Informed Trading in Government Bond Markets*

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

Shiyang Huang
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

We show that both hedge funds and mutual funds contribute to the price discovery in government bond markets using comprehensive administrative data from the UK. Our sample covers virtually all secondary market trades in gilts and contains detailed information on each individual transaction, including the identities of both counterparties. Hedge funds' daily trading positively forecasts gilt returns in the following one to five days, which is fully reversed in the following month. Part of this short-term return predictive pattern is due to hedge funds' ability to forecast other investors' future order flows. Mutual funds' trading also positively forecasts bond returns, but it operates at a longer horizon—over the next 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 changes in short-term rates.

Keywords: government bonds, return predictability, the yield curve, asset managers

1. Introduction

Government bond yields are the basis of virtually all other rates in the financial market—ranging from, for example, deposit rates, mortgage rates to firm discount rates. It is therefore crucial 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 a main source of variation in the term structure of risk-free interest rates. Fleming and Remolona (1997), for instance, show that macroeconomic announcements are responsible for some of the largest daily price movements in the US Treasury market. According to this view, trading activity in the bond market is mostly due to rebalancing and hedging needs and thus does not have large, persistent impact on bond yields.

An alternative view draws on the premise that investors are unequally informed. Differences in investors' subjective beliefs may stem from their differential access to non-public information; differences in opinions could also be driven by heterogeneity in how investors relate economic fundamentals (which may be publicly known) to the term structure of government bond yields. An immediate prediction of this mechanism is that trading by the better informed — those investors with privileged access to private information and/or with more accurate interpretations of public signals — should persistently and positively forecast future bond returns. As such, information-motivated trading helps impound private information into prices.

Our focus in this paper is on the second channel. A priori, it seems difficult for any investor (or investor group) to have a significant information advantage over the rest of the market in forecasting future government bond returns. For one thing, a large empirical literature on institutional investors has found little evidence that professional money managers are able to predict cross-sectional variation in stock or corporate bond returns (e.g., Wermers, 2000; Cici and Gibson, 2012). More related to our study, prior research

[1] The literature on the term structure of riskfree rates has focused primarily on the factor structure of yield movements across maturities (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.

on investors' market timing ability has largely concluded that institutions that actively shift their market exposures on average underperform their peers (e.g., Huang, Sialm and Zhang, 2011). As a result, it is an intriguing empirical question as to whether a subset of market participants have superior private knowledge about future government bond returns (which respond primarily to macroeconomic news).

Prior literature 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). The obvious drawbacks of the mutual fund data are 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 these shortcomings, but unfortunately do not include the identities of the counterparties in each transaction; consequently, prior research focuses mostly on the net trading, summed across all reported trades, between dealers and non-dealer investors.

We contribute to the debate of informed trading in the government bond market by exploiting comprehensive administrative data maintained by the Financial Conduct Authority (FCA) of the UK. The ZEN database contains all secondary-market trades in UK government bonds (gilts) of all FCA-regulated firms, or branches of UK firms 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 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 individual transactions (the date and time stamp, underlying security, transaction price, 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, our data cover 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 study whether any group of investors have a comparative advantage in this market and are able to profit from their information advantages.

For ease of interpretation, we aggregate all non-dealer investors in our sample into four categories: mutual funds, hedge funds, non-dealer banks, as well as insurance companies and pension funds (ICPFs). These four groups account for 14%, 4%, 6% and 4% of the aggregate trading volume in the gilt market, respectively. The largest share of trades in gilts (nearly 70%) takes place in the inter-dealer market. Together, these four groups of investors plus dealer banks are responsible for nearly 99% of all gilt transactions.

Our results reveal that both hedge funds and mutual funds have significant information advantages over other investors during our sample period (2011-2017), but operate at *different* horizons. Specifically, sorting all UK government bonds (with different maturities and vintages) into five groups based on the previous-day order flow of hedge funds, we find that the quintile of gilts heavily bought by hedge funds outperform the quintile heavily sold by 1.3bps (t-statistic = 2.80) in the following day, and 2.9bps (t-statistic = 3.16) in the following week, with an annualized Sharpe Ratio of 1.2. Interestingly, this return effect is 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: the one-week three-factor alpha of the long-short bond portfolio remains economically and statistically significant at 2.9bps (t-statistic = 3.55). This result also holds in a Fama-MacBeth regression setting and is stronger among the subsample of hedge funds that have performed better in the recent past.

In stark contrast, mutual funds' order flows have insignificant return predictive power in the first ten days, but become increasingly informative over the longer horizon. For example, if we again sort UK government bonds into five groups based on the previous-day order flow by mutual funds, the return spread between the top and bottom quintiles of gilts is an statistically insignificant 0.4bps (t-statistic = 0.95) in the following day, and an insignificant 1.7bps (t-statistic = 1.63) in the following week; the return spread then grows to 6.5bps (t-statistic = 2.59) by the end of month one, and to 15.1 bps (t-statistic = 2.56) by the end of month two. In a related exercise to increase test power, we sort all gilts into quintiles based on the previous-month order flow of mutual funds.

The return spread between the two extreme quintiles in the following month is 27.5 bps (t-statistic = 3.95), with an annualized Sharpe Ratio of 1.5. After controlling for the level, slope, and curvature factors, the three-factor adjusted monthly alpha is modestly reduced to 18bps (t-statistic = 3.75). 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%. Perhaps not surprisingly, order flows by non-dealer banks and ICPFs, across all holding horizons, have insignificant, and sometimes negative, return predictive power for future government bond returns.

We next turn to the sources of information advantages of both hedge funds and mutual funds. In a simple forecasting regression, daily order flows by hedge funds strongly and positively forecast order flows by other investor groups. For example, a one-standard-deviation increase in hedge fund trading on day t forecasts an increase in combined net purchase of the other three investor groups on day t+1 by 1.3% (t-statistic = 3.64). In other words, hedge funds have private knowledge about other investors' future order flows and profit from this information by front running other investors. This is also consistent with the finding the return forecasting pattern of hedge funds' order flows gradually reverts in the subsequent period. In sharp contrast, mutual funds' order flows have no predictive power for other investors' future order flows. Moreover, the combined order flows of mutual funds, non-dealer banks, and ICPFs do not predict hedge funds' trading.

Since mutual funds' superior performance is mostly realized in the one-to-two months following their trades, we tie the source of their abnormal returns to slower-moving variables. In particular, we link the change in average duration of mutual fund holdings to future variation in the level and slope factors of bond returns, which can explain over 90% of the variation in bond yield changes. In an array of time-series regressions, controlling for known predictors of the level and slope of the term structure (e.g. a set of forward rates as well as survey expectations), we find that mutual funds' shifts in portfolio durations are a strong predictor of future changes in short-term interest rates (the level factor). For example, a one-standard-deviation reduction in the average portfolio duration of mutual funds forecasts a 4.49bps (t-statistic = 3.01) increase in the one-year government bond yield. This result holds true for both changes in one-year spot rates and one-year forward rates (the latter of which is arguably a cleaner measure of changes in investor expectations). Interestingly, mutual funds' duration shifts are insignificantly related to future movements in the slope of the term structure.

Given that mutual funds have an information edge about future movements in short-term rates, we naturally link the return forecastability of their trades to macroeconomic announcements (which are known to have large impact on short-term interest rates). In particular, if the superior performance of mutual funds is a result of their a) privileged access to non-public information or b) better interpretations of noisy public signals about the macro-economy, we expect their positive returns to materialize when such information is eventually made public. Consistent with this view, we find that out of the 18bps abnormal return earned by mutual funds in the month after they put on the trades, 7.2bps are earned on just two days: one day with the monetary policy announcement following the Monetary Policy Committee (MPC) meeting and the other with announcements of monthly inflation rates and labor statistics. The other 20 days of the month are responsible for the remaining 10.8bps. Put differently, mutual funds earn 3.6bps on macro-announcement days and only 0.5bps on other days.

All in all, our evidence supports the notion that asset managers, both hedge funds and mutual funds, have a significant advantage in collecting and processing order-flow and macroeconomic information and are able to capitalize on their advantages through trading in the gilt market. In so doing, these investors also help impound information into gilt yields and expedite the price discovery process in this important benchmark market.

2. Literature Review

Our study is related to the vast literature on the predictability of the term structure of interest rates. Fama and Bliss (1987) find that forward-spot spreads predict spot rate changes in a long-run horizon (four years), and Cochrane and Piazzesi (2005) confirm a similar pattern using more recent data.

Our paper is also related to the studies on the price discovery in the government bond market. Brandt and Kavajecz (2004) find that order flows account for up to 26% of the day-to-day variation in yields on days without major macroeconomic announcements. Green (2004) examines the effect of order flows on intraday bond price changes surrounding U.S. macroeconomic news announcements, and finds a marginally significant effect over 30-minute intervals around news releases. Pasquariello and Vega (2007) show that the contemporaneous correlation between order flows and yield changes is relatively high when the dispersion of beliefs among market participants is high and public announcements are noisy. While these studies mainly test the contemporaneous correlation between order flow and yield changes by using inter-dealer order flow data, we extend these studies by directly using data from end-users – i.e. dealer-client trades, which are more likely to contain information about future bond price movements. We are also the first to show that order flows forecast bond returns in an out-of-sample forecasting setting by directly examining portfolio returns based on lagged order flows.

Our work is also related to the broad empirical literature on market microstructure. Chordia, Roll, and Subrahmanyam (2002) show that aggregate order imbalances are positively associated with contemporaneous market returns, and Chordia and Subrahmanyam (2004) obtain comparable results in the cross-section of stocks. In these papers, the return predictive power of order flows is marginally significantly after accounting for the autocorrelations in order flows. In the foreign exchange market, Evans and Lyons (2002) find that order flows are crucial for understanding how information is incorporated into concurrent exchange rates. Similar to our paper, Menkhoff, Sarno, Schmeling, and Schrimpf (2016) show the importance of dissecting order flows in the foreign exchange market – dealer-client order flows are highly informative about future movements in exchange rates.

