Do Mutual Funds Trade on Earnings News? The Information Content of Large Trades

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Abstract

Using monthly holdings data, we examine how mutual funds trade around earnings announcements. Our results show that mutual funds generally trade in the same direction as earnings surprises. Nevertheless, we find that a majority of mutual fund trades do not have predictive power of future earnings, whereas the top tercile of large trades by mutual funds contain information about future earnings. We show that the information content of these large mutual fund trades is partially attributed to but not fully subsumed by analyst activities. Moreover, our results show that large trades by mutual funds not only have a significantly positive effect on immediate market reactions to earnings news but also help incorporate information in future earnings into stock prices. Finally, we show evidence that mutual funds placing large trades on future earnings news are skilled and deliver significantly higher returns over the subsequent four quarters.

Keywords: Earnings announcements; Mutual fund trading; Large trades; Earnings response coefficients; Fund performance.

JEL Classification: G23; G14; M41

I. Introduction

The literature shows evidence that mutual fund managers are skilled in picking stocks. That is, managers of active mutual funds have the ability to pick stocks that outperform their benchmarks.[1] However, as noted in Baker, Litov, Wachter and Wurgler (2010), the literature is less clear on the sources of abnormal returns of mutual fund trades, whether they are due to fund managers' ability of trading on information about firm fundamentals such as earnings information and accruals, or other proprietary signals such as technical analysis.

So far, the literature presents mixed evidence on whether or not mutual funds possess and trade on information related to firm fundamentals. For instance, Baker, Litov, Wachter and Wurgler (2010) show evidence that recent buys of mutual funds on average significantly outperform recent sells over the next quarterly earnings announcement window. They interpret the results as evidence that mutual fund managers are able to trade profitably in part because they are able to forecast earnings-related fundamentals. On the other hand, Ali, Chen, Yao and Yu (2008) find that actively managed equity mutual funds on aggregate do not trade on the accruals anomaly, but the funds which trade on accruals show better performance. Akbas, Armstrong, Sorescu and Subrahmanyam (2015) find that mutual fund trades exacerbate well-known stock return anomalies. Aggregate flows to mutual funds appear to exacerbate cross-sectional mispricing, whereas hedge fund flows appear to attenuate aggregate mispricing. Using quarterly data on institutional holdings and mutual fund holdings, Edelen, Ince and Kadlec (2016) examine how institutions and mutual funds trade on a number of stock return anomalies related to firm

[1] For literature that shows evidence of stock-picking skill for mutual funds, please refer to Grinblatt and Titman (1993), Daniel, Grinblatt, Titman, and Wermers (1997), Chen, Jegadeesh, and Wermers (2000), Wermers (2000), and Kacperczyk, Sialm, and Zheng (2008). In particular, Wermers (2000) finds that actively managed mutual funds hold stocks that outperform the market index by 130 bps per year, of which 71 bps is due to talent in picking stocks that beat their benchmark portfolios.

fundamentals. They find that not only do institutional investors and mutual funds fail to tilt their portfolios to take advantage of anomalies, overall they trade contrary to anomalies and purchase overvalued stocks before well-known anomalies.

In this paper, we use monthly holdings data of mutual funds and examine whether mutual funds trade on earnings news. Due to data availability, existing studies have mostly relied on quarterly holdings data to examine mutual fund trades. Since there are earnings announcements every quarter for almost all firms, the quarterly data cannot distinguish time periods with earnings announcements and those without. More importantly, the quarterly data do not include information on intra-quarter trades. As shown in Kacperczyk, Sialm, and Zheng (2008), unobserved actions by some mutual funds from quarterly holdings data, namely intra-quarter trades, create values and overall have predictive power of future fund performance. Compared to quarterly holdings data used in previous studies, the main advantage of using monthly holdings data is that we can identify the month when the earnings announcement occurs for a given firm and examine how exactly mutual funds trade prior to, during and following the month of earnings announcements, with a focus on whether mutual funds trades contain information about future earnings.

The main research questions of our study are as follows. First, how do mutual funds trade around earnings announcements and, more importantly, do mutual fund trades contain information of future earnings? Second, does mutual fund trading improve market response to earnings news and help stock price discovery by incorporating information in future earnings into stock prices? Finally, do funds trading on future earnings news have superior skills and deliver higher returns than other funds? The main data used in our analysis is obtained from Morningstar with information on monthly holdings of mutual funds. The data is free of survivorship bias and covers the period from January 1998 to March 2015. Our results show that mutual funds tend to trade more during earnings announcement month than during other months, and typically with larger trade size. More importantly, consistent with Baker, Litov, Wachter and Wurgler (2010), our results show that mutual funds generally trade in the same direction as earnings news. We use both earnings surprise based on analyst earnings forecasts and abnormal returns during earnings announcement window as a proxy of earnings information. Our results show that there is an overall positive relation between earnings news and mutual fund demand, not only during and following earnings announcements but also prior to earnings announcements. Using the change of the number of mutual fund owners as an alternative measure of mutual fund demand, we find similar patterns.

A more important question is: do trades by mutual funds contain information about future earnings? Our results show that once we control for past earnings information and lagged stock returns, all mutual fund trades are not predictive of future earnings information. As documented in Edelen (1999), liquidity-motivated trading by mutual funds are not driven by information and deliver negative abnormal returns. Moreover, as documented in Wermers (1999) and Lou (2012), mutual funds tend to trade proportionally on positions in the existing portfolio. Motivated by these studies, we distinguish large trades versus small trades by mutual funds in our empirical analysis. We define trades by mutual funds as large if the size of the trade, after adjusting for fund flows, is ranked in the top tercile of all trades on a stock during a month. Such trades are discretionary active trades by fund managers instead of passive trades facilitating net fund flows. Our results show that these large trades by mutual funds have significant predictive power of future earnings. We show that the predictive power of large trades on future earnings remains significant even after we control for lagged earnings information, past stock returns, as well as various firm characteristics. Lan, Moneta and Wermers (2015) show that mutual funds with different investment horizons use different news related to firm fundamentals in their trading. Specifically, they show that mutual funds with long investment horizons have ability to obtain and process long-term firm fundamentals and earn superior long-term abnormal returns, whereas short-horizon funds buy stocks with better short-term cash flow news. We divide mutual funds in our sample into high turnover funds and low turnover funds. Our results show that the predictive power of large mutual fund trades for future earnings information is mainly driven by high turnover funds.

