Informed Trading in Government Bond Markets*

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Abstract

Using comprehensive administrative data from the UK, we examine trading by different investor types in government bond markets. Our sample covers virtually all secondary market trading in gilts and contains detailed information on each transaction, including the identities of both counterparties. We find that hedge funds' daily trading positively forecasts gilt returns in the following one to five days, which is then fully reversed in the following month. A part of this short-term return predictability is due to hedge funds' ability to predict 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 could 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, the trading of those who are better-informed (e.g., those with more accurate interpretations of public information) should persistently outperform the trading of the less-informed.

We focus on the second channel. A priori, it would seem difficult for any investor (or investor type) to acquire an information advantage over other participants in the government bond market given its depth and liquidity. Indeed, the large body of 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 (e.g., Huang,

[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, 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.

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 nondealer investors, summed across all reported trades.

We contribute to the debate on 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. Given that all gilt dealers are UK-domiciled and hence FCA-regulated institutions, the ZEN database effectively covers all trading activity in the UK government bond market.

Compared to the data sets 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 on all individual transactions (the date and time stamp, transaction price, transaction amount, etc.). Second, unlike the order flow data, we observe the identities of both counterparties in each transaction (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 has a comparative advantage in this market and, further, is able to profit from their information advantage.

For ease of comparison, we classify 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, and 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. For most of the paper, we focus on the first two institution types, hedge funds and mutual funds, which are 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 have a significant information advantage 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's net buying of hedge funds, we find that the tercile of gilts heavily bought outperform the tercile of gilts heavily sold by 1.28 *bps* (t-statistic = 2.80) on the following day, and by 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 becomes increasingly informative over a longer horizon. For example, the return spread between the top and bottom terciles of gilts, sorted by the previous day's mutual fund order flow, is a statistically insignificant 0.45 *bps* (t-statistic = 0.95) on 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's 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 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, when we extend 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%.[2]

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 fundamental value accurately and efficiently (more so than the average investor). 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).[3] We further isolate the part of mutual fund trading that can be relatively easily predicted, specifically, 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.

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 trade more aggressively and 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 could be uninformed), and b) learning about value-relevant information.

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[2] 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.

[3] 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.

We conduct a similar set of analyses for 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 predicting 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 an aggregate shift in mutual funds' 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.

We also analyze mutual funds' abnormal returns around various macroeconomic announcements (which are known to have a 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 each month, specifically, the day when monetary policy is announced and the day when inflation and labor statistics are announced. Put differently, mutual funds earn 3.62 *bps*/day on macro-announcement days and only 0.5 *bps*/day on other days.

Finally, in a series of additional analyses, we show that a) mutual fund and hedge fund trading activity is strongly correlated with existing proxies for informed trading (e.g., Amihud's price impact measure); b) both hedge funds and mutual funds trade more aggressively, as well as earn higher returns, in relatively more liquid bonds; c) daily hedge fund order flows strongly and negatively forecast future gilt returns in extreme market-volatility environments.

Overall, our evidence shows that 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 highlight the distinctions in the two groups' approaches to earning abnormal returns in the government bond market. While hedge funds gain from both predicting other investors' future demand and quick responses to the arrival of macroeconomic news, mutual funds profit from their ability to understand and forecast macroeconomic fundamentals.

Through their active trading, these professional managers help 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 study contributes to the literature on private information in the government bond market.[4] For example, Brandt and Kavajecz (2004) find that order imbalances in the interdealer market account for more than a quarter of the daily variation in Treasury yields on days without major macroeconomic announcements. Pasquariello and Vega (2007) further show that this relation between order flows and Treasury yields strengthens in times of high investor disagreement. Green (2004) shows that the arrival of macroeconomic news increases the level of information asymmetry in the government bond market, potentially due to investors' heterogeneous interpretations of the news.

While prior studies examine the contemporaneous correlation between aggregate interdealer order-flows and Treasury yields, we focus squarely on and show the strong return predictability of trading by various types of clients, such as hedge funds and mutual funds. We can do so because we observe a) complete, granular information on virtually all transactions in the gilt market, and b) the identities of both parties in each transaction.[5] We further tie the documented return pattern to the release of macro news (e.g., monetary policy announcements). Given that virtually all macro-news is public, our results provide direct evidence for the superior processing ability of public information by a subset of market participants.

Our work is also related to the vast literature on the information processing ability of different types of investors. While there is a large volume of evidence that sophisticated institutions, such as hedge funds and mutual funds, have private information on individual firms or industry sectors (e.g., Kacperczyk, Sialm, and Zheng, 2005; Cremers and Petajisto

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[4] There is a related literature on price discoveries in the government bond market. 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).

[5] 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 connections have on average better trading performance.

2009; Jiao, Massa, and Zhang, 2016; Chen, Da, Huang, 2019), there is little empirical support for their ability to profit from macro news. Our results provide strong evidence that sophisticated institutions (both hedge funds and mutual funds) have an information advantage over other investors in the government bond market, where price movements are mainly driven by macro news.[6]

Our results also add to the recent literature that proposes two types of arbitrage/speculative activities: i) to predict and potentially front-run other investors' future demand, and ii) to learn about the future fundamental value of the asset (e.g., Farboodi and Veldkamp, 2019). On the empirical side, Hendershott, Jones, and Menkveld (2011) and Van Kervel and Menkveld (2019) provide evidence that high frequency traders learn about other investors' future trading activity. Di Maggio, Franzoni, Kermani, and Sommavilla (2019) and Kondor and Pinter (2019) show that institutions connected to central brokers (in the broker network) and those connected to a larger number of dealers are better at predicting other investors' future order flows. Our work contributes to this strand of literature by jointly examining the two types of arbitrage/speculative activities (predicting order flows and predicting economic fundamentals). We provide direct support for the theory of Farboodi and Veldkamp (2019): both channels are important to arbitrageurs; interestingly, hedge funds and mutual funds seem to "specialize" in one of the two types of arbitrage activities.

Finally, our study contributes to the vast empirical literature on the predictability of the term structure of interest rates and Treasury security returns. Fama and Bliss (1987) show that forward-spot spreads predict future spot rate changes. Campbell and Shiller (1991) find that larger spreads between long-term and short-term yields forecast rising short-term yields and declining long-term yields. Cochrane and Piazzesi (2005) show 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

[6] Relatedly, 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 show that dealer-client order flows are informative about future movements in exchange rates.

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.

3. Data

We use regulatory bond transactions data, specifically, the ZEN database, which is 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 6,249 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), most of trades take place over the counter. The Gilt-Edged Market Makers (or GEMMs) are central to the functioning of the gilt market. These financial institutions (mainly large investment banks) are designated primary dealers in the gilt market and are 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, and the identities of the buyer and seller.

The gilt market consists of two tiers: an interdealer market in which dealers trade among themselves, and a dealer-client segment in which 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. Our paper focuses on dealer-client trades. The main client sectors are a) mutual funds, b) hedge funds, c) non-dealer banks, and d) pension funds and insurance companies (ICPF). We combine pension funds and insurance companies because of the similarities in their investment styles and objectives. For each day/month, we calculate the order flow (or trading activity) of each investor type in each gilt as:

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

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

Our sample spans the period of August 2011 through 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 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 could 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 and labor statistics, and the Monetary Policy Committee (MPC) meetings. MPC meeting dates are collected from the Bank of England, and other macro-announcement dates are published by the UK Office for National Statistics. We also obtain information on analysts' forecasts for the UK bank rate, the ten-year interest rate, the UK GDP growth rate, and the 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 20-year gilt and the 1-year gilt. The curvature factor is the average return of the 20-year and 1-year gilts, minus that of the 10-year gilt. Our results are robust to using the Bloomberg Barclays Sterling Gilts Total Return index as a proxy for the level factor, and to using the returns of the 30-year and 1-year gilts to construct the slope factor.