A number of recent papers find that aggregate capital flows into mutual funds in a particular sector (e.g. equity vs. fixed income) or a particular investment style (e.g. value vs. growth) are positively related to the contemporaneous sector or style returns, but negatively predict subsequent returns. Coval and Stafford (2007) and Frazzini and Lamont (2008) both analyze the return reversal pattern subsequent to mutual fund flow-induced trading to establish a price pressure effect. Lou (2012) focuses on the return continuation pattern that arises from the flow-performance relation, and, more importantly, the role of the return continuation in driving some well-known empirical regularities. Most of these studies analyze order flows using public data from quarterly regulatory filings, subject to the caveat that funds may intentionally window-dress these reports to hide their secretive trades (e.g., Agarwal, Jiang, Tang, and Yang, 2013).[2]

3. Data

Our UK bond data are from the ZEN database maintained by the Financial Conduct Authority (FCA). The dataset includes both government bonds and corporate bonds. The UK bond market is the third largest in the world with a total market value of 6,219 billion USD 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 takes place over-the-counter. Central to the functioning of the gilt market are the Gilt-Edged Market Makers (or GEMMs). These financial institutions are designated as primary dealers in the gilt market by the UK Debt Management Office (DMO), an executive agency of HMT responsible for managing the UK government's debt. The dealers (GEMMs) are mainly large investment banks, which are also the main market makers for the corporate bond market.[3]

The ZEN database contains reports for 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 UK bond markets. Each transaction report contains information on the transaction date and time, gilt International Identification Securities Number (ISIN), execution price, size of the transaction, as well as buyer/seller flag.

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[2] In untabulated tests, we show that portfolio returns sorted by quarterly order flows in our setting are economically small and statistically insignificant.

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

The 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 government bond market.[4] Our paper focuses on dealer-client trades that allow us to calculate the net trading demand in the gilt market. The main client sectors are mutual funds, hedge funds, banks, pension funds and insurance companies (ICPF). We combine pension funds and insurance companies due to their similar investment styles/behaviors. In each day/month, we measure the order flow (buy volume minus sell volume divided by buy volume plus sell volume) for each investor sector.

[Figure 1 about here]

Our sample period is August 2011 to December 2017. We match our transaction data with publicly available bond-specific information from the DMO and Datastream, including the bond issuance size, maturity, coupons, durations, prices, ratings, and accrued interest. Following prior literature (e.g. Bai, Bali and Wen, 2019), we only keep bonds with time-to-maturity longer than one year. This is because when a bond has less than one year to maturity, it is automatically deleted from major bond indices. Index-tracking investors will then need to adjust their bond holdings, which may cause big price movements. We also remove index-linked gilts where the index is often the inflation rate.

For macroeconomic news announcements, we focus on news about UK inflation, labor statistics (unemployment), and the Monetary Policy Committee (MPC) meetings.[5] The MPC dates are collected from the Bank of England website, and other news dates are collected from the UK Office for National Statistics. We also obtain information on

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

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

investors' forecasts for the UK bank rate, 10-year interest rate, UK GDP growth and inflation rate from Consensus Forecasts, an international survey of market participants compiled by Consensus Economics.

[Table 1 about here]

Our final sample includes 55 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 25 billion GBP and average duration is 10.8 years. Perhaps not surprisingly, order flows of each investor sector center around zero but with substantial cross-sectional and time-series variations. For example, monthly order flows of the mutual fund sector have a mean of 0.59% and a standard deviation of 19.23%; daily order flows of hedge funds have a mean of -1.41% and a standard deviation of 89.85%.

4. Empirical Results

We first aggregate the thousands of non-dealer investors in our sample into four categories: a) mutual funds, b) hedge funds, as well as c) non-dealer banks, and d) insurance companies and pension funds (ICPFs). We then examine the bond return predictability of the order flows of each of these investor types, using both a calendar-time portfolio approach and Fama-MacBeth regressions. For most part of the paper, we focus on mutual funds and hedge funds in our sample, the prototypical arbitrageurs in financial markets, and return to non-dealer banks and ICPFs in the robustness check section.

4.1. Daily Order Flows and Bond Returns

We start by analyzing the return predictability of investors' *daily* order flows. Specifically, we sort all government bonds in our sample into terciles based on the aggregate order flow by either hedge funds or mutual funds in each day. We then construct a long-short portfolio that goes long the top tercile and short the bottom tercile of government bonds.

Cumulative daily returns of these long-short portfolios are reported in Table 2.[6] The results show that order flows by hedge funds positively 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 order flows of hedge funds is 1.3*bps* (t-statistic = 2.801) in the following one day, which then grows to 2.9*bps* (t-statistic = 3.163) and 2.6*bps* (t-statistic = 2.327) in the following five and ten days, respectively. The return spread then becomes a statistically insignificant 1.32*bps* (t-statistic = 0.731) by the end of month one, and -1.5*bps* (t-statistic = -0.329) by the end of month two. This return predictive pattern is virtually unchanged after controlling for known risk factors (the level, slope and curvature factors).

[Table 2 about here]

In contrast, while mutual funds' trading also positively forecasts government bond returns, the return predictive pattern operates at a much longer horizon, over the next one to two months. Moreover, this return pattern does not revert as we extend our holding period to the following year. For example, as shown on the right-hand side of 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 mutual funds' daily order flows grows monotonically from 0.5*bps* (t-statistic = 0.946) to 15.1*bps* (t-statistic = 2.557). Again, this monotonic return predictive pattern is robust to controlling for the level, slope and curvature factors.

[Figure 2 about here]

The stark difference in daily-order-flow/future-return dynamics between hedge funds and mutual funds is also apparent in Figure 2, which shows the event-time

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[6] Appendix Table A1 reports the detailed information on the returns (alphas) for each tercile portfolio sorted by daily order flows of hedge and mutual funds.

cumulative returns of the long-short portfolio formed based on daily order flows. As can be seen from the figure, hedge funds' trading positively forecasts bond returns in the short run (and peaks in the first ten days), followed by a strong reversal in the subsequent month. Mutual funds' order flows, on the other hand, positively forecast bond returns only after the first 15 days.

4.2. Monthly Order Flow and Bond Returns

We next analyze bond return predictability of investors' monthly order flows. Specifically, at the end of each month, we sort all government bonds into terciles based on order flows by either hedge funds or mutual funds in the previous month and hold the long-short portfolio for the next one to twelve months. Portfolio returns are reported in Table 3.

[Table 3 about here]

As can be seen from the table, consistent with what we see with daily order flows, monthly mutual fund order flows significantly and positively forecast future bond returns, while monthly hedge fund order flows have no predictive power for 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 $6.6bps$ (t-statistic = 0.186) in the first month following portfolio formation. In contrast, the return spread between the top and bottom quintiles sorted by mutual funds' order flows is $27.5bps$ (t-statistic = 3.955) in the following month. Controlling for known risk factors (level, slope and curvature) has virtually no impact on this result. For example, the return spread sorted by mutual funds' order flows is only modestly reduced to $18.0bps$ (t-statistic = 3.751) in the following month.

[Figure 3 about here]

We again plot the event-time cumulative returns to the long-short portfolios sorted by monthly order flows of both hedge funds and mutual funds. As can be seen in Figure 3, hedge funds' trading does not predict future bond returns in any the event windows, ranging from one month to twelve months, which confirms the result in Panel A Table 3. Mutual funds' trading, on the other hand, strongly forecasts future bond returns in the following one to twelve months, without any sign of reversal. Put differently, the bond return predictability of mutual fund order flows is unlikely driven by the price impact caused by mutual funds' herding behavior (Cai, Han, Li and Li, 2019).

[Figure 4 about here]

We also plot the cumulative returns to the long-short government bond portfolios in *calendar time* in Figure 4. In the left panel, the long-short portfolio is ranked by daily order flows of mutual funds and hedge funds and is held for one day. In the right panel, the long-short portfolio is ranked by monthly order flows of mutual funds and hedge funds and is 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 our 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 the order flows of both mutual funds and hedge funds, along with a list of controls for known predictors of government bond returns. Similar to the portfolio approach, we conduct the regressions at both the daily and month frequencies. On the daily level, we have:

$$RET_{i,d+1} = \beta_0 + \beta_1 Order\ Flow\ of\ Mutual\ Funds_{i,d} + \beta_2 Order\ Flow\ of\ Hedge\ Funds_{i,d} + \gamma Control_{i,d} + \epsilon_{i,d+1},$$

where the dependent variable is bond i's return on day $d+1$. The main independent variables are the daily order flows of mutual and hedge funds on day d. The list of control variables includes issue size, bond maturity, and bond returns in the previous day and month.

Similarly, at the monthly level, we have:

$$RET_{i,m+1} = \beta_0 + \beta_1 Order\ Flow\ of\ Mutual\ Funds_{i,m} + \beta_2 Order\ Flow\ of\ Hedge\ Funds_{i,m} + \gamma Control_{i,m} + \epsilon_{i,m+1},$$

where the dependent variable is bond i's return in month $m+1$, and the main independent variables are the monthly order flows of mutual funds and hedge funds in month m.

[Table 4 about here]

The results of these Fama-MacBeth regressions are shown in Table 4. 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; 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, whereas monthly order flows of mutual funds significantly and positively predict future monthly bond returns.

5. Sources of Return Predictability

In this section, we investigate the sources of return predictability of hedge funds' and mutual funds' trading activity in the UK government bond market. Section 5.1 examines return predictability of *daily* hedge fund order flows, while Section 5.2 examines return predictability of *monthly* mutual fund order flows.

5.1. Sources of Return Predictability: Hedge Funds

A recent theoretical literature (e.g., Farboodi and Veldkamp, 2019) argues that arbitrageurs may engage in two types of arbitrage activities: a) some arbitrageurs try to predict the (non-information-driven) order flows of other investors and profit from such information by front running predictable order flows; b) some arbitrageurs may be more efficient in processing and responding to new information. We test both mechanisms in this section. Our first test examines the relation between hedge funds' daily order flows and future order flows of all other investors (includnig mutual funds, banks and ICPF). Our second test examines hedge funds' trading behavior and future profits around macroeconomic-news announcements (e.g., monetary policy, inflation, labor statistics announcements).

5.1.1. Predicting Order Flows of Other Investors

We test the first prediction by running the following panel regression:

$$Order\ Flow\ of\ Others_{i,d+t} = \beta_0 + \beta_1 Order\ Flow\ of\ Hedge\ Funds_{i,d} + \beta_2 Order\ Flow\ of\ Others_{i,d} + \gamma Control_{i,d} + \epsilon_{i,d+1},$$

where the dependent variable is the aggregate order flow of all other non-dealer investors (except hedge funds) on day $d+1$ (or the cumulative order flow in days $d+1$ to $d+5$). The main independent variable of interest is the order flow of hedge funds on day d. We control for the bond issue size, maturity, lagged bond returns and lagged order flows. We also include bond and day fixed effects in all specifications.

