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Dong Lou

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Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

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Abstract

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JEL Classification: N/A

Keywords: Government bonds, Informed trading, return predictability, asset managers

Dong Lou - d.lou@lse.ac.uk
LSE and CEPR

Informed Trading in Government Bond Markets*

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

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

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

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

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Abstract

Using comprehensive administrative data from the UK, we examine trading by different investor groups in government bond markets. Our sample covers virtually all secondary market trading in gilts and contains detailed information of 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' front-running other investors' future demand. 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.

Keywords: government bonds, informed trading, return predictability, asset managers

1. Introduction

Government bond yields are the basis of 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. 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 non-public information; differences in opinions could also be driven by heterogeneity in investors' 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 private information and/or more accurate interpretations of public information—should persistently outperform that of the less-informed.

Our focus in the paper is the second channel. A priori, it would seem difficult for any investor (or investor group) to acquire an information advantage over other market 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 the stock and corporate bond markets (e.g., Wermers, 2000; Cici and Gibson, 2012). More related to our study, prior research on investors' market timing ability has largely concluded that institutions that actively shift their market exposures on average underperform their peers

[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 (see, e.g., Litterman and Scheinkman, 1991), are responsible for nearly all the variation in yield changes.

(e.g., Huang, Sialm, and Zhang, 2011). It is therefore an intriguing empirical question as to 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 (e.g., Huang and Wang, 2014), and b) intraday order flow data acquired from one or more dealer banks (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 focus on aggregate trading between dealers and non-dealer investors, summed across all reported trades.

We contribute to the debate of informed trading in the government bond market by exploiting comprehensive administrative data in the UK. 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, or branches of UK institutions regulated in the European Economic Area (EEA). Given that all gilt dealers are UK-domiciled and hence FCA-regulated institutions, the ZEN database effectively covers the entirety of trading activity in the UK government bond market.

Compared to the datasets used in 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 of 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 (e.g., a transaction between a dealer bank and a bond mutual fund). Third, the ZEN database covers virtually all investors and all transactions; that is, 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 analyze the extent to which any group of investors have a comparative advantage in this market and, further, are able to profit from their information advantage.

For ease of comparison, we aggregate all 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.[2] For most part of the paper, we focus on the first two groups of institutions, hedge funds and mutual funds, the prototypical 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 are informed 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 at different horizons. Specifically, sorting all UK government bonds (with different maturities and vintages) into terciles based on the previous-day net buying 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) in 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 funds' trading has insignificant return predictive power in the first ten days but become increasingly informative over a longer horizon. For

[2] The largest share of trades in gilts (about 68%) takes place in the inter-dealer market. Together, these four groups of investors plus dealer banks (as well as government entities) are responsible for nearly all gilt transactions.

example, the return spread between the top and bottom terciles of gilts, sorted by the previous-day mutual fund order flow, is an statistically insignificant 0.45 *bps* (t-statistic = 0.95) in the 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%.[3]

We next turn to the sources of the information advantage of hedge funds and mutual funds. Recent theoretical work (e.g., Farboodi and Veldkamp, 2019) postulates that arbitrageurs can engage in two types of arbitrage activities: i) to predict and front-run other investors' demand, and ii) to learn about future asset/security value 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 net purchases by mutual funds in the following week by more than 1% (t-statistic = 4.32).[4] 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 mutual funds' flow-induced demand.

[3] As we show later in the paper, trading by non-dealer banks and ICPFs has insignificant and sometimes negative predictability for future government bond returns across all holding horizons.

[4] 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.

To analyze the second channel, we repeat our return predictability test of hedge fund trading separately for macro-announcement days and non-announcement days. Our results 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 on the sample of mutual funds. First, in contrast to the earlier 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 in the business of front-running others' demand. 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 (e.g., a set of forward rates plus survey expectations of future interest rates), we find that mutual funds' aggregate shift in their portfolio duration 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.[5]

Finally, we analyze 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 labor 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 asset managers, both hedge funds and mutual funds, have an advantage over other market participants in collecting, processing, and trading on information that is relevant for future gilt returns. In particular, our findings

[5] Interestingly, mutual funds' 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.