Our final sample consists of 55 UK government bonds. Panel A of Table 1 reports basic summary statistics of our sample. The average monthly gilt return is 0.45% with a standard deviation of 2.29%. The average issue size is £26 billion, 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%.

Panel B of Table 1 reports annualized share turnover between dealers and clients by institution-type and bond maturity. Two patterns are worth pointing out: a) government bonds with maturities between five and ten years have the highest turnover, most of which is contributed by hedge funds (20%) and mutual funds (more than 50%); b) non-dealer banks and hedge funds tilt their trading toward short-term government bonds, while insurance companies and pension funds (ICPFs) tilt their trading toward long-term bonds.

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 of this paper, we focus on the order flows of mutual funds and hedge funds, the prototypical arbitrageurs in financial markets. In Section 6, we extend our analysis to the trading behavior of non-dealer banks and ICPFs, both of which are unlikely to act as arbitrageurs in the gilt market.

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.[7] 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.[8] 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.[9] The return spread then becomes statistically insignificant 1.32 *bps* (t-statistic = 0.73) by the end of month one, and -1.28 *bps* (t-statistic = -0.31) by the end of month two. This return predictive pattern is virtually unchanged after controlling for known risk factors (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

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[7] 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.

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

[9] In Online Appendix Table A3, we further analyze intraday return predictability of hedge fund order flows, where the intraday return is measured as the percentage difference between the transaction price and the closing price of the same day. A long-short portfolio of government bonds sorted by hedge funds daily trading produces a three-factor alpha of 0.83 *bps* (t-statistic = 2.33) on the day of the transaction. This intraday return predictability rises to 2.35 *bps* (t-statistic = 2.56) right before macro-announcements.

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 types. The 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.

We further divide our sample into three subperiods: periods with low, high, and ultra-high market volatilities, with cutoffs at the 50th and 90th percentiles of the time-series distribution. Our main proxy for market volatility is innovations in the forward-looking VFTSE index (the counterpart of the VIX index in the UK market) constructed from FTSE 100 options. The results are similar if we instead use UK government bond market realized volatility to divide our sample period (reported in Appendix Figure A1); this is not surprising as the correlation between the two measures of market volatility is over 0.65.

As can be seen from the top panel of Figure 3, hedge fund daily order flows weakly predict future gilt returns in low market-volatility environments, and strongly and positively forecast gilt returns in high market-volatility environments. Interestingly, hedge fund order flows negatively forecast future gilt returns in ultrahigh market-volatility environments. In the bottom panel of Figure 3, we conduct similar analyses using the sample of mutual funds. In sharp contrast to our earlier finding for hedge funds, across all three subperiods, mutual fund daily order flows significantly and positively predict future gilt returns.[10] These results contribute to the recent debate on the role of arbitrage

[10] As shown in Appendix Table A4, the contemporaneous correlation between hedge fund order flows and government bond returns is the highest during extreme-volatility periods; on the other hand, there is no

trading (e.g., Brunnermeier, Nagel, and Pedersen, 2008) in the price discovery process. Specifically, mutual funds always trade in the same direction as future price movements, thus helping the price discovery process; hedge funds, in contrast, trade in the opposite direction of future price movements during ultrahigh market volatility periods, potentially harming the price discovery process.

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. Table 3 reports these portfolio returns.

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 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 4 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

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visible variation in the same correlation for mutual funds. There is also a slight increase in the volume share by hedge funds (i.e., trading volume of hedge funds divided by total volume) and a slight decrease in volume share by banks and ICPFs as volatility increases.

sign of reversal. In other words, the return predictive pattern of mutual fund trading is unlikely to be driven by herding behavior (Cai, Han, Li, and Li, 2019).

4.3. Fama-MacBeth Regressions

A potential concern with the calendar-time portfolio approach is that the documented return pattern could 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 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.[11]

We also examine variation in both trading intensity and return predictability between more and less liquid bonds. To this end, we divide all government bonds in our sample into two groups. The liquid subsample includes the on-the-run and first off-the-run government bonds of all maturities; the illiquid subsample includes the remaining bonds. Perhaps not surprisingly, hedge funds' trading in liquid bonds is 34% higher than their trading in illiquid bonds. Similarly, mutual funds' trading in liquid bonds is 36% higher than their trading in illiquid bonds.

In Online Appendix Table A8, we repeat the Fama-MacBeth return-forecasting regressions by further including a "liquid" dummy and its interactions with order flows of hedge funds and mutual funds. As shown in the first two columns, where the dependent variables are bond returns in the next one to five days, the coefficients on the interaction term of "order flows of hedge fund" and the "liquid" dummy are economically large and statistically significant. Column (3) then examines bond returns in the following month and finds that the coefficient on the interaction term of "order flows of mutual funds" and the "liquid" dummy is significantly positive. These results suggest that both hedge funds and mutual funds trade more aggressively, as well as earn higher returns, in relatively more liquid bonds.

5. Sources of Return Predictability

After having established the return predictive patterns of hedge funds' and mutual funds' trading activity, in this section, we now 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.

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[11] We also run a horse race among three measures of informed trading: a) the institution type (our main variable); b) number of dealer connections (Kondor and Pinter, 2019); and c) trading volume (or the number of trades). As shown in Online Appendix Tables A5−A7, both the institution type and number of dealer connections contain independent information about future bond returns.

5.1. Sources of Return Predictability: Hedge Funds

Recent theoretical studies (e.g., Farboodi and Veldkamp, 2019) argue that arbitrageurs could engage in two types of arbitrage activities: i) those that are able to predict the future demand of other investors and profit from front-running predictable order flows; ii) those that are 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) versus around non-announcement days.

5.1.1. Predicting Order Flows of Other Investors

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

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

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

Table 5 reports the regression results. In Columns (1)-(3) of Panel A, the dependent variable is the following-week order flow of mutual funds; in Panel B, the dependent variable is the following-week order flow of either non-dealer banks or ICPFs. As shown in the first three columns of Panel A, hedge funds' weekly order flows significantly and positively forecast mutual funds' future trading. For example, as shown in Column (1), a one-standard-deviation increase in hedge funds' order flow in a week forecasts an increase in net purchases by mutual funds of 0.81% (=89.85%×0.009, t-statistic = 3.80) in the following week. As shown in Panel B, hedge fund trading is largely unrelated to future order flows of non-dealer banks and ICPFs. Importantly, there is no similar order flow predictive pattern in the opposite direction. As shown in Online Appendix Table A9, 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 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 trading in each government bond as follows. First, using information on daily total net assets (TNA) and fund returns from Morningstar, we compute daily percentage capital flows to fund i as:

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

Next, we calculate fund i's flow-induced trading in bond j by assuming that the fund proportionally scales up or down its holdings in response to capital flows. Since mutual fund holdings information is available only at a monthly frequency (as reported by Morningstar), 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.[12]

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

[12] Our results are robust to using total mutual fund holdings in bond j in the previous month in the denominator of the flow-induced trading calculation.