[Table 5 about here]

Table 5 reports the regression results. The dependent variable in columns (1)-(3) is the order flow of all other investors in the following day, and that in columns (4)-(6) is the order flow of all other investors in the following five days. Across all regression specifications, we find that hedge funds' daily order flows significantly and positively forecast other investors' order flows. For example, as shown in column (1), a one-standard-deviation increase in hedge funds' daily order flow in day d forecasts an increase in net purchases by other investors of 1.16% (=89.85%×0.013, t-statistic = 3.652) in the following day. For reference, the average daily order flows of mutual funds, banks, and ICPFs are 0.15%, 0.14% and -1.22%, respectively (Table 1). This result is virtually unchanged after controlling for lagged order flows by other investors as well as a set of bond characteristics. Moreover, there is no similar order-flow predictive pattern in the reverse direction: as shown in Appendix Table A2, order flows by other investors (excluding hedge funds) do not predict future hedge funds' order flows.

5.1.2. Macro-News Announcements

In the second test, we examine whether hedge funds are able to digest public information faster than other market participants and as a result earn abnormal returns on macro-news announcement days. To this end, we examine a set of macro announcements, including monetary policy announcements right after the UK's Monday Policy Committee (MPC) meetings, as well as inflation and labor statistics announcements. More specifically, for each macro announcement, we sort all UK government bonds into terciles based on the daily hedge fund order flow 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) solely on the announcement day.

[Table 6 about here]

Table 6 reports returns to these long-short portfolios on macro announcement days. Panel A shows the results for all macro announcements, Panel B focuses solely on MPC announcements, and Panel C reports returns on announcement days of inflation and labor statistics. Across all panels, the long-short portfolio sorted by hedge funds' daily order flows earns substantially higher returns on macro-announcement days than the unconditional returns reported in Table 2. For example, as shown in Panel A, the long-short portfolio earns on average 2.5*bps* (t-statistic=2.264) on days with any macro announcements. Controlling for the level, slope and curvature factors has virtually no effect on this result. Interestingly, hedge funds seem to be earning higher returns around fundamental economic announcements than around monetary policy announcements: a return of 1.217bps (t-statistic=2.736) on MPC announcement days vs. 3.531bps (t-statistic=3.163) on inflation-labor-statistic announcement days.[7] Taken together, these results suggest that aside from forecasting other investors' order flows, hedge funds also have superior skills in processing and responding to macroeconomic information. Both these skills contribute to our documented return predictive pattern of hedge funds' daily order flows.

5.2. Sources of Return Predictability: Mutual Funds

We next turn to the sources of return predictability of mutual funds' order flows. To start, we examine whether mutual funds are also able to forecast order flows by other market participants. As shown in Appendix Table A4, mutual funds' order flows (at a monthly frequency) have no predictive power for future order flows by other market participants. This suggests that the monthly return predictability of mutual funds' trading is not due to their ability to front-run other investors, but more likely due to their ability to forecast fundamental information.

We conduct two related tests to shed more light on the types of information that mutual funds tend to trade on. First, since the level and slope factors can account for over 90% of the variation in yield changes, we link the trading activity of mutual funds to future changes in these two factors. This allows us to identify the aspect of the term structure that mutual funds have information on. Second, similar to our exercise on hedge fund trading, we decompose the monthly long-short portfolio returns sorted by lagged

[7] In Appendix Table A3, 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 announcement days. For alternative definitions of announcement-day returns, we consider the window (-1,1) around announcement days.

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

5.2.1. The Level and Slope Factors

In our first analysis, we link the trading activity of mutual funds to the level and slope of the term structure in a time-series test. Specifically, at the end of each month, we calculate the duration change of aggregate holdings by mutual funds (i.e., due to trading) in the previous month (in other words, the weighted average duration of government bonds bought by mutual funds minus that of government bonds sold). We then test the relation between this imputed duration change and future movements in the term structure. If mutual funds are indeed able to forecast changes in the shape of the term structure, we expect to see an increase in their average holdings duration shortly before a lower level of interest rates or a flatter term structure, and a decrease before a higher level of interest rates or a steeper term structure.

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

$$\Delta Interest\ Rate_{m+k} = a + b * Flow\ weighted\ Duration_m + \mathrm{c} * \ Controls_m + \ \epsilon_{i,m+1}.$$

The dependent variable is either the change in the one-year spot interest rate or change in the term structure slope (i.e., the twenty-year minus one-year yield) between months m and $m+k$ (where k ranges from one to three). Other control variables include the forward-spot spread (the difference between the one-year forward rate one or three months ahead and the one-year spot rate) as in Fama and Bliss (1987) and Cochrane and Piazzesi (2005).[8] We also include in the regression changes in investor forecasts for the short-term interest rate, GDP growth rate and inflation rate to control for information in the public domain but is not captured by forward rates.

[8] The 13-month and 15-month spot rates are calculated by linear interpolation with nearest available spot rates in each month.

[Table 7 about here]

Table 7 shows the regression results. As can be seen in Panel A, duration shifts of mutual fund government bond holdings 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 -1.728 (t-statistic = -3.01). Interestingly, duration shifts of mutual fund bond holdings do not forecast future changes in the slope of the term structure. Put differently, mutual funds as a group are able to predict changes in short term rates, but not changes in long-term rates.

5.2.2. Macro-News Announcements

Our second test links the return predictability of mutual funds' order flows to macroeconomic announcements. If the superior performance of mutual funds is indeed a result of their ability to forecast macroeconomic news before the public announcements, these abnormal returns should materialize when such information is made public. Similar to the analysis in Section 5.1.2, we examine the same set of macro announcements here – monetary policy announcements after the Monday Policy Committee (MPC) meetings, along with inflation and labor statistics announcements. We then decompose the monthly returns of the long-short government bond portfolio sorted by mutual funds' monthly order flows into macro-announcements-day returns and non-macro-announcement day returns.

[Table 8 about here]

The decomposition results are shown in Table 8. As can be seen from Panel A, the total monthly three-factor alpha earned by the long-short bond portfolio ranked by mutual fund order flows is 18bps (t-statistic = 3.751). Panel B shows that the same long-short portfolio earns a three-factor alpha of 3.6*bps* (t-statistic = 3.374) on any macro-news announcement day; Panels C and D further show that the three-factor alpha is 2.9*bps* (t-statistic = 1.787) on monetary policy announcement days and is 4.3*bps* (t-statistic = 3.613) on inflation and labor statistics announcement days. In other words, given that there are on average one MPC announcement and one inflation-labor-statistic announcement in each month, these results suggest that about 40% of the total monthly alpha (7.2bps out of 18bps) can be explained by just the two macro-announcement days.

6. Additional Analyses and Robustness Checks

This section provides additional robustness checks for our main empirical results. In Section 6.1, we use past returns to identify high- vs. low-skilled fund managers and examine whether there is any persistence in fund performance. In Section 6.2, we conduct several robustness checks, based on sub-samples and alternative definitions of bond returns. In Section 6.3, we examine return predictability of order flows by other investor sectors (non-dealer banks and ICPFs).

6.1. Persistence of Fund Performance

If our documented return pattern is indeed a reflection of investors' information collection/processing ability and to the extent that such ability is persistent over time, we expect this return pattern to be stronger among hedge funds and/or mutual funds with relatively higher prior performance.[9]

To exploit heterogeneity across hedge funds, in each day, we classify all hedge funds in our sample into two groups based on the median trading performance in the past quarter (92 days): those hedge funds above the median cutoff are labeled "more skilled"

[9] There is a vast empirical literature on the 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. Our data allow us to examine whether hedge funds and mutual funds have persistent skills in predicting government bond returns.

and those below the median cutoff are labeled "less skilled." We then sort all government bonds into terciles based on the order flows of either the more-skilled subset of hedge funds or the less-skilled subset. We also repeat the same exercise at a monthly frequency to divide all mutual funds in our sample into the more-skilled vs. less skilled groups, using data from the past 12 months.

[Table 9 about here]

The returns to the various long-short portfolios of government bonds are reported in Table 9. Panel A examines daily return predictability of high vs. low-skilled hedge funds' order flows, while Panel B examines monthly return predictability of high vs. low-skilled mutual funds' order flows. As can be seen from the left side of Panel A, daily order flows of more-skilled hedge funds strongly forecast bond returns in the subsequent day. Specifically, the long-short portfolio sorted by daily order flows of more-skilled hedge funds yields a three-factor alpha of 3*bps* (t-statistic = 2.343) in the following day. In contrast, daily order flows of less-skilled hedge funds have no significant predictive power for future bond returns, producing a three-factor alpha of 0.93*bps* (t-statistic = 1.205).

The contrast between high and low-skilled managers is even starker for the mutual fund sample. As shown in Panel B, the long-short portfolio of government bonds sorted by monthly order flows of more-skilled mutual funds yields a three-factor alpha of 20.1*bps* (t-statistic = 3.842) in the following month; in comparison, the same long-short portfolio sorted by order flows of the less-skilled subset of mutual funds produces an insignificant three-factor alpha of -1.9*bps* (t-statistic = -0.222) per month. In sum, the results in Table 9 confirm our conjecture that hedge funds' and mutual funds' superior performance in the UK government bond market is likely due to their ability to process and trade on information relevant to future bond returns.

6.2. Robustness Checks

We also conduct a number of robustness tests of our main results. As shown in Table 10, our results that daily hedge fund order flows and monthly mutual fund order flows can forecast future daily and monthly bond returns respectively, are robust to: a) subsample analyses (the first vs. second half of our sample), as well as alternative definitions of bond returns (based on the clean price).

[Table 10 about here]

6.3. Order Flows of Non-Dealer Banks and ICPFs

We have so far provided evidence that hedge funds and mutual funds have superior skills in forecasting future government bond returns. In particular, daily hedge fund order flows strongly forecast bond returns in the following one to five days, while monthly mutual fund order flows significantly forecast bond returns in the subsequent one to two months. In this section, we turn our attention to the other two main investor groups in the UK gilt market: non-dealer banks and insurance companies and pension funds (ICPFs).

To this end, we conduct identical analyses to those in Tables 2 and 3, but now focusing on order flows by non-dealer banks and ICPFs. Panel A of Table 11 shows the returns to the long-short government bond portfolio sorted by either group's *daily* order flows in the following day; Panel B reports the returns to the long-short portfolio sorted by either group's monthly order flows in the subsequent month.