highlight the distinctions in the two groups' approaches to earning abnormal returns in the government bond market. While hedge funds gain from both front-running other investors' future demand and quick responses to the arrival of macroeconomic news, mutual funds profit from their ability to understand and forecast macro-economic fundamentals. Through their active trading, these professional managers help impound private 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 discoveries in the government bond market.[6] Fleming and Remolona (1997) show that macroeconomic announcements are responsible for many of the largest daily price movements in the US Treasury market. 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 this correlation between investor order flows and Treasury yield changes increases in the dispersion of investor beliefs. While most prior studies examine the contemporaneous relation between macro-announcements/order-flows and Treasury yield changes, we focus squarely on the return predictability of trading by various types of institutions, such as hedge funds and mutual funds.[7] 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 parties in each transaction.

Our study also contributes to the vast empirical literature on the predictability of the term structure of interest rates, and relatedly, Treasury security returns. Fama and

[6] 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).

[7] In a contemporaneous study, Kondor and Pinter (2019) use the same regulatory transactions data in the UK to show that institutions with a larger number of dealer-bank connections have on average better trading performance.

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 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 Treasury yields/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 importantly related to contemporaneous movements in exchange rates. Menkhoff, Sarno, Schmeling, and Schrimpf (2016) further document that dealer-client order flows are informative 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 front-running other investors' future demand and/or learning about economic fundamentals.

3. Data

We use regulatory bond transactions data—the ZEN database—maintained by the Financial Conduct Authority (FCA) in the UK. 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 the trades take place over the counter. The Gilt-Edged Market Makers (or GEMMs) are central to the functioning of the gilt market.[8] These financial institutions (mainly large investment banks) are designated primary dealers in the gilt market; endorsed 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 of all secondary-market trades of UK-regulated firms, or branches of UK firms regulated in the European Economic Area (EEA). Given that all dealers are UK-domiciled and hence FCA-regulated institutions, our data cover virtually 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.[9] 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). We combine pension funds and insurance companies because of the similarities in their investment styles/objectives. For each day/month, we calculate the order flow (or trading activity) of each investor sector 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 group i in bond j in day/month t. In robustness checks, we use alternative definitions of orders flows (for

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

[9] 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 that in the dealer-client market.

example, scaled by the total outstanding amount or by the total trading volume of the gilt) and obtain similar results.

Our sample spans the period August 2011 to December 2017. We merge our transactions data with publicly available bond characteristics provided by the UK Debt Management Office and Datastream; the list of characteristics includes the bond issuance size, maturity, coupon, duration, prices, ratings, and accrued interest. Following 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, as they are often treated differently from the non-indexed gilts.

For macroeconomic news announcements, we focus on public announcements of UK inflation, labor statistics (i.e., the unemployment rate), and the Monetary Policy Committee (MPC) meetings.[10] 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 UK government bonds. 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.[11]

[10] The MPC is the UK counterpart of the US Federal Open Markets Committee (FOMC).

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

Our final sample consists of 55 UK government bonds. 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-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 relations to both contemporaneous and future bond returns using both a calendar-time portfolio approach and a Fama-MacBeth regression setting. For most part of this paper, we focus on the order flows of mutual funds and hedge funds, the prototypical arbitrageurs in financial markets; as a placebo, we analyze the trading behavior of non-dealer banks and ICPFs—both of which are unlikely to be informed—in Section 6.

4.1. Daily Order Flows and Bond Returns

We start by analyzing 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. Online Appendix Table A1 confirms this prediction. Gilts that are heavily bought by hedge funds in a day outperform those that are heavily sold by 0.92 *bps* (t-statistic = 2.31) in the same day. If we combine the trades by hedge funds with those by mutual funds, the results are even stronger: gilts heavily bought by hedge funds and mutual funds collectively in a day outperform those heavily sold by 1.82 *bps* (t-statistic = 3.91) in the same day.

To the extent that the market does not immediately and fully respond to hedge funds' and mutual funds' order flows, 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 in each day.[12] 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.[13] 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) in 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 at 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 (e.g., 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 the same table, as we increase the holding horizon from one day to two months, the return spread between the top and bottom terciles sorted by mutual funds' daily order flows 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 flow-return predictive pattern between hedge funds and mutual funds is also apparent in Figure 2, which shows the event-time cumulative returns to the long-short portfolios sorted by daily order flows of the two investor sectors. The

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[12] 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 instead sort all bonds into quintiles.