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

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

If hedge funds are indeed able to forecast mutual funds' flow-induced trading, an immediate prediction is that hedge fund trading should be more profitable in periods of relatively large mutual fund flow-induced trading in absolute terms. To test this prediction, we repeat the exercise in Table 2 by dividing our sample into two halves based on the aggregate absolute level of mutual fund flow-induced trading. Specifically, in each day, we sum up the *absolute value* of *FIT* across all gilts, and then split all trading days into two subperiods (high- versus. low-*FIT* periods) using the median cutoff of the aggregate absolute *FIT*. As shown in Online Appendix Table A10, 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 and low absolute *FIT* periods, *3.71* bps (*t*-statistic = 3.40) versus 1.77 *bps* (*t*-statistic = 1.49), respectively, 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 of 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 versus 3.53 *bps* (t-statistic = 3.16) on inflation/labor statistics announcement days.[13]

Taken together, these results indicate that hedge funds, aside from their ability to forecast other investors' future demand, also have superior ability to process and respond to macroeconomic information. Both skills likely contribute to the documented return predictive pattern of hedge funds' daily order flows.[14]

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 A12, monthly

[13] In Online Appendix Table A11, 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.

[14] In a back-of-the-envelope calculation, we provide an approximate bound for how much of this return predictability is due to hedge funds' predicting macroeconomic information. As shown in Tables 2 and 6, a long-short government bond portfolio sorted by daily hedge fund order flows generates 1.28 *bps* per day on average, and 2.5 *bps* on macro-announcement days. (Note that there are on average two macro-announcement days in each month.) If we believe that the 2.5 *bps* are entirely due to hedge funds' superior ability to process macro news, then the macro-information channel accounts for 18% (= 2.5*2/1.28*22) of the total return predictability. If instead we believe only the difference between 2.5 bps and 1.28 *bps* is due to hedge funds' ability to process macro news, then the macro-information channel accounts for about 9% of the total return effect.

mutual fund order flows have no predictive power for future demand of other investors (the results are similar for daily mutual fund order flows as shown in Table A8). In other words, the documented return predictive pattern of mutual fund trading is unlikely due to their ability to forecast 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 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' bond 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, dubbed $TradeWeightedDuration$. 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 20-year yield minus the 1-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).[15] We also include in the regression changes in analyst forecasts of i) the short-term interest rate, ii) the GDP growth rate, and iii) the inflation rate to control for information in the public domain but not captured by the forward rates.

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 can 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 or inflation and labor statistics announcements vs. days without such announcements. 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.

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

Table 8 shows the decomposition results. 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 is, 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. Note that even though hedge funds also earn higher abnormal returns on macro-announcement days than on non-announcement days (Section 5.1.2), mutual funds' abnormal returns on announcement days are even higher than those earned by hedge funds. In other words, mutual funds specialize more in processing/interpreting macro-economic announcements than hedge funds.

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- and. low-skilled and examine the persistence in their performance. Section 6.2 shows the relation between mutual fund/hedge fund trading and existing measures of informed trading. In Section 6.3, we analyze trading volume around macroeconomic announcements. Section 6.4 examines whether the order flows of hedge funds or mutual funds can predict future economic surprises. In Section 6.5, we conduct a series of robustness checks based on various sub-samples and alternative definitions of bond returns. In Section 6.6, 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.[16]

To capture heterogeneity across hedge funds, we re-estimate regression Equation (1) for each individual hedge fund for every day, 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 on day d, using daily data from the past three months. Intuitively, the coefficient estimate on the lagged order flow captures the fund's ability to forecast future bond returns. We then divide all hedge funds into two groups in each day: those above the cross-sectional median are labelled "high-skilled" and those below the median are labelled "low-skilled". Finally, we repeat the exercise in Table 2 to separately examine the return predictability of daily order flows of high-skilled and low-skilled hedge funds.

In a similar vein, for every month we re-estimate Equation (2) for each individual mutual fund using monthly bond returns and mutual fund order flows 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- versus low-skilled hedge funds. Panel B examines *monthly* return predictability of the order flows of high- versus 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

[16] 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 Pástor, 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.

bps (*t*-statistic = 2.34) in the following five days. In contrast, a similar long-short gilt portfolio sorted by order flows of low-skilled hedge funds produces an insignificant three-factor alpha of 0.93 *bps* (*t*-statistic = 1.21).

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

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

6.2. Correlations with Existing Proxies for Informed Trading

In this section, we examine the correlations between the intensity of mutual fund/hedge fund trading using our proprietary data and a series of existing proxies for informed trading using publicly available data.

We start with a measure of price impact motivated by Kyle (1985), defined as the absolute daily return divided by same-day trading volume (Amihud, 2002). We conduct a panel regression of price impact of day t on the contemporaneous fraction of orders submitted by hedge funds and mutual funds (dubbed "informed trading"). As shown in the first two columns of Panel A of Table 10, after controlling for issue size and maturity, the coefficient on "informed trading" is significantly positive, suggesting that on days with more informed trading by hedge funds and mutual funds, government bond prices respond more strongly to investor trading, consistent with market makers' pricing rule in Kyle (1985).

We then construct an alternative measure of price impact using high frequency data. Specifically, following Boehmer and Wu (2013), we measure daily price impact as the autocorrelation in 15-minute bond returns in that day.[17] Similar to the result above, informed trading by hedge funds and mutual funds is positively correlated with this contemporaneous measure of price impact, as shown in Columns (3) and (4) of Table 10 Panel A. In other words, informed trading is more likely to be associated with permanent price impact.

Finally, following Llorente, Michaely, Saar, and Wang (2002), we measure price impact using the correlation between the next-day return and today's signed volume. More specifically, we conduct a panel regression of bond returns of day $t+1$ on bond returns and trading volume of day t as well as the interaction term between the two variables. In each day, we divide all bonds into three subgroups based on the fraction of orders submitted by hedge funds and mutual funds. As can be seen from Panel B of Table 10, and consistent with the result in Llorente et al. (2002), in the subset of bonds with the highest fraction of informed trading, the coefficient on the lagged return is significantly negative and that on the interaction term (return×volume) is significantly positive. Put differently, informed trading indeed leads to a more permanent price impact.

In sum, these results confirm that the three commonly used proxies for informed trading (or permanent price impact) indeed capture what they are designed to capture. At the same time, these results lend further support to our hypothesis that hedge funds and mutual funds are informed in the government bond market.

6.3. Trading Volume around Macro-Announcements

If hedge funds and mutual funds are indeed skilled at interpreting public information, we should observe a spike in trading volume around the release of public news. Figure 5 shows the time variation in trading volume around macro announcements. Day 0 corresponds to the announcement day; weeks -2, -1, +1, +2 are the four calendar weeks around the announcement day. For ease of interpretation, we normalize daily trading volume in each period by the average daily trading volume in week -2 (i.e., daily volume in week -2 is normalized to 1).

[17] Not surprisingly, this high-frequency return autocorrelation is negative for all bond-day observations; in other words, a positive return in a 15-min window is usually followed by a negative return in the next 15 minutes.

The top panel examines trading volume by various institution types around macro announcements; The bottom panel studies trading volume in government bonds with different maturities.[18] As is clear from the top panel, both hedge funds and mutual funds increase their trading activity in days -1 and 0, consistent with our result that these sophisticated investors have a larger information advantage on information-rich days. Not surprisingly, both non-dealer banks and ICPFs also report higher trading on days -1 and 0. This is likely because non-dealer banks and ICPFs need to trade on the other side of hedge funds and mutual funds, since dealer banks are reluctant to have large directional exposures. The bottom panel shows a similar spike in trading volume on days -1 and 0 across all maturities.