[Table 11 about here]

In contrast to what we see for hedge funds and mutual funds, order flows by non-dealer bank and ICPFs do not have any predictive power for future bond returns at either the daily or monthly frequency. Across all specifications, the return spread between the top and bottom terciles sorted by order flows of either non-dealer banks or ICPFs is economically small and statistically insignificant and in some cases even negative. These results are consistent with our prior that hedge funds and mutual funds are the skilled arbitrageurs in the government bond market.

7. Conclusion

In this paper, we examine whether some investors are better informed than others in the government bond market by exploiting administrative transaction data from the UK. Our sample contains all secondary-market gilt trades of FCA-regulated investors. Given that all gilt dealers are UK-domiciled and hence FCA-regulated, our dataset effectively covers the entirety of trading activity in the UK government bond market. Moreover, our data provide detailed information on each individual transaction, including the identities of both counterparties. The granularity and completeness of our data thus enable us to systematically study whether any group of investors have a comparative advantage in this market and are able to profit from their information advantages.

Our results reveal that both hedge funds and mutual funds contribute to the price discovery in the government bond market, but they operate at different horizons. Specifically, hedge funds' daily trading positively forecasts gilt returns in the following one to five days, which is fully reversed in the following two months. Part of this short-term return predictive pattern can be attributed to hedge funds' ability to forecast other investors' future order flows. Mutual funds' trading also positively forecasts gilt returns but at a longer horizon, over the next one to two months; this return predictive pattern does not revert in the following year. Additional analyses reveal that mutual funds' superior performance is at least in part due to their ability to forecast future movements in short-term interest rates.

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Table 1: Summary Statistics

This table reports summary statistics of the UK government bond sample from 2011 August to 2017 December. Bond return, value outstanding, maturity, duration, yield, and credit rating are from DataStream and the UK Debt Management Office. Bond order flows are constructed by the transaction data from the ZEN database maintained by the UK Financial Conduct Authority. Order flow is defined as the net buy volume scaled by total volume for each sector for each month or for each day. The sample has three sectors: Funds, Banks, Pension funds and Insurance companies (ICPF). The table reports the mean, median, standard deviation (SD), $5^{\text{th}}/25^{\text{th}}/75^{\text{th}}/95^{\text{th}}$ percentiles, and No. Obs. is 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	2923
	Order Flow – Mutual Funds (%)	0.59	19.23	-35.50	-11.29	0.45	13.01	36.41	2923
	Order Flow - Hedge Fund (%)	-1.50	57.15	-100.00	-42.05	-1.21	37.74	100.00	2814
	Order Flow - Bank (%)	0.24	31.19	-56.40	-19.49	-0.17	21.26	58.91	2923
	Order Flow - ICPF (%)	-1.44	42.03	-73.69	-30.99	-1.54	28.40	70.39	2923
Daily	Bond Return (%)	0.02	0.53	-0.81	-0.16	0.01	0.21	0.86	59753
	Order Flow - Mutual Funds (%)	0.15	60.16	-98.90	-44.70	0.08	45.62	98.73	59753
	Order Flow - Hedge Fund (%)	-1.41	89.85	-100.00	-100.00	0.00	100.00	100.00	23870
	Order Flow - Bank (%)	0.14	74.93	-100.00	-79.97	0.00	79.96	100.00	50367
	Order Flow - ICPF (%)	-1.22	75.87	-100.00	-84.79	-0.05	80.46	100.00	47345
Monthly	Amount Outstanding (£B)	25.73	7.59	10.21	21.31	26.64	31.69	35.96	2923
	Time to maturity (Year)	16.16	13.82	1.81	4.69	10.02	26.26	43.76	2923
	Duration (Year)	10.80	7.48	1.70	4.29	8.65	16.83	23.79	2923
	Yield (%)	1.75	1.00	0.26	0.91	1.72	2.51	3.42	2923

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

This table reports the portfolio sorting ranked by the daily order flow of hedge funds and mutual funds, respectively. Order flow is defined as the net buy volume scaled by total volume hedge/mutual funds at each day. At each day, the bonds are equally sorted into three groups. All bonds are equally-weighted within each group. We report the return (alpha) spreads between the top and bottom groups ("High minus Low": H-L), and the various holding periods: 1 day (Panel A), 5 day (Panel B), 10 days (Panel C), 1 month (Panel D) and 2 months (Panel E). We report the raw return, the return adjusted with market factor (1F Alpha), and the return adjusted with market, slope and curvature factors (3F Alpha). The return and alphas are in basis points. T-statistics are computed based on standard errors with Newey-West correction and are reported below returns (alphas). Estimates of "High minus Low" (H-L) 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	**1.276**	**1.384**	**1.386**	0.453	0.342	0.337
	(2.801)	**(3.161)**	**(3.204)**	(0.946)	(0.722)	(0.712)

Panel B: Holding Period=5 Day						
	Hedge Funds			Mutual Funds		
	Return	Alpha (1F)	Alpha (3F)	Return	Alpha (1F)	Alpha (3F)
H-L	**2.877**	**2.935**	**2.935**	1.747	1.426	1.498
	(3.163)	**(3.318)**	**(3.554)**	(1.632)	(1.405)	(1.493)

Panel C: Holding Period=10 Day						
	Hedge Funds			Mutual Funds		
	Return	Alpha (1F)	Alpha (3F)	Return	Alpha (1F)	Alpha (3F)
H-L	**2.635**	**2.890**	**2.738**	2.576	1.275	1.472
	(2.327)	**(2.621)**	**(2.492)**	(1.699)	(0.846)	(0.978)

Panel D: Holding Period=1 Month						
	Hedge Funds			Mutual Funds		
	Return	Alpha (1F)	Alpha (3F)	Return	Alpha (1F)	Alpha (3F)
H-L	1.320	2.455	2.387	**6.508**	4.075	4.734
	(0.731)	(1.448)	(1.372)	**(2.585)**	(1.658)	(1.826)

Panel E: Holding Period=2 Months						
	Hedge Funds			Mutual Funds		
	Return	Alpha (1F)	Alpha (3F)	Return	Alpha (1F)	Alpha (3F)
H-L	-1.546	-1.031	-1.509	**15.109**	**7.658**	**5.658**
	(-0.329)	(-0.622)	(-0.931)	**(2.557)**	**(4.069)**	**(3.029)**

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

This table reports the portfolio sorting ranked by the monthly order flow of hedge funds and mutual funds, respectively. Order flow is defined as the net buy volume scaled by total volume for hedge/mutual funds in each month. In each month, the bonds are equally sorted into five groups. The portfolios are rebalanced every month and are held for one month. All bonds are equally-weighted within each group. We report the monthly raw return, the return adjusted with market factor (1F Alpha), and the return adjusted with market, slope and curvature factors (3F Alpha). The returns/alphas in basis points. T-statistics are computed based on standard errors with Newey-West correction. Estimates of 'High minus Low' (H-L) significant at the 5% level are indicated in bold.

Panel A: Hedge Funds						
Order Flow	Return	t-stat	Alpha (1F)	t-stat	Alpha (3F)	t-stat
1 (Low)	39.7	(2.317)	1.4	(0.380)	1.1	(0.268)
2	39.5	(2.126)	-4.6	(-1.064)	-4.7	(-1.062)
3	46.7	(2.433)	5.0	(0.957)	5.5	(1.169)
4	46.0	(2.741)	5.3	(1.012)	5.1	(0.881)
5 (High)	46.3	(2.828)	4.3	(0.694)	4.4	(0.696)
H-L	6.6	(0.186)	2.9	(0.307)	3.3	(0.317)

Panel B: Mutual Funds						
Order Flow	Return	t-stat	Alpha (1F)	t-stat	Alpha (3F)	t-stat
1 (Low)	29.5	(2.409)	-4.0	(-1.011)	-3.8	(-0.922)
2	42.9	(2.524)	-6.0	(-0.149)	-1.0	(-0.311)
3	44.7	(2.190)	-1.2	(-0.262)	-1.3	(-0.268)
4	50.1	(2.664)	3.8	(0.747)	3.4	(0.639)
5 (High)	57.1	(3.381)	13.6	(3.852)	14.2	(3.200)
H-L	**27.5**	(**3.955**)	**17.6**	(**3.564**)	**18.0**	(**3.751**)

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

This table reports Fama-MacBeth regressions of bond return on order flow for the hedge/mutual funds. Order flow is defined as the net buy volume scaled by total volume in each month/each day. Returns are in percentages. Size is the log of the amount outstanding in British pounds. Maturity is the residual maturity of the bond. Cross sectional regressions are run every calendar day/month, and the time-series standard errors are adjusted with Newey-West correction. In Panel A, the independent variable is the daily order flow. In Panel B, the independent variable is the monthly order flow. T-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Panel A: Daily Order Flows and Future Bond Returns

	R_{d+1}				$R_{d+1:d+5}$			
$Order\ Flow\ of\ Mutual\ Funds_d$	0.002		0.003	0.001	0.009		0.008	0.002
	(0.964)		(1.082)	(1.590)	(1.458)		(1.268)	(0.238)
$Order\ Flow\ of\ Hedge\ Funds_d$		0.006***	0.006***	0.003***		0.014***	0.012***	0.008**
		(2.689)	(2.853)	(2.713)		(3.142)	(2.712)	(2.208)
R_d				-0.026				-0.128***
				(-0.740)				(-2.788)
$Log(Market\ Cap)_d$				-0.006				0.071**
				(-1.234)				(2.179)
$Maturity_d$				0.099**				0.247
				(2.210)				(1.289)
Adj.R^2	-0.009	0.001	0.001	0.793	-0.009	0.009	0.001	0.819

Panel B: Monthly Order Flows and Returns				
		R_{m+1}		
$Order\ Flow\ of\ Mutual\ Funds_m$	0.398***		0.395***	0.153***
	(4.492)		(4.091)	(2.656)
$Order\ Flow\ of\ Hedge\ Funds_m$		0.035	0.039	0.004
		(0.932)	(0.968)	(0.371)
R_m				0.018
				(0.240)
$Log(Market\ Cap)_m$				-0.021
				(-0.857)
$Maturity_m$				0.022**
				(2.006)
Adj.R^2	0.014	0.006	0.022	0.759