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

figure reveals that hedge fund trading positively forecasts bond returns in the short run (which peaks after 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 analyze investors' monthly order flows and their relations to bond returns in the following year. Specifically, at the end of each month, we sort all government bonds into quintiles based on hedge funds' or mutual funds' order flows 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 earlier 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 funds' 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 event-time cumulative returns to 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 a herding behavior (Cai, Han, Li, and Li, 2019).

We also plot cumulative returns to 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 rebalance 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 earlier 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 an array of known predictors of government bond returns.

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

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

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:

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

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 are unable to 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

After establishing the return predictive patterns of hedge funds' and mutual funds' trading activity, in this section, we investigate the sources of such return predictability in the government bond market. Section 5.1 examines the mechanisms of the return predictability of *daily* hedge fund order flows, and Section 5.2 examines those of the return predictability of *monthly* mutual fund order flows.

5.1. Sources of Return Predictability: Hedge Funds

Recent theoretical studies (e.g., Farboodi and Veldkamp, 2019) argue that arbitrageurs may engage in two types of arbitrage activities: i) some are able to predict future demand of other investors and profit from front-running 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 (e.g., monetary policy, inflation, and labor 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 sector (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.[14] Importantly, there is no similar order flow predictive pattern in the opposite direction: as shown in Online 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; such flow-induced trading, collectively, 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

[14] 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 Online Appendix Table A3, are qualitatively the same as those reported in Table 5.

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.

To test this hypothesis, we follow Lou (2012) to calculate daily mutual fund flow-induced trade 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), throughout 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.[15]

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 a list of bond characteristics, the coefficients estimate on lagged hedge funds' order flows is 0.056 with a *t*-statistic of 2.73.[16]

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[15] Our results are 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.

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

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 larger mutual funds' capital flow induced trading in absolute terms. To test this prediction, we repeat the exercise in Table 2 by sorting our sample into two halves based on the aggregate absolute level of mutual fund flow-induced trading. Specifically, in 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 cutoff of the aggregate absolute *FIT*. As shown in Online 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 analyze a set of macroeconomic announcements, including monetary policy announcements by the Monetary Policy Committee (MPC), as well as inflation and labor statistics announcements. Specifically, for each macro announcement, we sort all gilts into terciles based on hedge fund order flows in 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 returns to 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 on MPC announcements and inflation/labor 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 labor/inflation statistics announcements than on monetary policy announcements: 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/labor statistics announcement days.[17]

Taken together, these results indicate that hedge funds, aside from their ability to forecast other investors' future demand, also have superior ability 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 Online Appendix Table A7, mutual fund order flows at a monthly frequency 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 their front-running 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—that is, 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

[17] In Online 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.

returns sorted by lagged 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: that is, 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 (e.g., 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).[18] We also include in the regression 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 but not captured by the forward rates.

[18] 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 of the same table, 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 labor statistics announcements vs. days without. More specifically, we decompose the monthly return to the long-short gilt portfolio sorted by lagged monthly mutual funds' 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 repeats 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 labor 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/labor 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.[19]

To capture heterogeneity across hedge funds, in every day we re-estimate regression equation (1) for each individual hedge fund, where the dependent variable is the bond return in day d+1 and the independent variable is the hedge fund's daily order flow in that bond in 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

[19] There is a vast empirical literature on performance persistence of asset managers (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.

bond returns. We then divide all hedge funds into two groups in 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 predictabilities of the daily order flows of high-skilled and low-skilled hedge funds going forward.

In a similar vein, in every month we re-estimate equation (2) for each individual mutual fund using monthly bond return and mutual fund order-flow data in 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 of the data 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.

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 (price changes only without accrued interest); c) alternative definitions of order flows (buy minus sell scaled by shares outstanding, for example).