6.4. Predicting Future Macroeconomic Surprises

We next examine whether hedge fund and mutual fund order flows contain useful information about future macroeconomic surprises. To this end, we use the time series of macro-surprises in Eguren-Martin and McLaren (2015). Following the methodology proposed by Swanson and Williams (2014), Eguren-Martin and McLaren (2015) construct a daily series of macroeconomic surprises for the UK based on a) over 100 macroeconomic indicators, and b) investor expectations from Bloomberg surveys of market participants. As shown in Eguren-Martin and McLaren (2015), there is a significant positive contemporaneous correlation between their economic surprise index and short-term interest rate movements.

The results are shown in Online Appendix Table A14. Panel A examines whether daily hedge funds' trade-weighted durations forecast macroeconomic surprises in the following one to five days. The coefficient is generally negative and marginally statistically significant at the five-day horizon (consistent with the result in Table 6). In other words, hedge funds reduce their portfolio durations before the arrival of macro news that is

[18] We report detailed trading volume around macro-announcement days by both institution-type and bond maturity in Online Appendix Table A13. We also show in Appendix Figure A2 that mutual funds' volume share (as a fraction of total daily volume) rises and banks' volume share declines, while hedge funds' and ICPF's volume shares stay roughly flat on the day of macro-announcements relative to the two weeks prior. This volume-share pattern persists for the next two weeks. These results are consistent with our main finding that mutual funds have an information advantage around macro-announcements.

generally associated with an increase in short-term rates. Panel B repeats the exercise for mutual funds. Monthly mutual funds' trade-weighted durations significantly and negatively forecast macroeconomic surprises in the following one to three months (consistent with the result in Table 7). Again, this result suggests that mutual funds shorten their portfolio durations before macro news associated with interest rate hikes.

6.5. 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 versus second half of our sample; b) alternative definitions of bond returns (price changes without accrued interest); and c) alternative definitions of order flows (buy minus sell scaled by shares outstanding, for example).

As shown in Online Appendix Table A15, our results are robust to all these different tweaks. In Panel A1, for instance, the long-short portfolio sorted by daily hedge fund order flows yields a three-factor alpha of 2.12 *bps* (t-statistic = 1.98) and 3.52 *bps* (t-statistic = 2.93) in the following five days in the first and second halves of our sample, respectively. The corresponding figures for mutual funds, shown in Panel B1, are 24.53 *bps* (t-statistic = 5.06) and 16.09 *bps* (t-statistic = 2.00) in the following month in the first and second halves of our sample. Panel A3 shows that the long-short portfolio of government bonds sorted by the alternative definition of daily hedge fund order flows yields a three-factor alpha of 2.41 *bps* (t-statistic = 2.24) in the following five days. Panel B3 shows that the long-short portfolio sorted by the alternative definition of monthly mutual fund order flows produces a three-factor alpha of 27.07 *bps* (t-statistic = 2.85) in the following month. These return figures are similar to those reported in Tables 2 and 3.

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

Thus far, we have focused on 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 major institutional groups in the gilt market: non-dealer banks and insurance companies and pension funds (ICPFs).

Specifically, we conduct the same analyses as in Tables 2 and 3, but now focusing on the order flows of non-dealer banks and ICPFs. Panel A of Online Appendix Table A16 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 find for hedge funds and mutual funds, order flows of non-dealer banks and ICPFs do not have any predictive power for future gilt returns at either the daily or monthly frequency. Across all specifications, returns to the long-short gilt portfolio sorted by order flows of either investor group are economically small and statistically insignificant, and even negative in some cases. These results are consistent with the view that hedge funds and mutual funds are the more-skilled investors in financial markets, and that they 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 on 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 but operate at very different horizons and through different mechanisms. On the one hand, hedge funds' daily order flows positively forecast gilt returns in the following one to five days, which is then fully reversed in the following two months. A part of this short-term return predictive pattern can be attributed to hedge funds' trading ahead of other investors' predictable order flows, especially mutual funds' 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; more importantly, 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 and detailed evidence for the types of arbitrage activity that hedge funds and mutual funds engage in. Specifically, 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 other investors' future demand. 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 return patterns (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 the summary statistics on our sample, which covers the period August 2011 through December 2017. Government bond returns, total market capitalizations (£ billions), maturity, duration, and bond yields are from DataStream and the UK Debt Management Office. Investors' order flows are from the ZEN database maintained by the Financial Conduct Authority (FCA). For each group of investors, on each day and/or each month, we calculate the order flow as the buy volume minus sell volume scaled by the total trading volume of this 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). Panel A reports the mean, median, standard deviation (SD), $5^{\text{th}}/25^{\text{th}}/75^{\text{th}}/95^{\text{th}}$ percentiles, and the number of observations. Panel B reports the turnover for bonds with different maturities.

Panel A: Basic Statistics

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 Funds (%)	-1.50	57.15	-100.00	-42.05	-1.21	37.74	100.00	2,814
	Order Flow — Banks (%)	0.24	31.19	-56.40	-19.49	-0.17	21.26	58.91	2,923
	Order Flow — ICPFs (%)	-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 Funds (%)	-1.41	89.85	-100.00	-100.00	0.00	100.00	100.00	23,870
	Order Flow — Banks (%)	0.14	74.93	-100.00	-79.97	0.00	79.96	100.00	50,367
	Order Flow — ICPFs (%)	-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

Panel B: Turnover between Dealers and Clients						
Maturity :		Mean	<5 Years	Between 5 and 10 Years	Between 10 and 30 Years	>30 Years
Turnover (Annualized)		151.28%	110.90%	228.59%	120.65%	152.97%
By sector	Banks	29.70%	34.92%	50.52%	16.46%	12.94%
	ICPFs	16.50%	10.51%	15.96%	17.46%	24.55%
	Hedge Funds	23.00%	21.84%	42.79%	14.26%	11.92%
	Mutual Funds	82.08%	43.63%	119.32%	72.47%	103.55%

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 on each day, we calculate the daily order flow of hedge funds (mutual funds) as the net buy volume scaled by the total trading volume of hedge funds (mutual funds). We then sort all gilts into three groups based on the daily order flows of hedge funds (mutual funds) and weigh the bonds equally within each group. We report the return (alpha) spreads between the top and bottom terciles ("High minus Low": H-L) on the following trading day (Panel A), five trading days (Panel B), ten trading days (Panel C), one month (Panel D), and two months (Panel E). We report the raw returns, alphas adjusted by the market factor (1F Alpha), and alphas adjusted by the market, slope, and curvature factors (3F Alpha). All returns and alphas are reported in basis points. *T*-statistics are computed based on standard errors with Newey-West corrections 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 weigh 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 corrections 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 variables are 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, and maturity. T-statistics are computed based on standard errors with Newey-West corrections 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

	$Return_{d+1}$			$Return_{d+1:d+5}$		
$Order\ Flow\ of\ Hedge\ Fund$	0.003***		0.004***	0.006**		0.006**
	(2.734)		(3.204)	(2.187)		(2.050)
$Order\ Flow\ of\ Mutual\ Func$		0.001	0.002		0.001	-0.001
		(1.120)	(1.480)		(0.201)	(-0.155)
$Return_d$	-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