Table 5: Hedge Funds' Order Flows and Future Non-Dealer Order Flows

This table reports panel regressions of daily market order flow (excluding hedge funds) on hedge funds' order flow. Order flow is defined as the net buy volume scaled by total volume in each day. We control for Size, Maturity, Trading Volume and lagged order flows with bond and day fixed effects. Size is the log of the amount outstanding in British pounds. Maturity is the residual maturity of the bond. Standard errors are double clustered at both time and bond dimensions. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Order Flow of Others$_{d+1}$			Order Flow of Others$_{d+1:d+5}$		
$Order\ Flow\ of\ Hedge\ Funds_d$	0.013***	0.013***	0.013***	0.005***	0.004**	0.005***
	(3.652)	(3.592)	(3.640)	(2.789)	(2.638)	(2.774)
$Order\ Flow\ of\ Others_d$	0.084***	0.074***	0.071***	0.045***	0.034***	0.033***
	(8.815)	(7.988)	(7.797)	(9.903)	(8.625)	(8.676)
$Size_d$		-0.197***	-0.185***		-0.218***	-0.211***
		(-13.854)	(-12.809)		(-16.937)	(-17.000)
$Maturity_d$		0.011	0.012		0.001	0.001
		(0.882)	(0.975)		(0.014)	(0.028)
$Volume_d$		0.012***	0.012***		0.010***	0.010***
		(3.382)	(3.270)		(5.423)	(5.322)
$Return_d$		-0.026	-0.045		0.455	0.452
		(-0.110)	(-0.192)		(0.820)	(0.826)
$Order\ Flow\ of\ Others_{d-1}$			0.028***			0.013***
			(4.156)			(2.745)
$Order\ Flow\ of\ Others_{d-2}$			0.015**			0.007**
			(2.193)			(2.012)
$Order\ Flow\ of\ Others_{d-3}$			0.008			0.007*
			(1.136)			(1.850)
$Order\ Flow\ of\ Others_{d-4}$			0.003			0.005
			(0.380)			(1.219)
Bond Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs.	23,556	23,556	23,498	23,466	23,466	23,408
Adj.R2	0.098	0.106	0.108	0.151	0.189	0.189

Table 6: Hedge Funds' Order Flows and Macro-News Announcements

This table reports the portfolio sorting results ranked by the daily order flow of hedge funds in the day before macroeconomic news announcements. The order flow is defined as the net buy volume scaled by total volume of hedge funds in the day before macroeconomic news announcement. News announcements include central bank meetings (MPC), inflation and labor statistics announcements. At each day, the bonds are equally sorted into three groups. All bonds are equally-weighted within each group. We report the return (alpha) spreads between the top and bottom groups ("High minus Low": H-L). We report the daily raw return, the return adjusted with market factor (1F Alpha), and the return adjusted with market, slope and curvature factors (3F Alpha). The returns (alphas) are in basis points. T-statistics are computed based on standard errors with Newey-West correction. Estimates of High minus Low (H-L) 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	**2.498**	**(2.264)**	**2.521**	**(2.405)**	**2.519**	**(2.624)**

Panel B: Central Bank Meetings (MPC)						
	Return	t-stat	Alpha (1F)	t-stat	Alpha (3F)	t-stat
H-L	0.903	(1.744)	**1.004**	**(1.966)**	**1.217**	**(2.736)**

Panel C: Inflation and Labor Announcements						
	Return	t-stat	Alpha (1F)	t-stat	Alpha (3F)	t-stat
H-L	**3.415**	**(2.957)**	**3.539**	**(3.167)**	**3.531**	**(3.163)**

Table 7: Mutual Funds' Order Flows and Interest Rate Changes

This table reports the predictive regression of different interest rate changes on bond duration (government bond). Based on the order flow of mutual funds, we form a flow-weighted average (modified) duration for government bond in each month. The dependent variables are short-term interest rate change (one-year rate), change of slope (twenty-year – one-year rate). Then independent variables include forward spread, change of consensus mean of analyst forecast, and time trend. All rates are in basis points. We control for changes in the forecast of interest rates, changes in the forecast of GDP growth rate, and the change in the forecast in the inflation. T-statistics are computed based on standard errors with Newey-West correction. *, **, *** indicate statistically significant at 10%, 5%, and 1% respectively.

Panel A: Predicting Changes in Short-term Interest Rates

	ΔIR_{m+1}		ΔIR_{m+3}	
$Flow - Weighted\ Duration_m$	-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)
$Time\ Trend$	0.078	0.085	0.252	0.263
	(3.25)	(2.89)	(2.67)	(2.62)
Adj. R^2	0.019	-0.020	0.160	0.135

Panel B: Predicting Changes in Term Spreads

	$\Delta Slope_{m+1}$		$\Delta Slope_{m+3}$	
$Flow - Weighted\ Duration_m$	-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)
$Time\ Trend$	0.023	0.023	-0.008	-0.013
	(0.35)	(0.36)	(-0.04)	(-0.07)
Adj. R^2	-0.025	-0.026	0.001	-0.009

Table 8: Mutual Funds' Order Flows and Macro-News Announcements

This table reports the contribution of macroeconomic news announcement in the holding period returns in Panel B of Table 3. News announcements include central bank meetings (MPC), inflation and labor statistics announcements. The order flow is defined as the net buy volume scaled by total volume of mutual funds in each month. In each month, the bonds are equally sorted into five groups. The portfolios are rebalanced every month and are held for one month. All bonds are equally-weighted within each group. For the holding period, we accumulate the daily returns at the day of macroeconomic news announcement. We report the raw return, the return adjusted with market factor (1F Alpha), and the return adjusted with market, slope and curvature factors (3F Alpha). The returns (alphas) are in basis points. T-statistics are computed based on standard errors with Newey-West correction. Estimates of High minus Low (H-L) significant at the 5% level are indicated in bold.

Panel A: Whole month return						
	Return	t-stat	Alpha (1F)	t-stat	Alpha (3F)	t-stat
H-L	**27.519**	(**3.955**)	**17.587**	(**3.564**)	**17.977**	(**3.751**)

Panel B: Average daily Returns on macro-news announcements						
	Return	t-stat	Alpha (1F)	t-stat	Alpha (3F)	t-stat
H-L	**3.031**	(**2.721**)	**3.094**	(**3.212**)	**3.615**	(**3.374**)

Panel C: Daily returns on Central Bank Meetings (MPC)						
	Return	t-stat	Alpha (1F)	t-stat	Alpha (3F)	t-stat
H-L	2.716	(1.735)	**2.847**	(**2.049**)	2.867	(1.787)

Panel D: Daily return of inflation and labor announcements						
	Return	t-stat	Alpha (1F)	t-stat	Alpha (3F)	t-stat
H-L	**3.504**	(**2.866**)	**3.487**	(**3.014**)	**4.294**	(**3.613**)

Table 9: High- and Low-Skilled Managers

This table reports the portfolio sorting ranked by order flow of hedge/mutual funds. In Panel A, hedge funds are split into two subgroups: high and low skill managers. In each day d, we calculate a sensitivity score for each fund based on a panel regression of daily flow and bond return between day d-92 and day t-1. The funds are classified into high (low) skill managers if their sensitivity scores are higher (lower) than the median value. The portfolio is constructed based on the order flow from high or low skill managers separately. We report the daily raw return, the return adjusted with market factor (1F Alpha), and the return adjusted with market, slope and curvature factors (3F Alpha). In Panel B, mutual funds are split into two subgroups: high and low skill managers. In each month t, we calculate a sensitivity score for each fund based on a panel regression of monthly flow and bond return between month t-11 and month t. The funds are classified into high (low) skill managers if their sensitivity scores are higher (lower) than the median value. The portfolio is constructed based on the order flow from high or low skill managers separately. We report the monthly raw return, the return adjusted with market factor (1F Alpha), and the return adjusted with market, slope and curvature factors (3F Alpha). T-statistics are computed based on standard errors with Newey-West correction. Estimates of High minus Low (H-L) significant at the 5% level are indicated in bold.

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

	High Skilled Hedge Funds			Low Skilled Hedge Funds		
	Return	Alpha (1F)	Alpha (3F)	Return	Alpha (1F)	Alpha (3F)
Low	7.548	-1.292	-0.996	9.354	0.531	0.583
	(1.341)	(-1.209)	(-0.971)	(1.578)	(-0.214)	(-0.112)
High	10.473	1.946	1.982	9.918	1.086	1.514
	(1.891)	(1.586)	(1.648)	(1.756)	(1.016)	(1.274)
H-L	**2.925**	**3.238**	**2.978**	0.564	0.555	0.931
	(2.254)	**(2.528)**	**(2.343)**	(1.210)	(1.080)	(1.205)

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	15.0	-8.7	-7.6	27.0	3.2	2.6
	(0.985)	(-2.255)	(-2.827)	(1.654)	(0.545)	(0.466)
High	40.1	11.6	12.5	28.1	0.0	0.7
	(2.421)	(2.693)	(2.894)	(1.697)	(0.254)	(0.186)
H-L	**25.0**	**20.3**	**20.1**	1.0	-2.3	-1.9
	(4.180)	**(3.239)**	**(3.842)**	(0.132)	(-0.282)	(-0.222)

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

This table reports the robustness checks for Panel A of Table 2 and Panel B of Table 3. In Panel A, the sorting variable is the daily order flow of hedge funds and holding period is one day. We report subsample analysis in Panel A1 and the predictability of daily order flow on the bond price changes (excluding coupons) in Panel A2. The portfolios are rebalanced every day and are held for five days. In Panel B, the sorting variable is the monthly order flow of mutual funds and holding period is one monthly. We report subsample analysis in Panel B1 and the predictability of daily order flow on the bond price changes (excluding coupons) in Panel B2. The portfolios are rebalanced every month and are held for one month. We report the monthly raw return, the return adjusted with market factor (1F Alpha), and the return adjusted with market, slope and curvature factors (3F Alpha). T-statistics are computed based on standard errors with Newey-West correction. Estimates of High minus Low (H-L) 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)	11.460	(1.678)	-0.281	(-0.269)	0.004	(0.004)
5 (High)	14.668	(2.245)	2.301	(2.356)	2.551	(2.614)
H-L	**2.668**	(**2.110**)	**2.630**	(**2.139**)	**2.647**	(**2.095**)
2014 November - 2017 December						
1 (Low)	4.915	(0.639)	-2.587	(-2.687)	-2.157	(-2.246)
5 (High)	8.569	(1.105)	1.181	(1.239)	1.360	(1.476)
H-L	**3.654**	(**2.871**)	**3.769**	(**2.987**)	**3.517**	(**2.926**)

Panel A2: Predicting Bond Price Changes						
	Return	t-stat	Alpha (1F)	t-stat	Alpha (3F)	t-stat
1 (Low)	3.534	(0.677)	-0.217	(-0.301)	-1.452	(-1.209)
5 (High)	6.587	(1.278)	2.849	(4.227)	1.900	(1.783)
H-L	**3.053**	(**3.558**)	**3.066**	(**3.624**)	**3.352**	(**2.275**)