As shown in Table 10, our results are robust to all these different tweaks. For instance in Panel A1, 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 two groups of institutional investors, hedge funds and mutual funds, the prototypical arbitrageurs in financial markets, and have provided strong evidence that both groups have superior skills in forecasting future government bond returns. In this section, we examine the behavior of the other two institutional groups in the gilt market: non-dealer banks and insurance companies and pension funds (ICPFs).

Specifically, we conduct the same analyses in Tables 2 and 3, but now focusing on the order flows of non-dealer banks and ICPFs. Panel A of Online Appendix Table A8 shows the next-day return to 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 to 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 see 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, returns to 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 are the more skilled investors in financial markets, who gain at the expense of other groups of investors.

7. Conclusion

We examine the role of institutional investors, such as hedge funds and mutual funds, in the government bond market. Our administrative data from the UK cover virtually all secondary-market transactions in gilts and provide detailed information of each individual transaction—including the identities of both counterparties. The granularity and completeness of our data enable us to analyze 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 are informed in the gilt market, and that 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' front-running other investors' future demand, especially mutual funds' capital-flow induced trading. Mutual funds' order flows, on the other hand, also positively predict bond returns, but over a longer horizon of one to two months; this return pattern does not revert in the following year. Additional analyses reveal that mutual funds' superior performance 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 distinctions 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 front run other investors' future demand. (There is also some evidence that hedge funds become more informed right 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 their 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.

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Table 1: Summary Statistics

This table reports summary statistics of 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 from DataStream and the UK Debt Management Office. Investors' order flows are from the ZEN database maintained by the UK Financial Conduct Authority (FCA). For each group of investors, in each day and/or each month, we calculate its 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), $5^{th}/25^{th}/75^{th}/95^{th}$ 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 returns to calendar-time long-short gilt portfolios sorted by daily order flows of hedge funds and mutual funds. For each bond in 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) in the following one 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 returns to 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 results of Fama-MacBeth regressions of bond returns on order flows of hedge funds and mutual funds. In Panel A, the main independent variable is the daily order flows of hedge funds and mutual funds, and the dependent variable is the next one-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}			$Ret_{d+1:d+5}$		
$Order\ Flow\ of\ Hedge\ Funds_d$	0.003***		0.004***	0.006**		0.006**
	(2.734)		(3.204)	(2.187)		(2.050)
$Order\ Flow\ of\ Mutual\ Funds_d$		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}		
$Order\ Flow\ of\ Mutual\ Funds_m$	0.183***		0.185***
	(2.826)		(2.771)
$Order\ Flow\ of\ Hedge\ Funds_m$		-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 (non-dealer banks, or insurance companies and pension funds (ICPF)) on lagged hedge fund order flow. For each bond in 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 in days d+1 to d+5. In columns (4)-(6), the dependent variable is flow-induced trading of mutual funds (*FIT*) in 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 ICPF in days d+1 to d+5. In columns (4)-(6), the dependent variable is order flows of banks in 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 levels, 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						
	ICPF			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 returns to the long-short gilt portfolio sorted by daily hedge fund order flows on macroeconomics news announcement days. Macroeconomic news includes Monetary Policy Committee (MPC) meetings and announcements of inflation and labor statistics. In 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 returns to the long-short gilt portfolio on any macroeconomic news announcement days. Panel B reports returns to the long-short portfolio on MPC meeting days, and finally Panel C reports returns to the long-short portfolio on inflation and labor 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 Labor 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: that is, the weighted average duration of government bonds bought by mutual funds minus that 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). 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 10%, 5%, and 1% 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)
$Forward\ Spread_m$		-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 returns to 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 labor 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 in Panel B of Table 3. Panel B reports returns to the long-short gilt portfolio on any macroeconomic news announcement days. Panel C reports returns to the long-short portfolio on MPC meeting days, and finally Panel D reports returns to the long-short portfolio on inflation and labor 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 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 in Table 2 for both types of hedge funds. In Panel B, we classify mutual funds into high-skilled and low-skilled based on return predictability of their monthly order flows using data in the past 12 months. We then repeat the portfolio sorting exercise in Table 3 for both types 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 Mutual 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 number of shares 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: 2011 August - 2014 October

	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)
2014 November - 2017 December						
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: 2011 August to 2014 October						
	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**)
2014 November to 2017 December						
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)**