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

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

This table reports results of panel regressions of trading by mutual funds (or non-dealer banks, or insurance companies and pension funds (ICPF)) on lagged hedge fund order flow. For each bond in each five-day window, 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 from day d+1 to d+5. In columns (4)-(6), the dependent variable is flow-induced trading of mutual funds (*FIT*) from day d+1 to d+5. Panel B reports the results of hedge fund order flows predicting other investors' trading. In columns (1)-(3), the dependent variable is order flows of ICPFs from day d+1 to d+5. In columns (4)-(6), the dependent variable is order flows of non-dealer banks from day d+1 to d+5. Other control variables include size, maturity, and 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)
$Order\ Flow\ of\ Mutual\ Funds_{d-4:d}$		0.061***	0.058***		0.033***	0.033***
(or $FIT_{d-4:d}$)		(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)
$Order\ Flow\ of\ Mutual\ Funds\ _{d-9:d-5}$			0.038***			0.003
(or $FIT_{d-9:d-5}$)			(6.216)			(0.249)
$Order\ Flow\ of\ Mutual\ Funds\ _{d-14:d-10}$			0.013**			-0.002
(or $FIT_{d-14:d-10}$)			(2.251)			(-0.219)
$Order\ Flow\ of\ Mutual\ Funds\ _{d-19:d-1\text{!}}$			0.011*			0.000
(or $FIT_{d-19:d-15}$)			(1.792)			(0.017)
$Order\ Flow\ of\ Mutual\ Funds_{d-24:d-20}$			0.004			-0.028***
(or $FIT_{d-24:d-20}$)			(0.687)			(-2.924)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	46,939	46,815	45,755	22,848	22,719	22,144
Adj. R^2	0.046	0.071	0.068	0.555	0.562	0.564

Panel B: Predicting Other Investors' Trading						
	ICPFs			Non-Dealer Banks		
	(1)	(2)	(3)	(4)	(5)	(6)
	$Order\ Flow_{d+1:d+5}$			$Order\ Flow_{d+1:d+5}$		
$Order\ Flow\ of\ Hedge\ Funds_{d-4:d}$	0.007	0.007	0.007	-0.005	-0.006	-0.007
	(1.007)	(0.970)	(0.927)	(-0.691)	(-0.785)	(-0.961)
$Order\ Flow_{d-4:d}$		0.046***	0.040***		0.021*	0.020*
		(4.329)	(3.875)		(1.822)	(1.715)
$Size_d$		2.246	2.495		-0.813	0.322
		(0.660)	(0.728)		(-0.322)	(0.124)
$Maturity_d$		-0.230***	-0.178***		-0.182***	-0.165***
		(-7.429)	(-5.738)		(-7.311)	(-6.163)
$Volume_{d-4:d}$		-0.001	-0.001		-0.001*	-0.001*
		(-1.431)	(-0.832)		(-1.901)	(-1.686)
$Return_{d-4:d}$		0.034***	0.027***		0.021***	0.018***
		(5.059)	(4.419)		(3.972)	(3.794)
$Order\ Flow_{d-9:d-5}$			0.020**			-0.007
			(2.627)			(-0.700)
$Order\ Flow_{d-14:d-10}$			0.014*			0.002
			(1.867)			(0.276)
$Order\ Flow_{d-19:d-15}$			0.018*			0.009
			(1.873)			(0.953)
$Order\ Flow_{d-24:d-20}$			0.026***			0.018**
			(3.242)			(2.232)
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. On the day before each macroeconomic news announcement, we calculate the daily hedge fund order flow as the net buy volume scaled by the total trading volume of hedge funds. We then sort bonds into three groups and weigh the bonds equally within each group. Panel A reports the returns to the long-short gilt portfolio on any macroeconomic news announcement days. Panel B reports the returns to the long-short portfolio on MPC meeting days, and finally Panel C reports the 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 corrections and are reported in parentheses. Long-short portfolio returns significant at the 5% level are indicated in bold.

Panel A: All Macroeconomic-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: specifically, the weighted average duration of government bonds bought by mutual funds minus the weighted average duration of government bonds sold by mutual funds, dubbed $Trade\ Weighted\ Duration$. In Panel A, the dependent variables are changes in the short-term interest rate (one-year rate) one or three months ahead. In Panel B, the dependent variables are the changes in the slope of the term structure of interest rates, i.e., the difference between the twenty-year bond yield and one-year bond yield. Other control variables include the forward spread, changes in analyst forecasts of interest rates, changes in analyst forecasts of the GDP growth rate, changes in analyst forecasts of the inflation rate, and a time trend. All dependent variables are in basis points. *T*-statistics are computed based on standard errors with Newey-West corrections and are reported in parentheses. *, **, and *** indicate statistically significant at the 10%, 5%, and 1% level, respectively.

Panel A: Predicting Changes in Short-term Interest Rates

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

Panel B: Predicting Changes in Term Spreads

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

Table 8: Mutual Fund Order Flows and Macroeconomic-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 weigh the bonds equally within each group. The long-short portfolios are held for one month. Panel A repeats the result of Panel B of Table 3. Panel B reports returns to the long-short gilt portfolio on any macroeconomic news announcement days. Panel C reports 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 corrections 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 Labor Statistics Ann Days						
	Return	T-stat	Alpha (1F)	T-stat	Alpha (3F)	T-stat
H-L	**3.50**	**(2.87)**	**3.49**	**(3.01)**	**4.29**	**(3.61)**

Table 9: Persistence in Return Predictability

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

This table reports the relations between hedge fund/mutual fund trading and existing proxies for informed trading (or permanent price impact) using publicly available data. Panel A reports panel regressions of contemporaneous measures of informed trading on hedge funds/mutual funds trading. In columns (1) and (2), the dependent variable is the absolute daily return divided by the same-day trading volume in £ billions (Amihud, 2002). In columns (3) and (4), the dependent variable is the intraday autocorrelation of 15-minute bond returns. The key independent variable, $Hedge\ and\ Mutual\ Fund\ Trading_d$, is the fraction of daily orders contributed by hedge funds and mutual funds on day d. In Panel B, following Llorente, Michaely, Saar, and Wang (2002), we measure price impact using the correlation between next-day returns and previous-day signed trading volumes. More specifically, we conduct a panel regression of bond returns on day d+1 on bond returns and trading volume of day d as well as the interaction term between the two variables. On each day, we divide all bonds into three subgroups based on the fraction of orders submitted by hedge funds and mutual funds. Other control variables include size, maturity, and trading volume. Bond and time fixed effects are included in all regression specifications. 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: Mutual Fund/Hedge Fund Trading and Contemporaneous Price Impact

	$\frac{\lvert Return_d \rvert}{Volume_d}$		$Return\ Autocorrelation_d$	
	(1)	(2)	(3)	(4)
$Hedge\ and\ Mutual\ Fund\ Trading_d$	0.114***	0.115***	0.096***	0.067***
	(3.762)	(5.572)	(3.823)	(2.707)
$Volume_d$		-0.178***		0.066***
		(-8.069)		(13.736)
$Size_d$		-0.016		-0.227***
		(-0.564)		(-10.370)
$Maturity_d$		0.003***		-0.001
		(4.741)		(-0.001)
Fixed Effects	Yes	Yes	Yes	Yes
No. Obs.	60,776	60,776	42,247	42,247
Adj. R^2	0.125	0.421	0.297	0.302