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)	32.7	(1.344)	-10.8	(-2.501)	-12.6	(-4.062)
5 (High)	53.8	(2.272)	11.5	(2.564)	11.9	(4.172)
H-L	**21.2**	(**2.980**)	**22.3**	(**3.342**)	**24.5**	(**5.056**)
2014 November to 2017 December						
1 (Low)	18.0	(1.492)	-5.9	(-0.980)	-5.6	(-1.048)
5 (High)	44.8	(2.746)	11.8	(2.282)	10.5	(2.280)
H-L	**26.8**	(**2.232**)	17.6	(1.903)	**16.1**	(**2.000**)

Panel B2: Predicting Bond Price Changes						
	Return	t-stat	Alpha (1F)	t-stat	Alpha (3F)	t-stat
1 (Low)	-2.3	(-0.176)	-37.0	(-7.787)	-37.0	(-8.218)
5 (High)	20.5	(1.331)	-18.7	(-5.748)	-18.2	(-6.205)
H-L	**22.8**	(**3.606**)	**18.3**	(**3.199**)	**18.8**	(**3.864**)

Table 11: Order Flows and Future Bond Returns
Non-Dealer Banks, Pension funds and Insurance companies (ICPFs)

This table reports the portfolio sorting ranked by order flow for each sector (Non-Dealer Banks and Pension funds and Insurance companies (ICPF)). Order flow is defined as the net buy volume scaled by total volume for each sector in each day/month. In Panel A, the sorting variable the daily order flow of each sector (Banks/ICPF) and the holding period is one day. In Panel B, the sorting variable the monthly order flow of each sector (Banks/ICPF) and the holding period is one month. In each day (month), the bonds are equally sorted into five groups. The portfolios are rebalanced every day(month) and are held for one day(month). All bonds are equally-weighted within each group. We report the daily (monthly) raw return, the return adjusted with market factor (1F Alpha), and the return adjusted with market, slope and curvature factors (3F Alpha) in Panel A (Panel B). T-statistics are computed based on standard errors with Newey-West correction. Estimates of 'High minus Low' (H-L) 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	9.664	(1.904)	-0.588	(-0.627)	-0.202	(-0.209)
High	10.422	(2.191)	0.641	(0.825)	0.988	(1.300)
H-L	0.757	(0.640)	1.229	(0.992)	1.190	(0.930)
ICPF						
	Return	t-stat	Alpha (1F)	t-stat	Alpha (3F)	t-stat
Low	10.321	(1.797)	-0.535	(-0.942)	-0.554	(-0.991)
High	11.659	(1.926)	0.505	(0.804)	0.362	(0.593)
H-L	1.338	(1.406)	1.040	(1.052)	0.917	(0.938)

Panel B: Monthly Order Flows and Bond Returns						
Non-Dealer Banks						
	Return	t-stat	Alpha (1F)	t-stat	Alpha (3F)	t-stat
Low	48.5	(2.641)	0.9	(0.193)	0.0	(0.000)
High	52.3	(2.975)	6.9	(1.310)	6.3	(1.170)
H-L	3.8	(0.709)	6.1	(1.103)	6.3	(1.052)
ICPF						
	Return	t-stat	Alpha (1F)	t-stat	Alpha (3F)	t-stat
Low	40.3	(2.641)	00.8	(0.307)	0.4	(0.162)
High	38.8	(1.902)	-6.3	(-1.002)	-6.4	(-1.007)
H-L	-1.6	(-0.168)	-7.2	(-0.988)	-6.8	(-1.019)

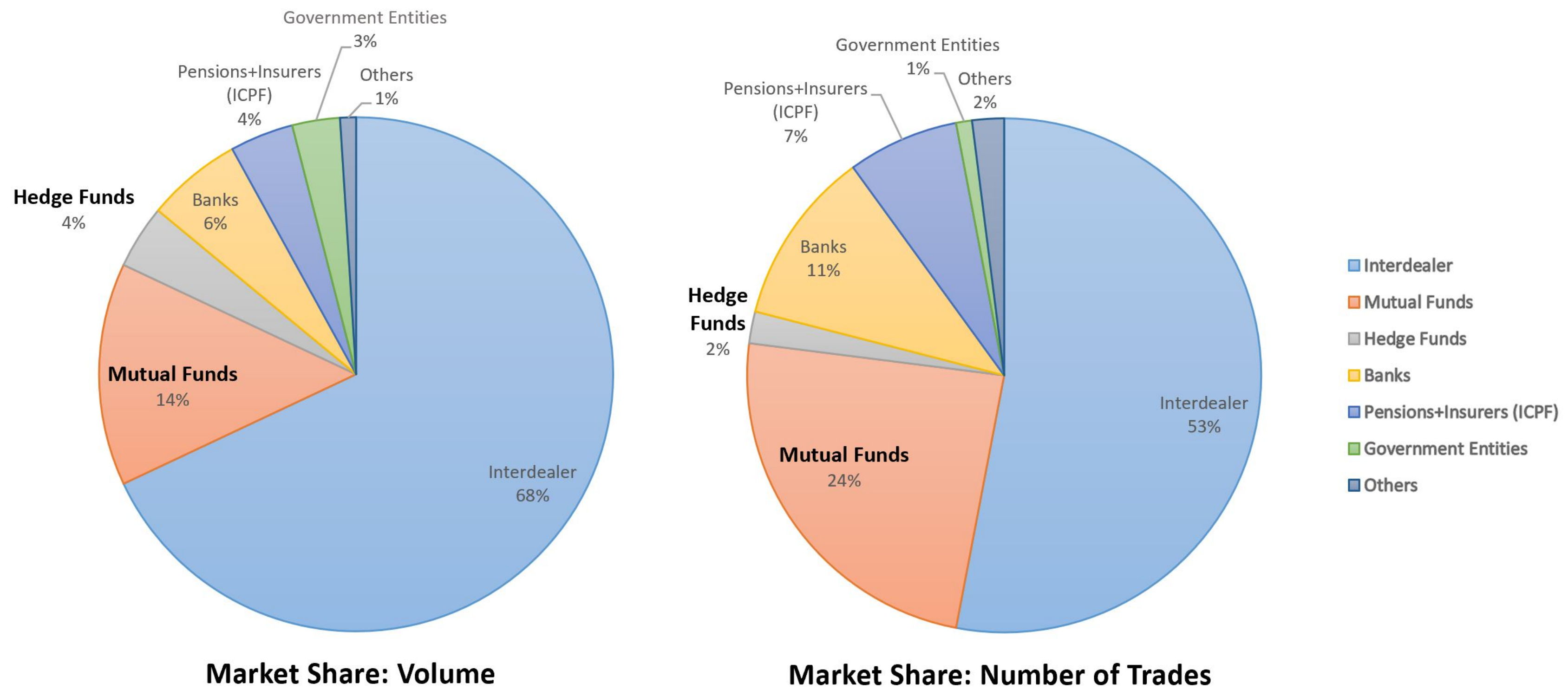

Figure 1: UK Government Bond Market Shares by Investor Sectors
This figure displays the sector breakdown of total volume and number of trades on UK government bond. Volume and number of trades are constructed by using transaction data from the from the ZEN database maintained by the UK Financial Conduct Authority (FCA). The sample period is from 2011 August to 2017 December.

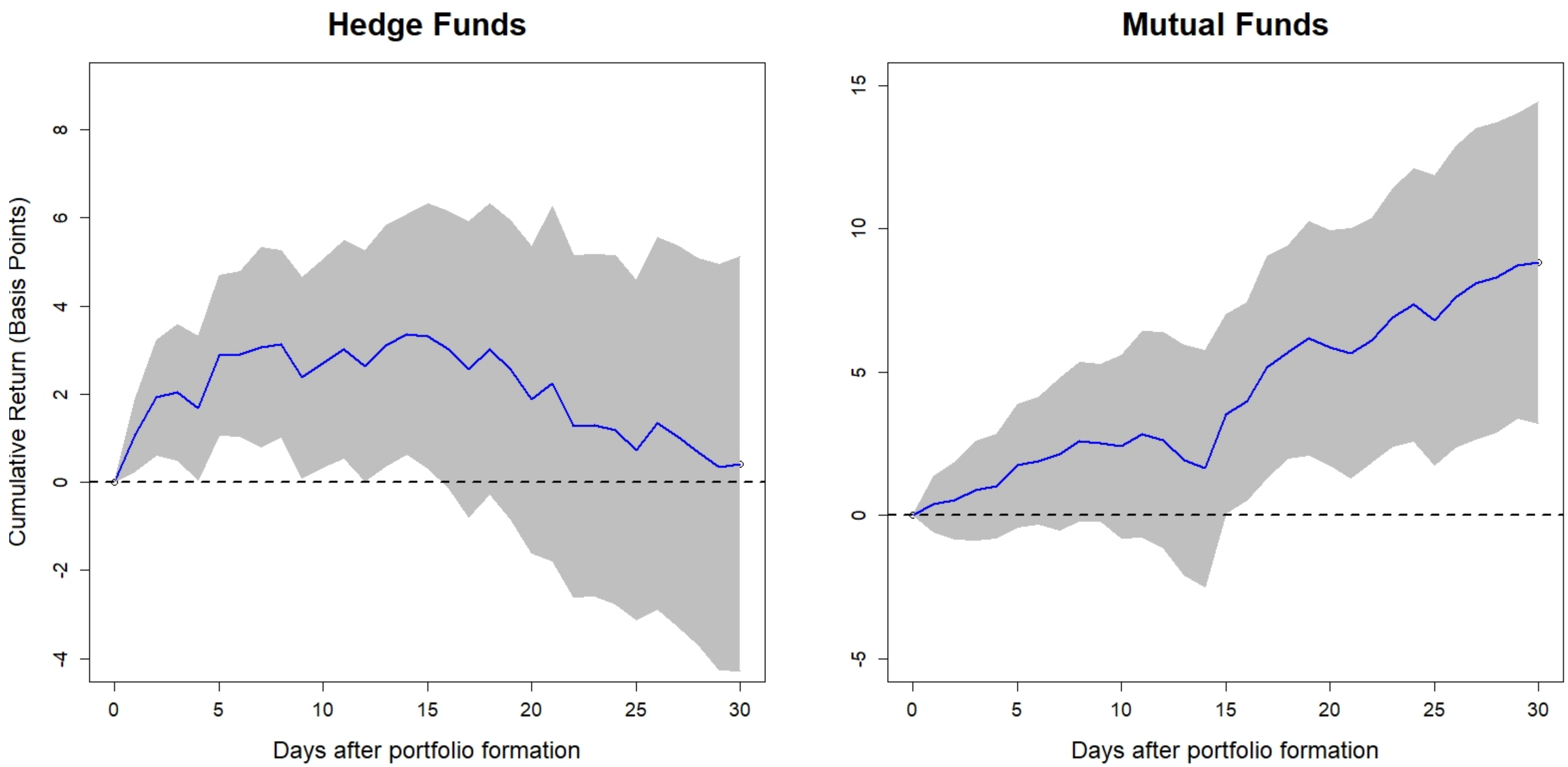

Figure 2: Event-Time Long-Short Portfolio Returns – Sorted by Daily Order Flows
This figure shows the holding period return of the long-short portfolio based on bond order flow in the Hedge Funds and Mutual Funds sector. In each day, the bonds are equally sorted into three groups based on order flow from low to high. The figures below show the returns of the long-short portfolio (High order flow group minus Low order flow group). The portfolios are rebalanced every day and are held for *one, two, fifi 30 days*. The 95% confidence intervals shown in grey area are calculated based on block bootstrap standard errors.