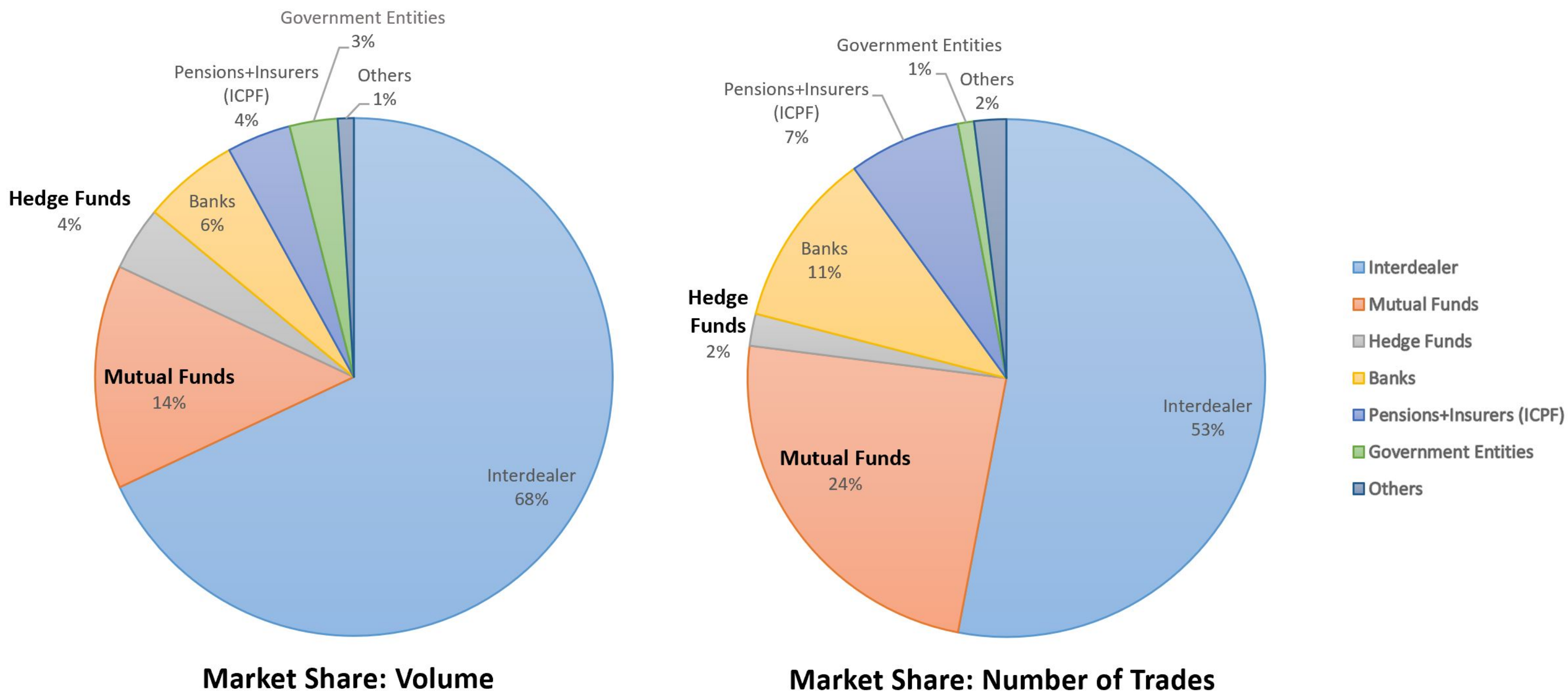

Figure 1: UK Government Bond Market Shares by Investor Type
This figure shows the breakdown of the total trading volume and number of trades in the UK government bond market. Trading volume and the number of trades are constructed using the ZEN database maintained by the Financial Conduct Authority (FCA).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