In addition, as documented in Brown, Wei and Wermers (2014), analyst revisions have strong influence on mutual fund herding, especially for downgrades. The literature shows that analyst tends to issue revisions of earnings forecasts prior to and in response to earnings announcements (Zhang, 2008). Ayers, Li, and Yeung (2011) find that analyst-based earnings surprises after earnings announcements affect large traders' post-announcement trading. We further control for the role of analysts in information production, proxied by analyst coverage, the number of revisions, and average revision of earnings forecasts. Our results show that the predictive power of large mutual fund trades on future earnings is partly attributed to but not fully subsumed by analyst activities.

Furthermore, we show that large trades by mutual funds have a significantly positive effect on immediate market reactions to earnings surprises, as measured by earnings response coefficients (ERC). Stocks with more large trades by mutual funds experience significantly stronger immediate market reaction to earnings surprises, evidence that unexpected information in earnings announcement is incorporated more quickly into stock prices. Moreover, as documented in Bernard and Thomas (1990), investors underreact to earnings news and stock prices do not fully reflect the implications of current earnings for future earnings. They show that there is a significantly positive serial correlation between current earnings announcement returns and future earnings announcement returns up to the next four quarters. We examine whether large trades by mutual funds help stock price discovery by incorporating information in future earnings into current stock prices. Our results show that for stocks with more large trades by mutual funds, there is a weaker serial correlation between current earnings announcement returns and future earnings announcement returns over the next four quarters. We interpret the findings as evidence that large trades by mutual funds not only have a significantly positive effect on immediate market reactions to earnings news but also help incorporate future earnings information into current stock prices.

Finally, we examine whether mutual funds that trade on future earnings information have superior skills and deliver significantly higher returns. We compute the covariance between a fund's demand of a stock prior to earnings announcements and earnings surprises of subsequent earnings announcements. The covariance measures the extent to which trades by a fund are related to future earnings news. We examine the association between the covariance measure and future fund performance. Again, to focus on those funds placing large trades in the same direction of future earnings, we compute the covariance measures separately based on all trades by mutual funds and only large trades by mutual funds. Our results show that when we sort funds based on the covariance calculated from all trades, there is no significant differences in future fund performance. However, when we sort funds based on the covariance calculated from only large trades, there is a significant association with future fund performance, as measured by both gross and net fund returns. Those funds that place large trades on earnings news are skilled and deliver significantly higher returns up to next four quarters.

The rest of the paper is structured as follows. Section II describes the data used in our study. Section III presents main empirical findings, with further analysis in Section IV. Section V concludes.

II. Data and Methodology

The monthly holdings data of mutual funds is obtained from Morningstar and is free of survivorship bias, i.e., once a fund enters the database it remains in the database until it ceases to exist. The data has been used in studies by Elton, Gruber, Blake, Krasny and Ozelge (2010), Elton, Gruber and Blake (2011, 2012)[2]. Compared to the quarterly holdings from Thompson Reuters, the Morningstar holdings data are much more complete. In fact, until 2008 Morningstar was the source for the CRSP data. As shown in Elton, Gruber and Blake (2012), the distribution of objectives of funds is almost identical between the Morningstar sample and the sample of CRSP funds. That is, they do not find difference between funds that voluntarily provide monthly holdings data and those that do not. Following Elton, Gruber, Blake, Krasny and Ozelge (2010) and Elton, Gruber and Blake (2012), we restrict our sample to active U.S. domestic equity funds. Following the literature (e.g., Kacperczyk, Sialm, and Zheng, 2008), we exclude funds equity holdings out of total portfolio value less than 80% or more than 105% This way, balanced funds and funds with leverage positions are excluded from our sample. We manually check and eliminate index funds and specialty funds. Funds with fewer than 10 stock holdings or less than eight monthly holdings data in a year are excluded. To mitigate potential incubation or back-

[2] Elton, Gruber, Blake, Krasny and Ozelge (2010) use monthly holdings data to examine several well-known hypotheses of mutual fund behavior, such as momentum trading, tax-motivated trading, window dressing, and tournament behavior and find different results based on quarterly holdings data. Elton, Gruber and Blake (2011) show that ranking funds based on alpha computed from monthly holdings data leads to better ex post alphas than ranking based on alpha computed from quarterly holdings. Elton, Gruber and Blake (2012) also find that using quarterly data misses 18.5% of the round-trip trades made by the average fund manager relative to monthly data.

filling bias (Elton, Gruber, and Blake, 2001; and Evans, 2010), we also exclude funds with TNA less than $5 million. The original sample contains an average of 1,292 funds per month. Our final sample include 130,089 fund-month observations with 1,872 unique funds and an average of 687 funds per month. The sample period is from January 1998 to March 2015.[3]

Table I reports summary statistics of fund characteristics of our mutual fund sample. Fund characteristics include total net assets (TNA), age, expense ratio, turnover, cash holding and the number of stocks in the portfolio. Fund age is defined as the time (years) a fund is in the CRSP Survivor-Bias-Free US Mutual Fund Database. Fund TNA, expense ratio, turnover and cash holdings are also obtained from the CRSP database. Both fund TNA and expense ratio are reported at the fund-class level. The number of stocks in the portfolio is calculated as the total number of stocks in the portfolio each month. Each month, we compute the cross-sectional mean and median of each variable and the table reports the time series averages of these statistics. The mean of fund TNA is higher than the median, suggesting that fund size is highly skewed to the right. The average fund age is about 13 years. The average number of stocks held in a mutual fund portfolio is 134 and the median is 74.