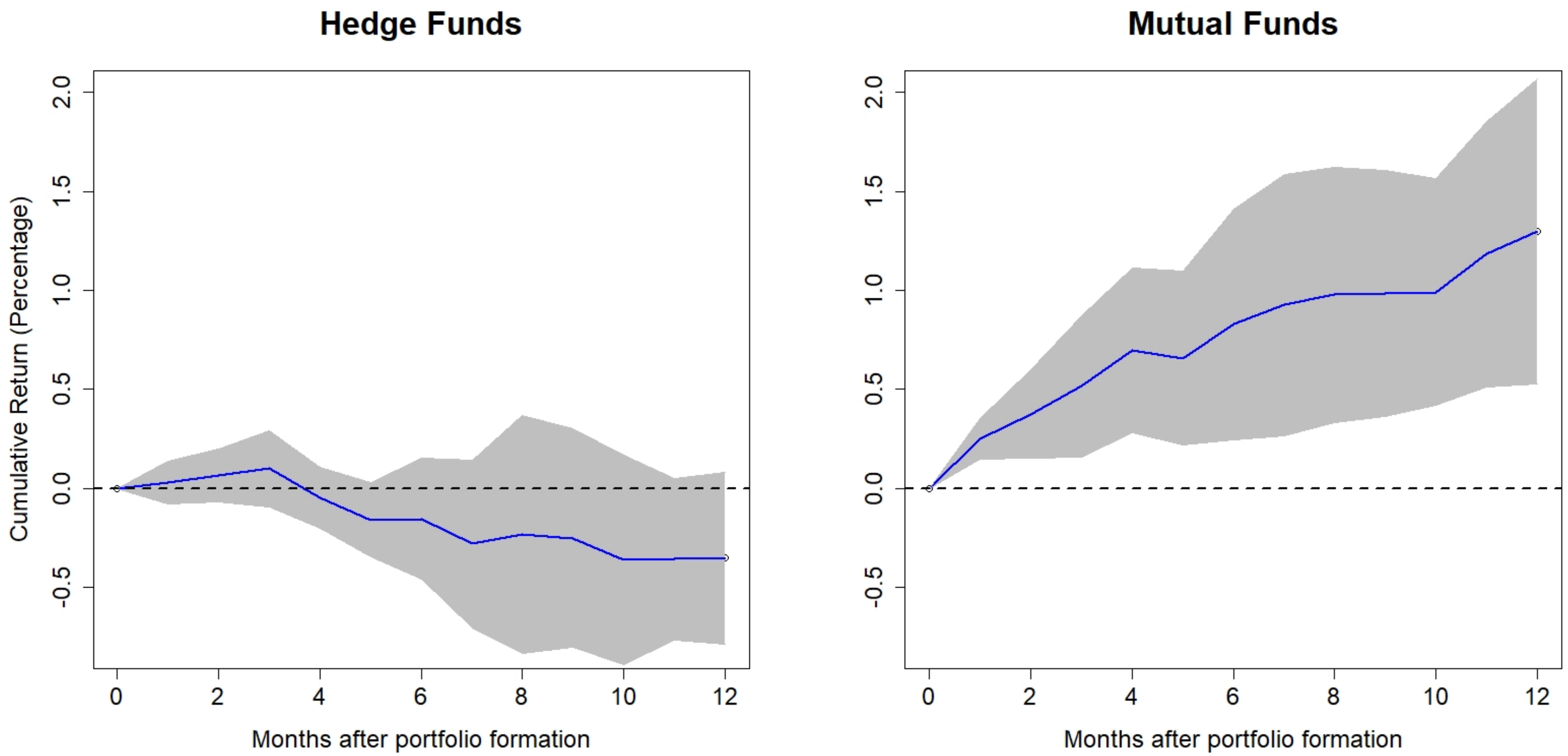

Figure 3: Event-Time Long-Short Portfolio Returns – Sorted by Monthly Order Flows
This figure shows the long-term holding period return of the long-short portfolio based on bond order flow in the Hedge Funds and Mutual Funds sector. In each month, the bonds are equally sorted into five groups based on fund order flow from low to high. The figures below show the returns of the long-short portfolio (High order flow group minus Low order flow group). The portfolios are rebalanced every month and are held for *one, two, or twelve months*. The 95% confidence intervals shown in grey area are calculated based on block bootstrap standard errors.

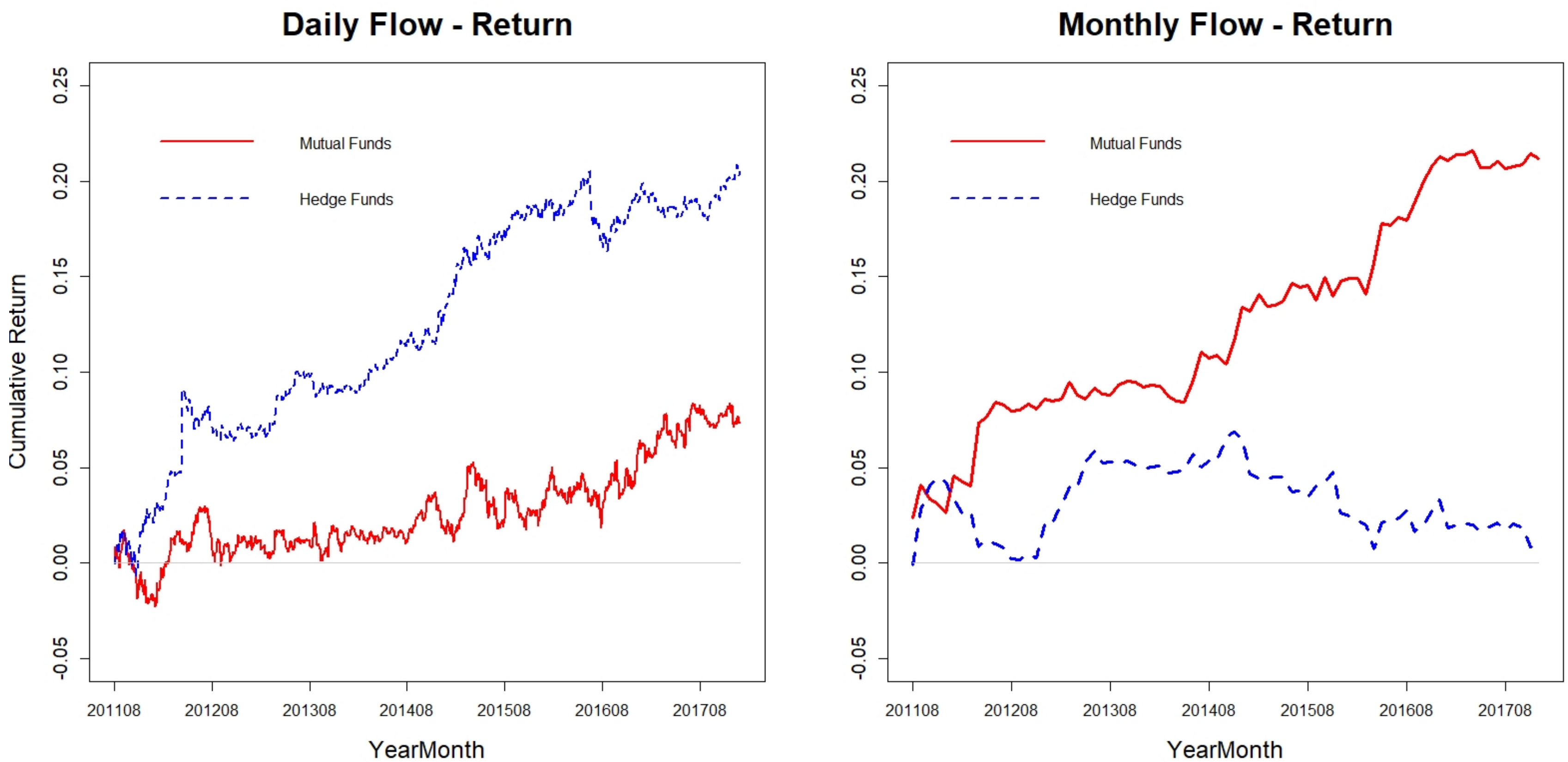

Figure 4: Calendar-Time Cumulative Portfolio Returns
This figure shows the cumulative return of the long-short portfolio based on the bond order flow in the Hedge Funds and Mutual Funds sector. In each day/month (left panel, right panel), the bonds are equally sorted into three/five groups based on daily/monthly order flow from low to high. The figures above show the returns of the long-short portfolio (High order flow group minus Low order flow group). The daily/monthly portfolios are rebalanced every day/month and are held for one day/month. The sample period is from 2011 August to 2017 December.