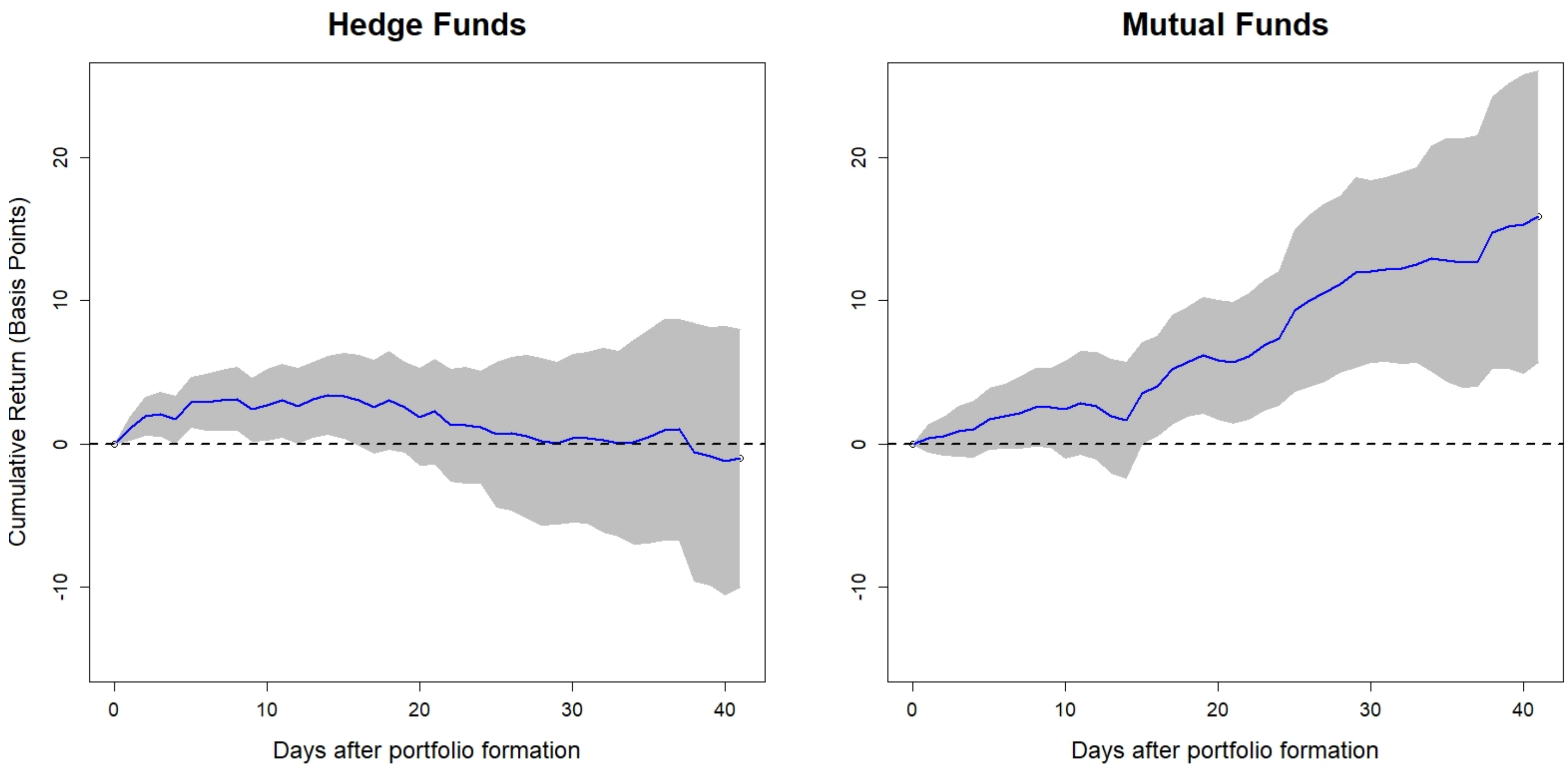

Figure 2: Event-Time Long-Short Portfolio Returns – Sorted by Daily Order Flows
This figure shows event-time returns to the long-short portfolio sorted by daily order flows of hedge funds and mutual funds. In each day, we sort all gilts into three groups based on hedge fund/mutual fund order flows and 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-bootstraped standard errors.