Our stock sample includes common stocks traded on NYSE, AMEX, or NASDAQ. The key variable used in our analysis is analyst forecast error (FE). Following Livnat and Mendenhall (2006), we compute analyst forecast error (FE) as follows:

$$FE_{i,t} = \frac{(X_{i,t} - \widetilde{X}_{i,t})}{P_{i,t}} \tag{1}$$

where $X_{i,t}$ is primary earnings per share before extraordinary items for firm i in quarter t and $P_{i,t}$ is the price per share for firm i at the end of quarter t from Compustat. Both $X_{i,t}$ and $P_{i,t}$ are

[3] As noted in Elton, Gruber and Blake (2011), the Morningstar data include monthly holdings observations for only a very small number of funds before 1998.

unadjusted for stock splits and $\widetilde{X}_{i,t}$ is the median of forecasts reported to I/B/E/S in the 90 days prior to the earnings announcement. The total number of firm-quarter FE observations from I/B/E/S is 241,978 with 10,683 unique number of stock during our sample period from January 1998 to March 2015. After merging with common stocks (SHRCD = 10 or 11) traded on NYSE, AMEX, or NASDAQ (EXCHED = 1, 2, or 3) in the CRSP stock database, we have 188,477 observations with 8,684 unique number of stocks. We exclude stocks with price less than one dollar at the beginning of the quarter, and the final sample has 199,042 FE observations with 9,220 unique number of stocks.

Stock returns and firm characteristics are obtained from CRSP monthly data, Compustat database, and I/B/E/S database. Following Fama and French (1993), the market capitalization (SIZE) is calculated and updated at the end of each June as the stock price times the number of shares outstanding. The book-to-market ratio (B/M) is also calculated and updated at the end of each June using book value for the fiscal year ending in calendar year t-1 divided by market capitalization at the end of December of year t-1. The book value is equal to the book value of stockholders' equity plus balance sheet deferred taxes and investment tax credits minus the book value of preferred stocks, as defined in Fama and French (1993). The Amihud (2002) illiquidity (ILLIQ) is calculated as the ratio of absolute daily return to dollar trading volume and averaged over the quarter. Since the trading volume on NASDAQ is double-counted (Atkins and Dyl, 1997; Nagel, 2005), we adjust the turnover of NASDAQ stocks by a factor of 1/2. Following Ang, Hodrick, Xing, and Zhang (2006), idiosyncratic volatility (IVOL) is estimated under the Fama-French three-factor model:

$$r_{i,t} = \alpha_i + \beta_{i,MKT} MKT_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \varepsilon_{i,t} \tag{2}$$

The model is estimated using daily returns in a quarter and idiosyncratic volatility ($IVOL_t$) is obtained as $\sqrt{\text{var}(\varepsilon_{i,t})}$. Number of mutual fund is total number of mutual fund investors hold the stock each month. Leverage (LEV) is calculated as total assets divided by book equity. Analyst coverage (COV) is the number of analysts covering the firm based on data from I/B/E/S.

For each stock, we also calculate mutual fund ownership (MFO) as the number of shares held by mutual funds in our sample in month *t* divided by total number of shares outstanding, that is,

$$MFO_t = \frac{(\#\text{ of shares held by mutula funds})_t}{(\text{total }\#\text{ of shares outstanding})_t} \tag{3}$$

The change of mutual fund ownership is calculated as the difference in mutual fund ownership from previous month.

$$\Delta MFO_t = MFO_t - MFO_{t-1} \tag{4}$$

In addition, we also calculate the number of mutual fund owners (#MF) for all stocks each month. For convenience, we often refer to the change of ownership of a fund in a stock during a month as a trade in our subsequent discussions.

Table II reports summary statistics of FE and other firm characteristics. Each quarter, we compute the cross-sectional summary statistics (5%, 25%, mean, median, 75%, 95%, and StDev) of FE and firm characteristics. This table reports the time series average of the summary statistics. Table 2 shows that there are on average 2,614 stocks per quarter during our sample period. The mean and median of forecast error are very close to 0, indicating that on average analysts' consensus forecasts are close to actual earnings per share. The average market cap is $49.677 million. The average mutual fund ownership is 4.58% and the median is 3.75%. The average number of mutual fund owners is 31 and the median is 22.

III. Empirical Analysis

A. Mutual Fund Trading Around Earnings Announcements

The first question of our research is: do mutual funds trade on earnings news and, more importantly, do mutual fund trades contain information about future earnings? The literature so far presents mixed evidence that mutual funds trade on information related to firm fundamentals, such as earnings information, accruals, etc. Using quarterly holdings data of mutual funds, Baker, Litov, Wachter and Wurgler (2010) show evidence that recent buys of mutual funds on average significantly outperform recent sells by about 10 basis points (bp) over the 3-day window around the next quarterly earnings announcement. This gap reflects skill in both buying and selling: stocks bought by the average fund earn significantly higher subsequent announcement return than matching stocks, while stocks sold earn lower returns than matching stocks. Baker, Litov, Wachter and Wurgler (2010) interpret the results as evidence that mutual fund managers are able to trade profitably in part because they are able to forecast earnings-related fundamentals. In a related paper, Cai and Lau (2015) construct a measure of mutual fund manager skill based on performance of mutual fund trades during subsequent earnings announcement windows and show that this skill measure indeed predicts future mutual fund returns. Nallareddy and Ogneva (2017) show that overall mutual fund managers appear to avoid stocks with deteriorating fundamentals. In addition, mutual funds that hold stocks with lower average accrual quality earn significantly higher returns. On the other hand, several studies fail to find supporting evidence that mutual funds trade on firm fundamentals. Ali, Chen, Yao and Yu (2008) find that actively managed equity mutual funds on aggregate do not trade on the accruals anomaly, but the funds which trade on accruals show better performance. Akbas, Armstrong, Sorescu and Subrahmanyam (2015) find that mutual fund trades exacerbate well-known stock return anomalies. Specifically, aggregate flows to mutual funds appear to exacerbate cross-sectional mispricing, particularly for growth, accrual, and momentum anomalies, whereas hedge fund flows appear to attenuate aggregate mispricing. Using quarterly data on institutional holdings and mutual fund holdings, Edelen, Ince and Kadlec (2016) examine how institutions and mutual funds trade on stock return anomalies, such as net operating assets, gross profitability, investment to assets, etc. They find that not only do institutional investors and mutual funds fail to tilt their portfolios to take advantage of anomalies, overall they trade contrary to anomaly prescriptions and purchase overvalued stocks before well-known anomalies.[4]