Panel B: Dynamic Volume-Return Relations			
		$Return_{d+1}$	
	Low	Medium	High
	(1)	(2)	(3)
$Return_d \times Volume_d$	-0.005	-0.001	0.005**
	(-0.989)	(-0.110)	(2.042)
$Return_d$	0.100	0.040	-0.090*
	(0.988)	(0.388)	(-1.743)
$Volume_d$	0.001	0.001	-0.001
	(0.199)	(0.354)	(-0.170)
$Size_d$	-0.004	0.010	-0.008
	(-0.566)	(1.025)	(-0.949)
$Maturity_d$	0.001	-0.015	0.011*
	(0.113)	(-1.584)	(1.734)
Fixed Effects	Yes	Yes	Yes
No. Obs.	27,014	27,960	27,595
Adj. R^2	0.634	0.721	0.728

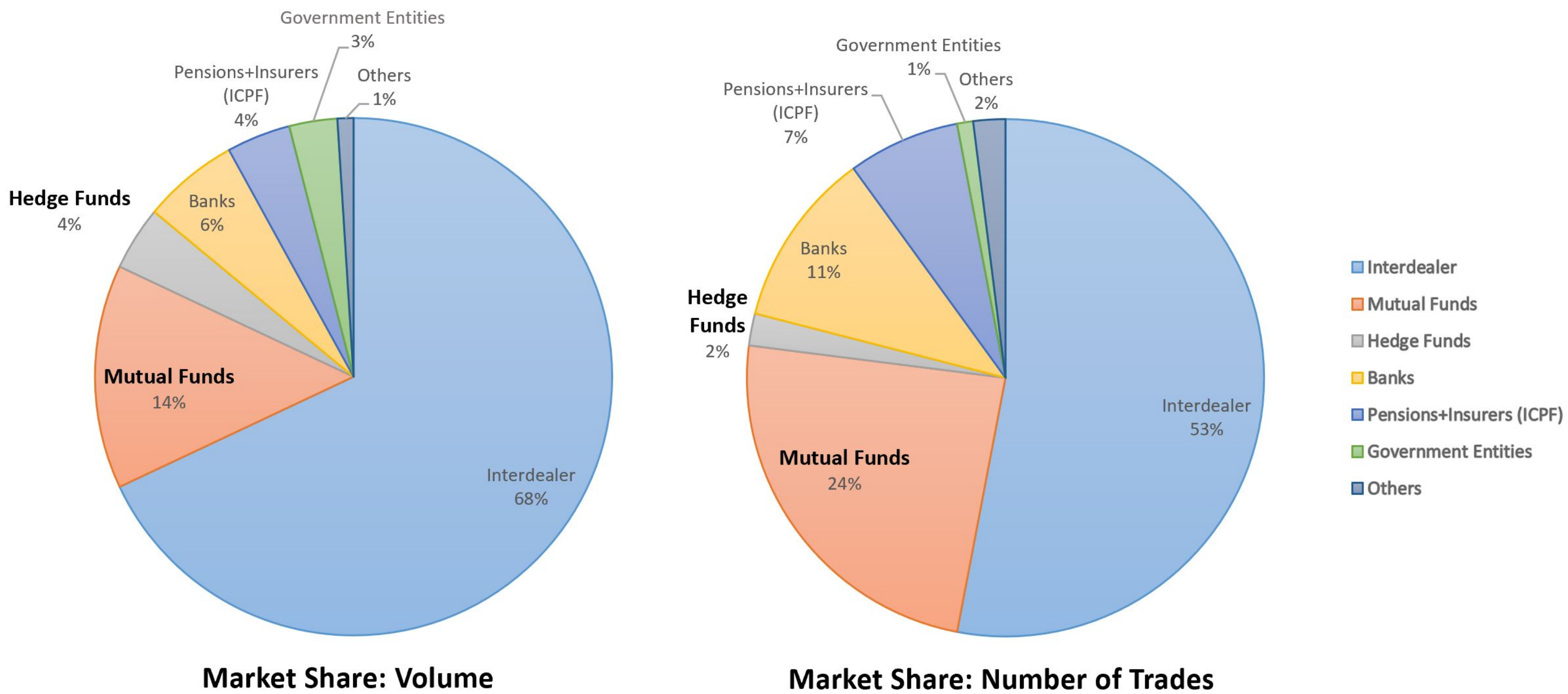


Figure 1: UK Government Bond Market Shares by Investor Type

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.