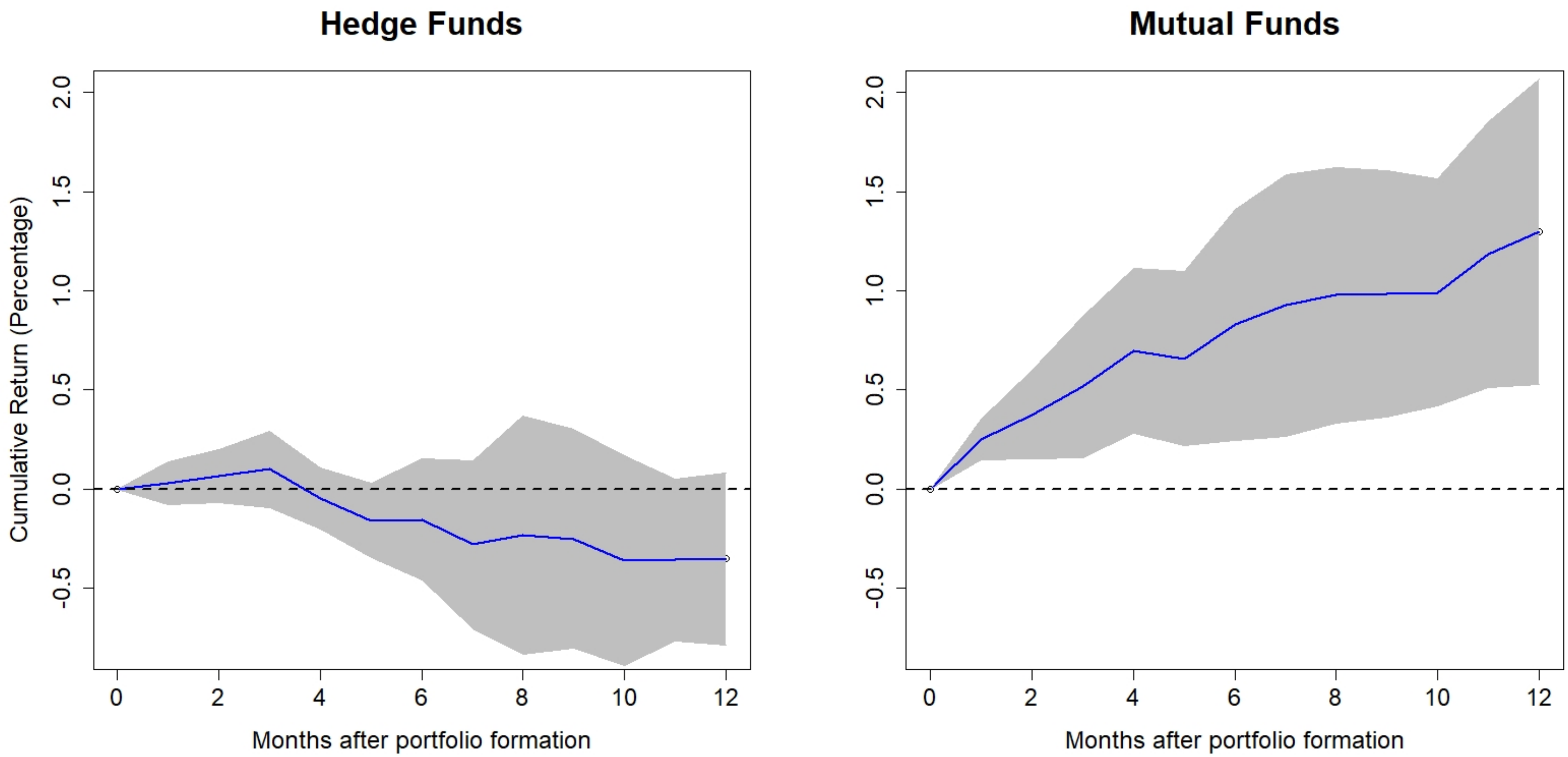

Figure 3: Event-Time Long-Short Portfolio Returns – Sorted by Monthly Order Flows
This figure shows event-time returns to the long-short portfolio sorted by monthly order flows of hedge funds and mutual funds. In each month, we sort all gilts into five groups based on hedge fund/mutual fund order flows 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-bootstraped standard errors.