To address the first part of the question, we identify months with earnings announcements versus those without earnings announcements for each stock in our sample. A month is classified as earnings announcement (EA) month for a firm if there is an earnings announcement during the month. We use two proxies to measure earnings information in our analysis, one is analyst forecast error defined in Section II and the other is cumulative abnormal return over the three-day announcement window (CAR[-1, 1]) centered at the earnings

[4] The literature also presents mixed evidence on whether or not institutional investors in general trade on earnings news and other accounting information. Ali, Durtschi, Lev and Trombley (2004) find evidence of institutions trading on information about future earnings. They document an association between changes in institutional ownership during a calendar quarter and abnormal returns at the time of subsequent announcements of quarterly earnings. However, the result is driven by the portfolio returns of the extreme deciles of changes in institutional ownership. Bushee and Goodman (2007) find a positive relation between overall institutional demand and future earnings announcement returns. Based on daily institutional trading, Campbell, Ramadorai and Schwartz (2009) and Hendershott, Livdan and Schurhoff (2015) find that institutional trading predicts earnings surprises and other news. Nevertheless, Ali, Hwang and Trombley (2000) argue that sophisticated investors, such as institutional investors, fail to profit from the negative relation between the accrual component of earnings and future annual stock returns. Lewellen (2010) find that institutional investors do not seem to bet on accruals and other main stock return predictive characteristics.

announcement date. For this reason, we also exclude earnings announcements on the first trading of a month as a robustness check and confirm that our results are consistent.

To examine whether mutual funds trade more on earnings announcement months, we calculate the mean and median of the absolute value of change of mutual fund ownership (|ΔMFO|) and mutual fund trade size for each firm during EA months and non-EA months, respectively. Mutual fund trade sizes are measured by both the absolute value of the change of ownership by individual funds and dollar amount of the trade by individual funds. The dollar amount of mutual fund trade is calculated as the number of shares traded by a fund times the stock price at the end of the month. For each firm, we calculate the mean and median of the absolute values of these three variables for EA month and no-EA month separately.

Table III reports the cross-sectional mean and median for EA month and no-EA month as well as their differences. The results in Table III show that there is significant higher change in MF ownership during EA month than other months. This is evidence that there is more active trading by mutual funds during months where firms announce earnings than during other months. In addition, the average trading size by mutual funds is significantly higher during EA month than other months.

To answer the question of how mutual funds trade on earnings news, we perform the following analysis. Each quarter, stocks are assigned to FE quintiles using the breakpoints of previous quarter. For each firm, we then identify the earnings announcement month (EAM). We calculate the mean and median of mutual fund demand (ΔMFO). The time horizons include the month prior to earnings announcement (EAM[-1]), the two-month period including the month prior to and the month of earnings announcement (EAM [-1, 0]), and the two-month period following the earnings announcement (EAM[1, 2]). We calculate time series averages of the mean and median and their difference of these variables. As noted earlier, we also use the cumulative abnormal returns during the three-day announcement window (CAR[-1, 1]) as a proxy of earnings information and perform similar analyses.

Table IV reports the mean and median of mutual fund demand (ΔMFO) for all quintiles sorted on FE in Panel A and CAR[-1, 1] in Panel B. The results in both panels show that while the relation between mutual fund demand and earnings news does not appear to be linear, as expected the average mutual fund demand for stocks in Q5 is significantly higher than for those in Q1 during the two-month period including the month prior to and the month of earnings announcement (EAM [-1, 0]) as well as the two-month period following the earnings announcement (EAM[1, 2]). More importantly, the differences in mutual fund demand between Q5 and Q1 are also significantly positive during the month prior to earnings announcement (EAM[-1]). This finding is consistent with evidence presented in Baker, Litov, Wachter and Wurgler (2010) that mutual fund managers trade in the same direction as future earnings news. The significant differences in media in both panels suggest that mutual funds trade in the same direction as earnings surprises for more than half of the stocks in the top and bottom deciles. Overall, the results in Table IV show that mutual funds not only trade on contemporaneous and lagged earnings news, but also trade in the same direction of future earnings information.

Table V reports the mean and median of the change in the number of mutual fund owners (Δ#MF) for all quintiles sorted on FE in Panel A and CAR[-1, 1] in Panel B. The change in the number of mutual fund owners (Δ#MF) is used as an alternative measure of mutual fund demand. Since the number of mutual funds in our sample increases over time as more mutual funds enter the database, the change in the number of mutual fund owners might be upward biased. To mitigate the bias, we exclude those mutual funds that enter the database the first time when we calculate the change of the number of mutual fund owners for stocks. The patterns in Table V are consistent with those in Table IV. Both the mean and median change in the number of mutual fund owners for stocks in Q5 are significantly higher than for those in Q1. The differences are significant over all time horizons, including the month prior to earnings announcement (EAM[-1]). Compared to the results in Panel A based on FE quintiles, the results based on CAR[-1, 1] quintiles in Panel B show a more monatomic relation between the change in the number of mutual fund owners and earnings news, even during the month prior to earnings announcement (EAM[-1]).

B. Mutual Fund Trading and Future Earnings Information

The results in the previous subsection show that mutual funds trade generally in the same direction of earnings surprises, including future earnings surprises. However, as we noted the relation between mutual fund demand and earnings news does not appear to be linear, suggesting that mutual fund demand is determined by variables beyond earnings surprises. In this section, we examine the relation between mutual fund demand and future earnings in a multivariate framework by controlling for the effect of past firm performance and various firm characteristics. The literature shows that mutual fund demand may be driven by past firm performance and subject to the constraints of investment objectives.