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

This table reports the full tables for Table 2. The portfolio sorting ranked by the daily order flow of hedge funds and mutual funds, respectively. Order flow is defined as the net buy volume scaled by total volume hedge/mutual funds at each day. At each day, the bonds are equally sorted into three groups. All bonds are equally-weighted within each group. We report the return (alpha) spreads between the top and bottom groups ("High minus Low": H-L), and the various holding periods: 1 day (Panel A), 5 day (Panel B), 10 days (Panel C), 1 month (Panel D) and 2 months (Panel E). We report the raw return, the return adjusted with market factor (1F Alpha), and the return adjusted with market, slope and curvature factors (3F Alpha). The return and alphas are in bps. T-statistics (T-stat) are computed based on standard errors with Newey-West correction and are reported below returns (alphas). Estimates of "High minus Low" (H-L) 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)	1.264	1.197	-0.760	-2.070	-0.751	-2.044	1.515	1.546	-0.331	-0.895	-0.340	-0.916
2	1.715	1.759	-0.335	-1.180	-0.317	-1.125	2.196	1.972	-0.033	-0.086	0.040	0.105
3 (High)	2.540	2.653	0.624	2.228	0.635	2.261	1.968	2.021	0.011	0.032	-0.003	-0.009
H-L	**1.276**	**2.801**	**1.384**	**3.161**	**1.386**	**3.204**	0.453	0.946	0.342	0.722	0.337	0.712

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)	8.862	1.976	-1.330	-1.785	-1.082	-1.492	8.600	2.051	-1.012	-1.293	-0.801	-1.014
2	9.916	2.060	-0.898	-1.155	-0.526	-0.681	11.721	2.301	0.499	0.517	0.786	0.858
3 (High)	11.739	2.657	1.605	2.147	1.853	2.723	10.347	2.353	0.414	0.498	0.697	0.849
H-L	**2.877**	**3.163**	**2.935**	**3.318**	**2.935**	**3.554**	1.747	1.632	1.426	1.405	1.498	1.493

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)	18.422	2.401	-2.222	-2.514	-1.461	-1.703	17.216	2.615	-1.896	-1.746	-1.230	-1.089
2	19.712	2.244	-1.697	-1.805	-0.657	-0.689	22.918	2.618	0.190	0.174	0.761	0.729
3 (High)	21.057	2.723	0.668	0.752	1.277	1.405	19.763	2.626	-0.722	-0.678	0.170	0.157
H-L	**2.635**	**2.327**	**2.890**	**2.621**	**2.738**	**2.492**	2.576	1.699	1.275	0.846	1.472	0.978

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)	40.619	2.891	-3.124	-2.328	-2.066	-1.462	37.611	3.264	-3.340	-1.962	-2.857	-1.586
2	44.038	2.814	-1.198	-0.828	-0.047	-0.032	45.370	3.012	-1.817	-1.110	-0.370	-0.221
3 (High)	41.939	3.007	-0.669	-0.505	0.322	0.237	44.075	3.164	0.663	0.394	1.946	1.095
H-L	1.320	0.731	2.455	1.448	2.387	1.372	**6.508**	**2.585**	4.075	1.658	4.734	1.826

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)	75.265	2.514	3.945	3.658	4.539	4.264	65.498	2.434	0.450	0.403	1.551	1.455
2	79.102	2.642	3.457	3.056	4.844	4.246	87.507	2.579	3.580	3.337	3.854	3.815
3 (High)	73.719	2.441	2.914	2.721	3.030	3.118	80.607	2.533	8.108	7.616	7.209	6.809
H-L	-1.546	-0.329	-1.031	-0.622	-1.509	-0.931	**15.109**	**2.557**	**7.658**	**4.069**	**5.658**	**3.029**

Table A2: Non-Dealer Order Flows and Future Hedge Funds' Order Flows

This table reports panel regressions of hedge funds' order flow on daily market order flow (excluding hedge funds). Order flow is defined as the net buy volume scaled by total volume in each day. We control for Size, Maturity, Trading Volume and lagged order flows with bond and day fixed effects. Size is the log of the amount outstanding in British pounds. Maturity is the residual maturity of the bond. Standard errors are double clustered at both time and bond dimensions. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

	Order Flow of Hedge Funds$_{d+1}$			Order Flow of Hedge Funds$_{d+1:d+5}$		
$Order\ Flow\ of\ Hedge\ Funds_d$	0.172***	0.172***	0.110***	0.071***	0.071***	0.028**
	(15.226)	(15.130)	(5.675)	(8.963)	(9.038)	(2.461)
$Order\ Flow\ of\ Others_d$	-0.008	-0.009	0.005	-0.008	-0.010	0.020
	(-0.396)	(-0.467)	(0.112)	(-0.628)	(-0.788)	(0.929)
$Size_d$		-0.033	0.172		-0.037	0.176*
		(-0.924)	(1.612)		(-1.197)	(1.920)
$Maturity_d$		-0.003	0.033		0.022	-0.063
		(-0.129)	(0.684)		(0.941)	(-1.129)
$Volume_d$		-0.025**	-0.018		-0.003	-0.014
		(-2.371)	(-0.896)		(-0.595)	(-1.124)
$Return_d$		4.504	5.638		-6.424***	-5.706*
		(1.463)	(1.149)		(-3.358)	(-1.858)
$Order\ Flow\ of\ Hedge\ Funds_{d-1}$			0.035*			0.006
			(1.884)			(0.601)
$Order\ Flow\ of\ Hedge\ Funds_{d-2}$			0.018			-0.003
			(0.851)			(-0.310)
$Order\ Flow\ of\ Hedge\ Funds_{d-3}$			0.012			0.007
			(0.679)			(0.594)
$Order\ Flow\ of\ Hedge\ Funds_{d-4}$			0.021			0.020*
			(1.152)			(1.693)
Bond Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs.	13,267	13,267	3,653	20,421	20,421	4,536
Adj.R2	0.142	0.143	0.324	0.094	0.095	0.297

Table A3: Hedge Funds' Order Flows and Macro-News Announcements

This table reports the portfolio sorting results ranked by the daily order flow of hedge funds in the day before macroeconomic news announcement. News announcements include central bank meeting (MPC), inflation and labor statistics announcements. At each day, the bonds are equally sorted into three groups. All bonds are equally-weighted within each group. We consider alternative order flows and alternative holding periods around macro-news announcement. The alternative order flow includes the past one day's order flow of hedge funds, past two days' order flow of hedge funds, and past three days' order flow of hedge funds. The alternative return windows include the return at the announcement day and the (-1,1) around the announcement days. We report the return (alpha) spreads between the top and bottom groups ("High minus Low": H-L). We report the daily raw return, the return adjusted with market factor (1F Alpha), and the return adjusted with market, slope and curvature factors (3F Alpha). Then returns (alphas) are in basis points. *T-statistics* are computed based on standard errors with Newey-West correction. Estimates of High minus Low (H-L) significant at the 5% level are indicated in bold.

Panel A: Predicting returns at the announcement days						
Sorting Variable	Return	*t*-stat	Alpha (1F)	*t*-stat	Alpha (3F)	*t*-stat
	All Macro News					
Past 1 day's order flow	**2.498**	**2.264**	**2.521**	**2.405**	**2.519**	**2.624**
Past 2 days' order flow	**4.123**	**3.355**	**4.304**	**3.310**	**4.098**	**3.644**
Past 3 days' order flow	**3.425**	**3.160**	**3.530**	**3.346**	**3.356**	**3.750**
	Central Bank Meeting (MPC)					
Past 1 day's order flow	0.903	1.744	**1.004**	**1.966**	**1.217**	**2.736**
Past 2 days' order flow	**4.690**	**2.555**	**5.027**	**2.487**	3.988	1.909
Past 3 days' order flow	**3.235**	**2.348**	**3.330**	**2.322**	**2.336**	1.276
	Inflation and Labor Announcement					
Past 1 day's order flow	**3.415**	**2.957**	**3.539**	**3.167**	**3.531**	**3.163**
Past 2 days' order flow	**3.415**	**2.957**	**3.539**	**3.167**	**3.531**	**3.163**
Past 3 days' order flow	**2.984**	**2.873**	**2.982**	**2.858**	**2.979**	**2.867**

Panel B: Predicting returns at (-1,1) around the announcement days						
	All Macro News					
Past 1 day's order flow	**8.721**	**4.264**	**8.685**	**4.193**	**8.514**	**4.289**
Past 2 days' order flow	**5.301**	**2.737**	**5.276**	**2.692**	**5.141**	**2.746**
Past 3 days' order flow	**4.542**	**2.514**	**4.486**	**2.474**	**4.379**	**2.461**
	Central Bank Meeting (MPC)					
Past 1 day's order flow	**8.502**	**2.928**	**8.503**	**3.010**	**7.459**	**2.862**
Past 2 days' order flow	**7.616**	**2.578**	**7.625**	**2.574**	**6.792**	**2.563**
Past 3 days' order flow	**7.129**	**2.858**	**7.128**	**2.840**	**6.207**	**2.796**
	Inflation and Labor Announcement					
Past 1 day's order flow	**9.107**	**3.312**	**9.003**	**3.623**	**9.008**	**3.789**
Past 2 days' order flow	**3.203**	**2.083**	**3.165**	**2.129**	**3.330**	**2.456**
Past 3 days' order flow	1.584	0.868	1.390	0.906	2.399	1.719

Table A4: Mutual Funds' Order Flows and Future Non-Dealer Order Flows

This table reports panel regressions of monthly market order flow (excluding mutual funds) on mutual funds' order flow. Order flow is defined as the net buy volume scaled by total volume in each day. We control for Size, Maturity, Trading Volume and lagged order flows with bond and month fixed effects. Size is the log of the amount outstanding in British pounds. Maturity is the residual maturity of the bond. Standard errors are double clustered at both time and bond dimensions. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

	Order Flow of Others$_{m+1}$		
$Order\ Flow\ of\ Mutual\ Funds_m$	-0.001	-0.040	-0.039
	(-0.042)	(-1.495)	(-1.553)
$Order\ Flow\ of\ Others_m$	0.016	-0.024	-0.011
	(0.640)	(-0.958)	(-0.466)
$Size_m$		-0.204***	-0.197***
		(-6.906)	(-5.734)
$Maturity_m$		-2.988**	-2.598*
		(-2.006)	(-1.682)
$Volume_m$		0.006	0.001
		(0.680)	(0.138)
$Return_m$		-0.888*	-0.601
		(-1.720)	(-1.131)
$Order\ Flow\ of\ Others_{m-1}$			-0.029
			(-1.286)
$Order\ Flow\ of\ Others_{m-2}$			-0.048**
			(-2.096)
$Order\ Flow\ of\ Others_{m-3}$			-0.001
			(-0.060)
$Order\ Flow\ of\ Others_{m-4}$			0.013
			(0.619)
Bond Fixed Effects	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
# of Obs.	2,869	2,848	2,653
Adj. R^2	0.070	0.088	0.073