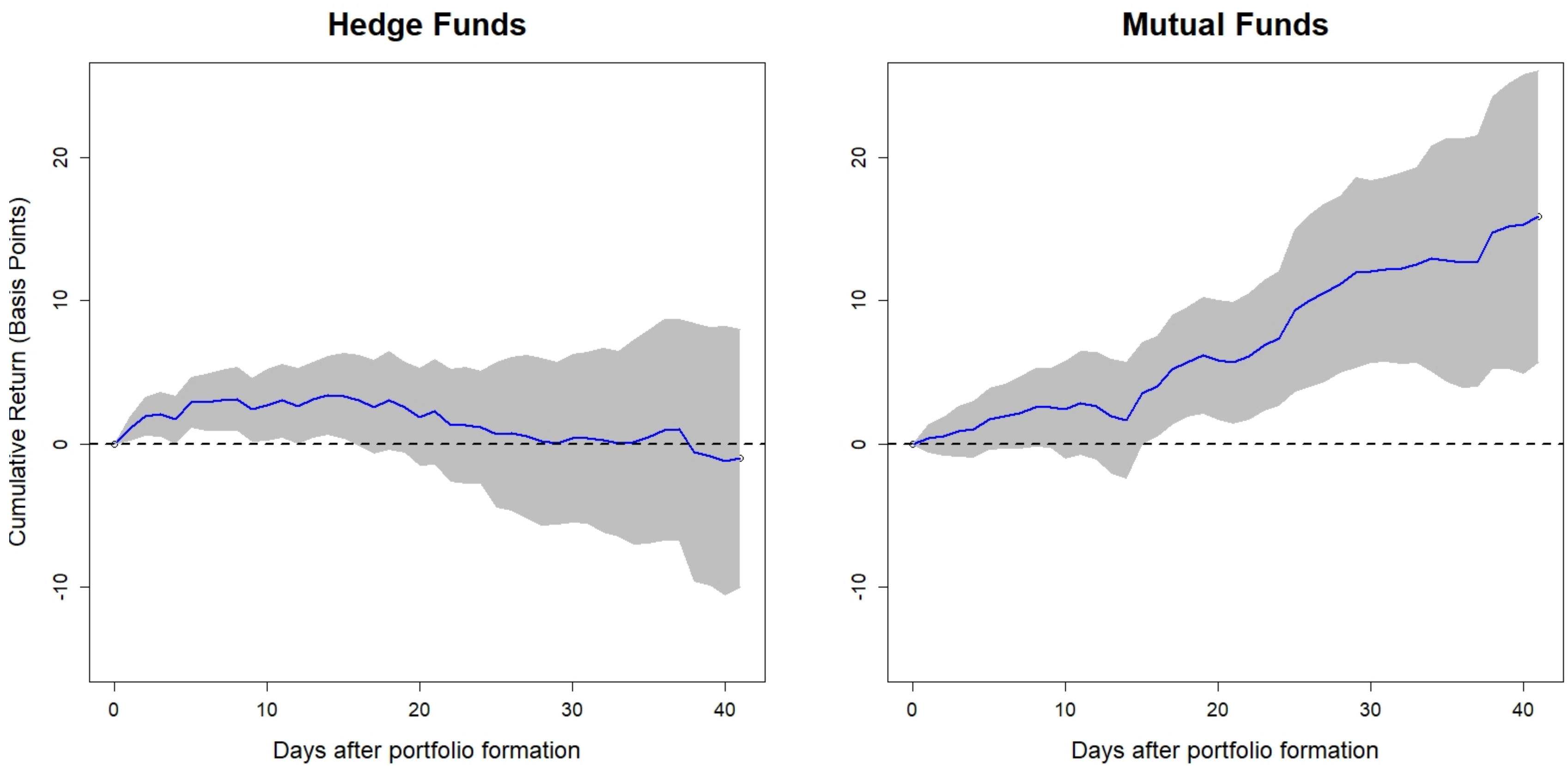


Figure 2: Event-Time Long-Short Portfolio Returns – Sorted by Daily Order Flows

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

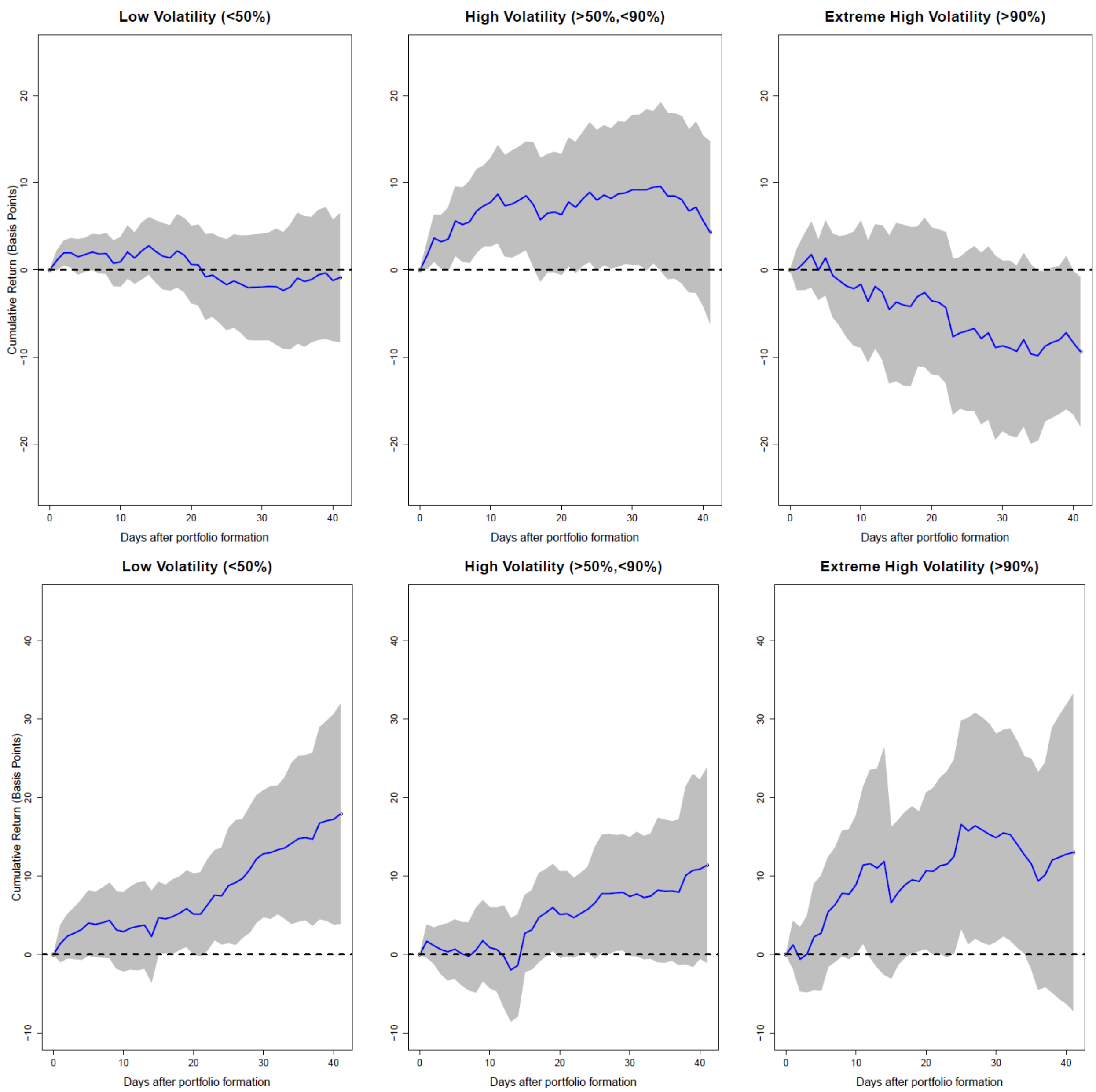


Figure 3: Subsample Analysis of Event-Time Long-Short Portfolio Returns
This figure shows subsample analyses of event-time returns to the long-short portfolio sorted by daily order flows of hedge funds (top panel) and mutual funds (bottom panel). We divide our sample into three subperiods—periods with low, high, and ultra-high market volatility, with cutoffs at the 50th and 90th percentiles of the time-series distribution. Our proxy for market volatility is the forward-looking VFTSE index (the counterpart of the VIX index in the UK market), which is constructed from FTSE 100 options. We normalize the volatility level by the average VFTSE index levels in the past three months.