Each quarter, we perform Fama-MacBeth regressions of the rank of analyst forecast error (FE) during the month of earnings announcement (EAM0) on the mutual fund demand in the previous month ($\Delta MFO_{t\text{-}1m}$) and various control variables. Specifically, we perform the following quarterly regressions:

$$FE_{i,t} = \alpha_t + \beta_{1t} \Delta MFO_{i,t-1m} + \sum_{k=1}^{K} \gamma_{kt} X_{ki,t} + \varepsilon_{i,t+T} \tag{5}$$

where $FE_{i,t}$ denotes the rank of analyst forecast error from zero to one with an increment of 0.1, ΔMFO_{t-1m} denotes the demand of mutual fund over the previous month. Control variables include lagged analyst forecast error (FE_{Qt-1}), market capitalization (SIZE), book to market ratio (B/M), idiosyncratic volatility (IVOL), the Amihud illiquidity ratio (ILLIQ), leverage (LEV), and lagged returns ($LRET_{[t-1m,t]}$, $LRET_{[t-6m,t-1m]}$, $LRET_{[t-12m,t-6m]}$). Lagged analyst forecast error (FE_{Qt-1}) is included to control for past earnings news, and lagged returns are included to control for past stock performance.

Table VI reports time series average of coefficient estimates of quarterly regressions and their Newey-West t-statistics. The results based on the univariate regression (model (1)) are consistent with the sorting results and show a significantly positive relation between mutual fund demand and future earnings surprises. However, once the lagged earnings surprises are included, the relation becomes weaker although remains significant. This is evidence that part of the mutual fund trading is driven by past firm performance, consistent with results in Tables IV and V. We further include lagged stock returns and various firm characteristics (models (3) and (4)). Once the lagged stock returns are included as control variables in the regressions, the coefficient of ΔMFO_{t-1m} is no longer significant. We interpret this as evidence that mutual fund demand is largely driven by past firm performance and stock returns. After controlling for past firm performance and stock returns, all mutual fund trades do not contain information of future earnings.

Motivated by arguments in Edelen (1999) that liquidity-motivated trading by mutual funds deliver negative abnormal returns. In addition, as documented in Wermers (1999) and Lou (2012), mutual funds tend to trade net fund flows proportionally on positions in the existing portfolio. In our analysis, we distinguish large trades versus small trades by mutual funds in our analysis. First, we calculate the dollar amount fund flow for each fund during a month:

$$FLOW_t^j = TNA_t^j - TNA_{t-1}^j \left(1 + r_t^j\right) \qquad (6)$$

where TNA_t^j denotes total net asset of fund j at the end of month t, and $r_{i,t}$ denotes return of fund j during month t. For each fund, we then construct the following flow adjusted trade in a given stock:

$$AdjTrade_{i,t}^j = Trade_{i,t}^j - FLOW_t^j / N \qquad (7)$$

where $Trade_{i,t}^j$ denotes fund j's trade on stock i in month t, calculated as the number of shares traded by fund j on stock i times stock i's price at the end of the month, $FLOW_t^j$ denotes the dollar amount net flow of fund j in month t, and N is the number of stocks held in fund j's portfolio. The implicit assumption of the flow adjustment is that fund trades equally on all stocks to facilitate the demand of flow flows. For example, when net fund flow is positive, the fund purchases all stock with equally amount. The adjusted trade size is a proxy of abnormal trade on a given stock. We confirm that the results are consistent when we perform our analysis based on unadjusted mutual fund trades.

Given the above adjusted trade size, we classify a trade by mutual funds on a stock as large if it is in the top tercile of all trades ranked by trade size in a given month, and small otherwise. The large trades are not passive trades by mutual funds to facilitate net fund flows but active trades at the discretion of fund managers. Based on the classification, we calculate mutual fund demand of large trades and small trades separately, denoted by $\Delta MFO(L)_{t-1m}$ and $\Delta MFO(S)_{t-1m}$. We replicate the regressions by regressing the decile rank of analyst forecast error

(FE) during the month of earnings announcement (EAM0) on both large trade demand and small trade demand of mutual funds in the previous month and various control variables, i.e.:

$$FE_{i,t} = \alpha_t + \beta_{1t}\Delta MFO(L)_{i,t-1m} + \beta_{2t}\Delta MFO(S)_{i,t-1m} + \sum_{k=1}^{K}\gamma_{kt}X_{ki,t} + \varepsilon_{i,t+T} \quad (8)$$

where ΔMFO(L) is the demand of mutual funds with large trades and ΔMFO(S) is the demand of mutual funds with small trades. Control variables are the same as in Eq. (5).

The results of the above regressions are reported in the right panel of Table VI. The results show that when the past earnings information is controlled for, mutual fund demand of large trades has significant predictive power of future earnings news, whereas mutual fund demand of small trades has no predictive power of future earnings news. The results remain consistent even after we control for past stock returns and various firm characteristics. The results suggest that while the small trades driven by fund flows are unlikely related to information as shown in Edelen (1999), the large trades by mutual fund are informative of future earnings.