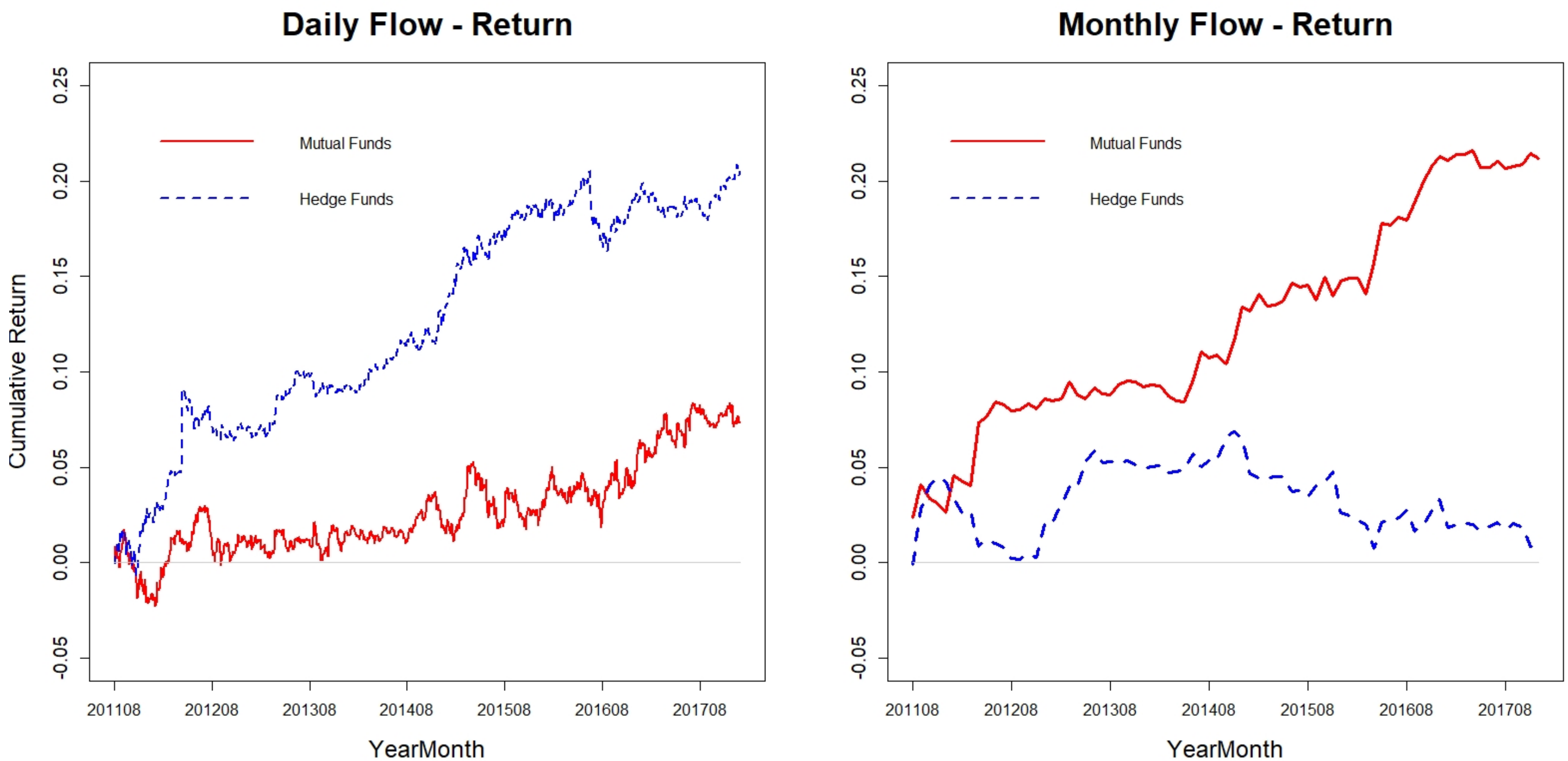

Figure 4: Calendar-Time Cumulative Portfolio Returns

This figure shows the cumulative return of the long-short portfolio sorted by hedge fund and mutual fund order flows. In the left panel, in each day, we sort gilts into three groups by 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.