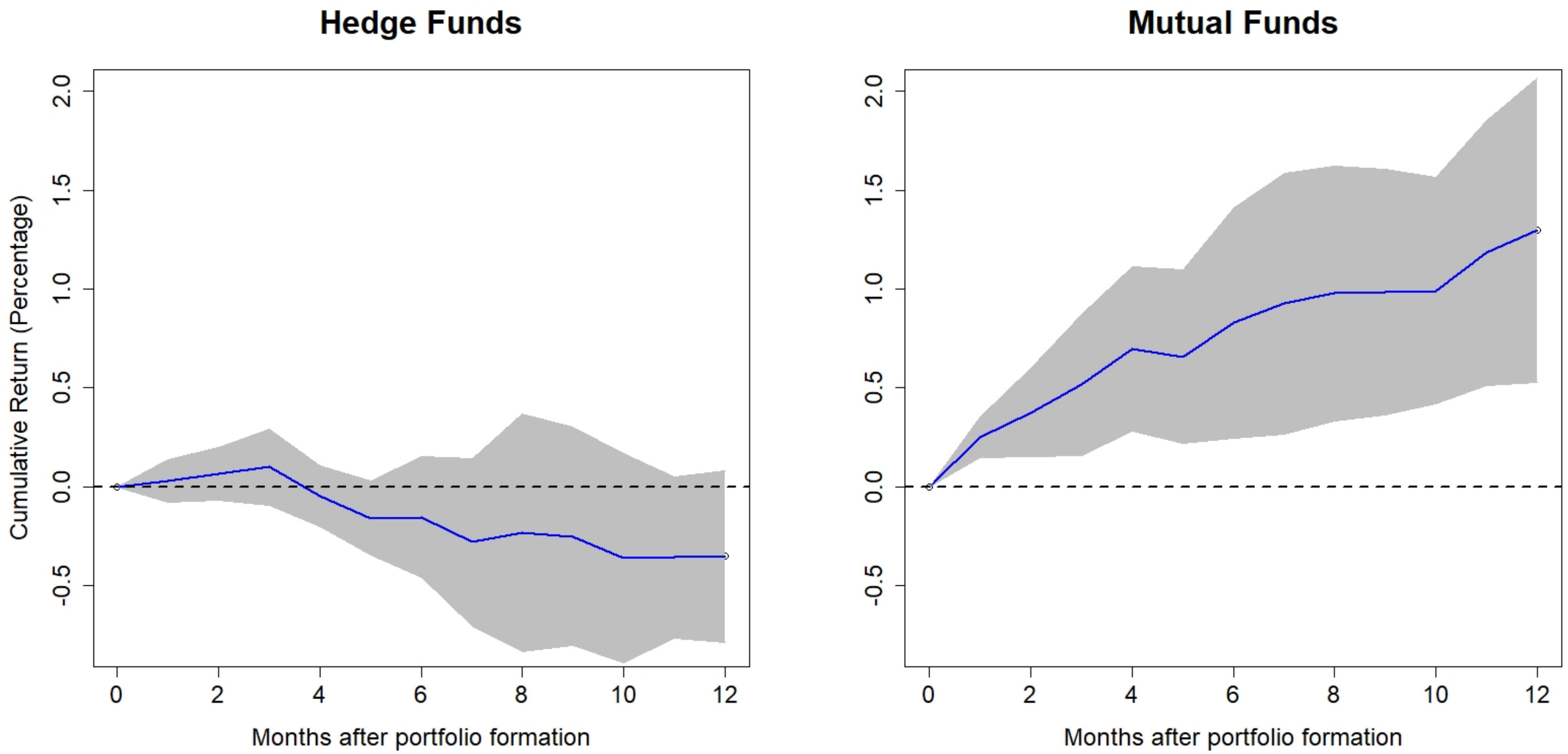
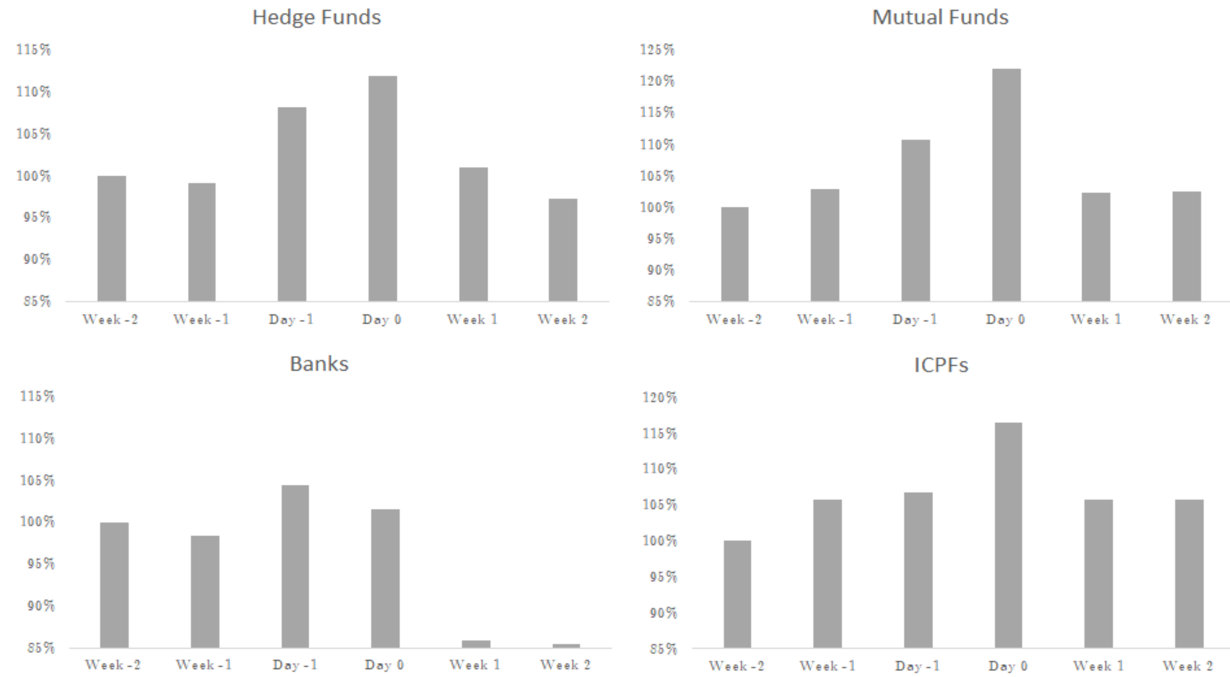
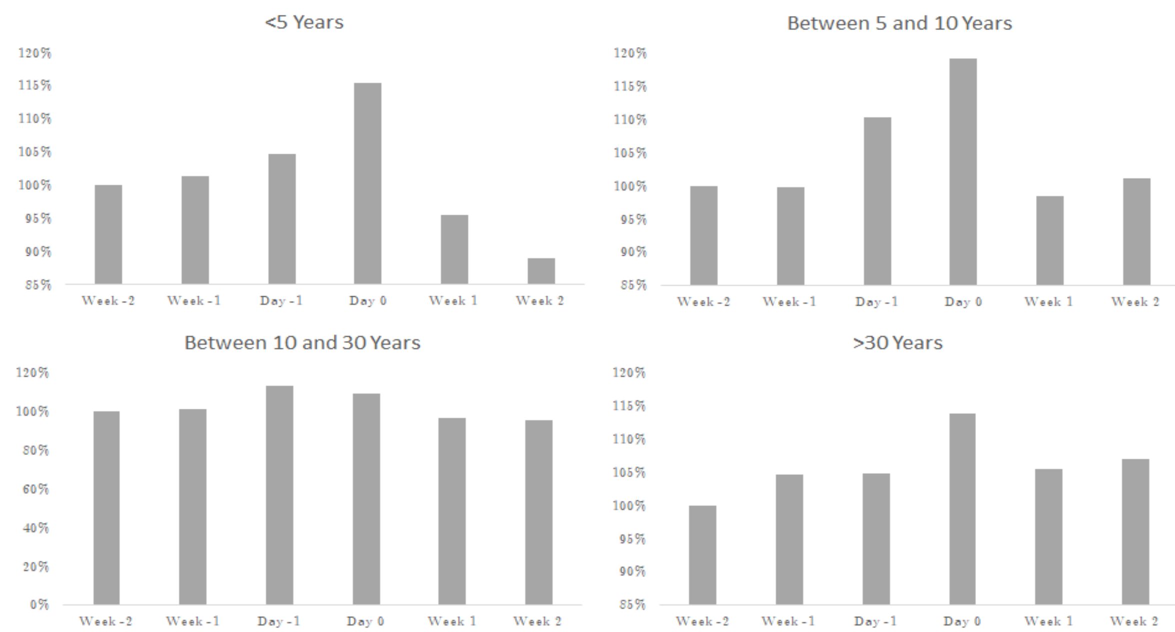


Figure 4: Event-Time Long-Short Portfolio Returns – Sorted by Monthly Order Flows
This figure shows event-time returns to the long-short portfolio sorted by monthly order flows of hedge funds and mutual funds. In each month, we sort all gilts into five groups based on hedge fund/mutual fund order flows 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-bootstrapped standard errors.



Panel A: Trading Volume of Different Investor Types



Panel B: Trading Volumes of Bonds with Different Maturities

Figure 5: Daily Trading Volumes around Macroeconomic Announcements
This figure shows the dynamics of daily trading volumes of different investor types (top panel) and of bonds with different maturities (bottom panel) around macroeconomic-news announcements. Day 0 corresponds to the announcement day. Weeks -2, -1, 1, and 2 are the two calendar weeks before and the two calendar weeks after the announcement day. For ease of interpretation, we normalize daily trading volume in each period by the average daily trading volume in week -2 (i.e., daily volume in week -2 is normalized to 1).