Lan, Moneta and Wermers (2015) document that mutual fund trading strategies are related to investment horizons. They find that mutual funds with long investment horizons have ability to obtain and process long-term firm fundamentals and earn superior long-term abnormal returns, whereas short-horizon funds buy stocks with better short-term cash flow news.[5]

[5] Similar patterns are documented for institutional investors. For instance, Bushee (2001) finds evidence that transient institutions tend to be short-term focused investors and their interest is based on the likelihood of short-term trading profits. On the other hand, non-transient institutions provide long-term and stable ownership to firms because they are geared toward longer-term dividend income or capital appreciation. Ke and Petroni (2004) find that transient institutional investors can anticipate a break in a series of consecutive earnings at least one quarter before the break quarter. Yan and Zhang (2009) find that trading of short-term institutional investors is positively related to future earnings surprises. Hu, Ke and Yu (2017) show evidence that transient institutions correctly interpret small negative earnings surprises in the absence of access to management's private information. However, based on daily

We further separate mutual funds in our sample into high turnover funds and low turnover funds according to the data on fund turnover in the CRSP database. A fund is classified as a high-turnover fund if its turnover is above the median in a quarter and a low-turnover fund otherwise. For all stocks, we then calculate $\Delta MFO(L)_{t-1m}$ and $\Delta MFO(S)_{t-1m}$ separately for high turnover funds and low turnover funds. We replicate the regressions in Eq. (8) for mutual fund demand by high turnover funds and low turnover funds separately. As shown in Table VII, the results we observed from Table VI is mainly driven by the demand of high turnover funds. That is, mutual fund demand in large trades by high turnover funds has significant predictive power of future earnings news, whereas mutual fund demand by low turnover funds, large or small trades, has no predictive power of future earnings news.

IV. Further Analysis

A. Mutual Fund Trading and Future Earnings Information: The Role of Analysts

The results in the previous section show that not all mutual fund trades are predictive of future earnings information. Yet, large trades placed by mutual funds are informative of future earnings. In this section, we perform further analysis and examine the role of analysts in the positive relation between large trades by mutual funds and future earnings news. Ayers, Li, and Yeung (2011) find that analyst-based earnings surprises after earnings announcements affect large traders' post-announcement trading. Brown, Wei and Wermers (2014) show that analyst revisions has strong influence on mutual fund herding, especially for downgrades. They find that

institutional trades Chakrabarty, Moulton, and Trzcinka (2017) find that a majority of short-term institutional trades lose money, evidence inconsistent with institutional investors being informed.

mutual fund tend to buy stocks together after consensus analyst upgrade and sell stocks together after downgrade. Even after control for stock characteristics, this relation still strong. They also find that analyst downgrades have stronger influence on mutual fund herding.

To examine analyst revisions around earnings announcement, for each firm we calculate the average number of analyst revisions and average revision of earnings forecasts during the month prior to earnings announcement (EAM[-1]), the month of earnings announcement (EAM[0]), and the two months following earnings announcement (EAM[1] and EAM[2]). We then calculate the average number of analyst revisions and average revision for all stocks and stocks in each FE decile.

Table VIII reports the time series average of the number of analyst revisions and average revision for all stocks and stocks in each FE decile. The results show that the average number of analyst revisions is the highest during the month of earnings announcement (EAM [0]) for all stocks. As documented in Zhang (2008), analysts tend to issue revisions on future earnings immediately in response to earnings announcements. There are also active revisions during the month prior to earnings announcements. Analysts are relatively quiet during the month after earnings announcements. The results also show that overall analyst revisions of earnings forecasts are negative. During the announcement month, the revisions are highly correlated with earnings surprises, namely more downward revisions for firms issuing negative unexpected earnings. The same pattern is observed during the month prior to earnings announcements. This is evidence that analyst revisions are predictive of future earnings surprises. During the month after earnings announcements, analysts continue to revise earnings forecasts in the same direction of earnings surprises.

To examine the extent to which the positive relation between large trades by mutual funds and future earnings is driven by analyst revisions, we replicate the regressions in Eq. (8) by further including analyst revisions as control variables. That is,

$$FE_{i,t} = \alpha_t + \beta_{1t}\Delta MFO(L)_{i,t-1m} + \beta_{2t}\Delta MFO(S)_{i,t-1m} + \beta_{3t}COV_{i,t-1} + \beta_{4t}\#REV_{i,t} + \beta_{5t}REV_{i,t+1}$$
$$+\sum_{k=1}^{K}\gamma_{kt}X_{ki,t} + \varepsilon_{i,t+T} \qquad (9)$$

where we include three additional control variables related to analyst activities, namely analyst coverage (COV), the number of analyst revisions (#REV), and revision (REV). COV is the number of analysts covering the stock during the previous quarter. #REV is defined as the number of analyst revisions of earnings forecasts for the current quarter during the same period. REV is defined as the average of revisions of the earnings forecasts for the current quarter. We confirm that the results are consistent when we calculate #REV and REV based on analyst earnings forecasts for the current fiscal year.

Table IX reports the results of the regressions in Eq. (9). The results show that all three proxies of analyst activities are significantly related to future earnings surprises. In particular, consistent with the pattern in Table VII, analyst revision of earnings forecasts has a significantly positive relation with future earnings surprises. Nevertheless, even after controlling for analyst activities, there remains a significantly positive relation between larges trades by mutual funds and future earnings news. The results confirm that the predictive power of future earnings by large mutual trades is not subsumed by information produced by analysts, proxied by analyst coverage, the number of revisions, and revision of future earnings.

B. Mutual Fund Trading and Earnings Response Coefficient

In this section, we examine whether mutual fund trading has a significant effect on earnings response coefficient (ERC). If mutual fund managers are sophisticated and skilled, their trades should help to incorporate earnings information into stock prices.

