40	(1.72)

Table A7: Mutual Fund Order Flows and Future Non-Dealer Order Flows

This table reports the results of panel regressions of monthly aggregate order flows (excluding mutual funds) on lagged monthly mutual fund order flows. For each bond in month *m*, we calculate the aggregate market order flow as the net buy volume scaled by the total trading volume in the market (excluding mutual funds). The independent variable is the mutual fund order flow in month *m*, and the dependent variable is the aggregate market order flow in month *m*+1. Other control variables include the bond size (the logarithm of the bond's total market capitalization), maturity (the logarithm of time-to-maturity), trading volume, lagged bond returns, lagged order flows, as well as time fixed effects. *T*-statistics, based on standard errors clustered at both the time and bond level, are reported in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

	$Order\ Flows\ of\ Others_{m+1}$		
$Order\ Flows\ of\ Mutual\ Funds_m$	0.019	-0.019	-0.028
	(0.797)	(-0.943)	(-1.373)
$Order\ Flows\ of\ Others_m$	0.057*	0.016	0.020
	(1.957)	(0.522)	(0.733)
$Size_m$		-0.088***	-0.012
		(-2.800)	(-0.295)
$Maturity_m$		-0.001	0.001
		(-0.499)	(0.306)
$Volume_m$		0.018**	0.005
		(1.988)	(0.790)
$Return_m$		-0.892*	-0.557
		(-1.688)	(-1.044)
$Order\ Flow\ of\ Others_{m-1}$			0.006
			(0.278)
$Order\ Flow\ of\ Others_{m-2}$			-0.016
			(-0.769)
$Order\ Flow\ of\ Others_{m-3}$			0.034*
			(1.892)
$Order\ Flow\ of\ Others_{m-4}$			0.051**
			(2.555)
Time Fixed Effects	Yes	Yes	Yes
No. Obs.	2,869	2,848	2,653
Adj. R^2	0.035	0.046	0.040

Table A8: Order Flows and Future Bond Returns
Non-Dealer Banks, Insurance Companies and Pension Funds (ICPFs)

This table reports the returns of calendar-time long-short gilt portfolios sorted by daily (monthly) order flows of non-dealer banks and insurance companies and pension funds (ICPFs). In Panel A, the sorting variable is daily order flows of non-dealer banks and ICPFs. In Panel B, the sorting variable is monthly order flows of non-dealer banks and ICPFs. In Panel A, for each bond on each day, we calculate the daily order flow of non-dealer banks (ICPFs) as the net buy volume scaled by the total trading volume of non-dealer banks (ICPFs). We then sort all gilts into three groups based on the daily order flows of non-dealer banks (ICPFs) and weight the bonds equally within each group. In Panel B, for each bond in each month, we calculate the monthly order flow of banks (ICPFs) as the net buy volume scaled by the total trading volume of non-dealer banks (ICPFs). In both panels, we report the raw returns, alphas adjusted by the market factor (1F Alpha), and alphas adjusted by the market, slope, and curvature factors (3F Alpha). All returns and alphas are reported in basis points. *T*-statistics are computed based on standard errors with Newey-West correction and are reported in parentheses. Long-short portfolio returns significant at the 5% level are indicated in bold.

Panel A: Daily Order Flows and Bond Returns						
Non-Dealer Banks						
	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
Low	9.66	(1.90)	-0.59	(-0.63)	-0.20	(-0.21)
High	10.42	(2.19)	0.64	(0.83)	0.99	(1.30)
H-L	0.76	(0.64)	1.23	(0.99)	1.19	(0.93)
ICPFs						
	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
Low	10.32	(1.80)	-0.54	(-0.94)	-0.55	(-0.99)
High	11.66	(1.93)	0.51	(0.80)	0.36	(0.59)
H-L	1.34	(1.41)	1.04	(1.05)	0.92	(0.94)

Panel B: Monthly Order Flows and Bond Returns						
Non-Dealer Banks						
	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
Low	48.48	(2.64)	0.86	(0.19)	0.01	(0.00)
High	52.27	(2.98)	6.92	(1.31)	6.30	(1.17)
H-L	3.79	(0.71)	6.07	(1.10)	6.30	(1.05)
ICPFs						
	Return	*T*-stat	Alpha (1F)	*T*-stat	Alpha (3F)	*T*-stat
Low	40.31	(2.64)	0.84	(0.31)	0.41	(0.16)
High	38.75	(1.90)	-6.35	(-1.00)	-6.36	(-1.01)
H-L	-1.56	(-0.17)	-7.19	(-0.99)	-6.79	(-1.02)