Each quarter, we perform Fama-MacBeth regressions of cumulative abnormal return during the earnings announcement window ($CAR_t[-1,1]$) on decile rank of analyst forecast error (FE), its interaction with a dummy variable of high absolute mutual fund demand ($d^{|\Delta MFO|}$) and various control variables:

$$CAR[-1,1]_{i,t} = \alpha_t + \beta_{1t} FE_{i,t} + \beta_{2t} d^{|\Delta MFO(L)|} \times FE_{i,t} + \beta_{4t} d^{|\Delta MFO(L)|}{}_{i,t} + \sum_{k=1}^{K} \gamma_{kt} X_{ki,t} + \varepsilon_{i,t+T} \qquad (10)$$

where $d^{|\Delta MFO(L)|}$ is equal to 1 if the absolute value of ΔMFO(L) is higher than median value of all stocks in the earnings announcement month and 0 otherwise. The dummy variable $d^{|\Delta MFO(S)|}$ is equal to 1 if the absolute value of ΔMFO(S) is higher than median value of all stocks in the earnings announcement month and 0 otherwise. Mutual fund demand of large trades and small trades (ΔMFO(L) and ΔMFO(S)) is defined same as in Section III.B. Control variables include mutual fund demand (ΔMFO), firm characteristics, namely market capitalization (SIZE), book to market ratio (B/M), the Amihud illiquidity ratio (ILLIQ), idiosyncratic volatility (IVOL), leverage (LEV), analyst coverage (COV), number of analyst revisions (#REV), and a revision dummy (REV) for upgrade, neutral, or downgrade, as well as lagged returns ($LRET_{[t-1m,t]}$, $LRET_{[t-6m,t-1m]}$, $LRET_{[t-12m,t-6m]}$). IN addition, we also include a stock's earnings persistence (AC_{CF}), and earnings uncertainty (σ_{CF}). As shown in Collins and Kothari (1989), these variables are important determinants of ERCs. The systematic risk (Beta) is the coefficient of market return under the Fama-French three-factor model in Eq. (2) estimated from daily returns.

Earnings persistence (AC_{CF}) and earnings uncertainty (σ_{CF}) are the coefficient of the AR(1) term and the standard error of the residuals of the AR(1) model of earnings per share (EPS), namely:

$$EPS_{i,t} = C_i + AC_{CF,\mathrm{i}} EPS_{i,t-1} + \varepsilon_{i,t} \tag{11}$$

The model is estimated over past eight quarters with minimum six observations.

Table X reports time series average of coefficient estimates of quarterly regressions and their Newey-West t-statistics. The results show that the coefficient estimates of the decile rank of analyst forecast error is significantly positive. That is, there is a significant immediate market reaction to earnings news. Consistent with Aboody, Lehavy, and Trueman (2010), earnings announcement returns have a negative relation with lagged returns. More importantly, the coefficient estimates of the interaction term between large trade dummy and analyst forecast error ($d^{|\Delta MFO(L)|}$*FE) are significantly positive in all regressions. In terms of control variables, the coefficients of lagged return ($LRET_{[t-1m,t]}$) and idiosyncratic volatility are significantly negative in all regressions. The coefficients of Amihud illiquidity ratio are significantly positive in all regressions. The coefficients of market cap are negative in all regressions and significant in regression 2. The coefficients of analyst coverage are negative in all regressions and significant in regression 4. This is evidence that large trades by mutual funds have a significantly positive effect on earnings response coefficient and help quickly incorporate earnings information into stock prices.

C. Mutual Fund Trading and Stock Price Discovery

Bernard and Thomas (1990) document that firms reporting unexpected negative earnings subsequently underperform those reporting unexpected positive earnings. They argue that one of the possible explanation of the underreaction is that investors fail to recognize the implications of current earnings for future earnings and as such stock prices do not fully reflect the information of future earnings. As shown in previous sections, large trades by mutual funds contain information about future earnings. Thus, we expect these trades to help incorporate information in future earnings into stock prices. Wermers (1999) argue that mutual fund herding can accelerate the price discovery process of stocks. Ke and Ramalingegowda (2005) show that trading by transient institutional investors following earnings announcements help to incorporate future earnings information into stock prices.

Each quarter, we perform Fama-MacBeth regressions of cumulative abnormal return during the earnings announcement window in quarter t+1 to t+i (CAR[-1, 1] $_{[t+1,\, t+i]}$, i=1, 2, and 4) on cumulative abnormal return during the earnings announcement window in quarter t (CAR $_t$) and its interaction with a large trade dummy variable ($d^{|\Delta MFO(L)|}$),and various control variables:

$$CAR_{i,[t+1,t+i]} = \alpha_t + \beta_{1t} CAR_{i,t} + \beta_{2t} d^{|\Delta MFO(L)|} \times CAR_{i,t} + \beta_{4t} d^{|\Delta MFO(L)|}{}_{i,t} + \sum_{k=1}^{K} \gamma_{kt} X_{ki,t} + \varepsilon_{i,t+T} \quad (12)$$

where $CAR_{i,[t+1,t+i]}$ is cumulative abnormal return during the earnings announcement window in quarter t+1 to t+i, with i = 1, 2 and 4. Control variables include the decile rank of analyst forecast error (FE), mutual fund demand of large trades and small trades (ΔMFO(L) and ΔMFO(S)),market capitalization (SIZE), book to market ratio (B/M), the Amihud illiquidity ratio (ILLIQ), idiosyncratic volatility (IVOL), leverage (LEV), analyst coverage (COV), number of analyst revisions (#REV), average analyst revision (REV), and lagged returns (LRET$_{[t-1m,t]}$, LRET$_{[t-6m,t-1m]}$, LRET$_{[t-12m,t-6m]}$).

Table XI reports time series average of coefficient estimates of quarterly regressions in Eq. (12) and their Newey-West t-statistics. The result show that the coefficient estimates of CAR $_t$ are positive and significant in all regressions. That is, consistent with Bernard and Thomas (1990), cumulative abnormal return during the earnings announcement window in quarter t has a significantly positive relation with future earnings announcement returns, up to the next four quarters. More importantly, the coefficient estimates of the interaction term between large trade dummy variable and earnings announcement return ($d^{|\Delta MFO(L)|}$*CAR_t) are negative and significant in all regressions. The results are robust to controlling for past stock returns, various firm characteristics, as well as proxies of analyst activities.

D. Trading on Earnings News and Fund Performance

Finally, one important question is: are funds that trade on future earnings information skilled? More importantly, do these funds deliver higher returns to investors? To address the questions, we construct the following measure to capture the extent to which a fund's trades are predictive of future earnings information. Specifically, for each fund during a given quarter, we compute the covariance between all trades occurred during the month prior to a firm's earnings announcement and analyst forecast errors of the announcement. That is:

$$COV(\Delta MFO_{i,t}^{j}, FE_{i,t+1}) = \frac{\sum_{i=1}^{N} \Delta MFO_{i,t}^{j} \times FE_{i,t+1}}{N} \tag{13}$$

where $\Delta MFO_{i,t}^{j}$ denotes the demand of stock *i* by fund *j* in month *t*, $FE_{i,t+1}$ denotes the rank of analyst forecast error of stock *i* in moth *t+1* adjusted by its mean, and N denotes the number of stocks traded by mutual fund *j* during months prior to earnings announcement. Since there are no sufficient numbers of earnings announcements during some months, the above measure is computed at quarterly frequency. Each quarter, we then sort funds into quintiles based on the above measure and compute the average returns of funds in each quintile over subsequent quarters.

Table XII reports the average returns of each fund quintile, differences in fund returns between the top, middle and bottom quintiles, the differences in three-factor alphas and four-factor alphas between the top and bottom quintiles up to the next four quarters. We calculate both gross fund returns (before expenses) and net fund returns (after expenses). The results show that when funds are ranked based on the covariance between all trades and analyst forecast errors, the return and alpha spreads between the top and bottom quintile funds are positive but statistically insignificant. Nevertheless, once we rank funds based on the covariance between large trades and analyst forecast errors, the return spreads become significant up to the next four quarters. Overall, compared to net fund returns, the differences in gross fund returns between top, middle and bottom quintiles are slightly more significant. We interpret the findings as evidence that mutual funds placing large trades with information on future earnings are skilled and deliver higher returns to investors.

V. Conclusion

Existing literature documents evidence of stock picking skills by mutual funds, but offers scant evidence on the source of such skills, whether funds trading on information on firm fundamentals or simply other proprietary technical signals. In this paper, we use monthly holdings data and examine how mutual funds trade around earnings announcements. Our results show that mutual funds generally trade in the same direction as earnings news. Nevertheless, we find that a majority of mutual fund trades do not have predictive power of future earnings, whereas the top tercile of large trades by mutual funds contain information about future earnings. We show that the information content of these large mutual fund trades is partly attributed to but not fully subsumed by analyst activities. Moreover, our results show that large trades by mutual funds have a significantly positive effect on immediate market reactions to earnings surprises and help incorporate information in future earnings into stock prices. Finally, we show evidence that funds with large trades on future earnings news are skilled with higher returns over subsequent four quarters.

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Table I: Summary Statistics of Fund Characteristics

This table reports summary statistics of fund characteristics for the mutual fund sample. Fund characteristics include fund total net assets (TNA), age, expense ratio, turnover, cash holding and the number of stocks held in fund portfolio. Fund age is defined as the time (years) a fund is in the CRSP Survivor-Bias-Free US Mutual Fund Database. Fund TNA, expense ratio, turnover and cash holdings are also obtained from the CRSP database. Each month we compute the cross-sectional mean and median of each variable. The table reports the time series averages of these statistics. The sample period is from January 1998 to March 2015.

Fund Characteristics	Mean	Median
No. of funds	687	
Fund TNA ($mil)	782	199
Fund age	13.27	9.74
Expense ratio (%)	1.18	1.19
Turnover (%)	85.85	67.92
Cash holdings (%)	3.72	2.56
Numbers of Stocks in the Portfolio	134	74

Table II: Summary Statistics of Analyst Forecast Error and Firm Characteristics

This table reports summary statistics of analyst forecast error (FE) and firm characteristics for the stock sample. Firm characteristics include market capitalization (SIZE), book to market ratio (B/M), the Amihud illiquidity ratio (ILLIQ), idiosyncratic volatility (IVOL), leverage (LEV), mutual fund ownership (MFO), the number of mutual fund owners (#MF), and analyst coverage (COV). SIZE is calculated at the end of each June. B/M is calculated at the end of each June using book value for the fiscal year ending in calendar year t-1 divided by market capitalization at the end of December of year t-1. ILLIQ is calculated as the ratio of absolute daily return to dollar trading volume and averaged over the quarter. IVOL is the standard error of the residual of the Fama-French 3-factor model estimated from daily returns over the quarter. LEV is calculated as book debt to total assets where book debt is total assets minus book equity. MFO is calculated as the number of shares held by mutual funds divided by total number of shares outstanding each month. #MF is the number of mutual fund owners of the stock each month. COV is the number of analysts covering the firm. We calculate the mean, median, standard deviation (StDev), 5^{th}, 25^{th}, 75^{th} and 95^{th} percentiles and the number of observations (N) of each variable each quarter. The table reports the time series average of these statistics. The sample period is from January 1998 to March 2015.

Variable	N	5%	25%	Mean	Median	75%	95%	StDev
FE	2755	-0.017	-0.001	-0.002	0.000	0.002	0.012	0.065
SIZE ($bil)	2755	0.064	0.246	4.851	0.737	2.486	18.795	19.031
B/M	2024	0.096	0.254	0.624	0.442	0.734	1.516	1.105
ILLIQ	2755	0.000	0.001	0.413	0.007	0.044	0.729	4.853
IVOL	2755	0.010	0.016	0.027	0.024	0.034	0.056	0.016
LEV	2026	0.109	0.268	0.446	0.441	0.601	0.827	0.219
MFO	2755	0.001	1.228	4.547	3.704	6.726	12.514	4.121
ΔMFO	2755	-0.335	-0.006	0.229	0.041	0.306	1.365	0.734
#MF	2755	0.058	10.145	30.753	22.058	40.000	91.464	33.433
COV	2699	1.145	3.377	8.694	6.580	12.065	23.217	7.101

Table III: Mutual Fund Trading – EA Month vs. Non-EA Month

For each firm, we compute the mean of absolute change of mutual fund ownership (|ΔMFO|%), mutual fund trade size, calculated as the number of shares traded by a fund divided by total shares outstanding (in percent) and the dollar amount of the trade, during the earning announcement (EA) months and non-EA months, separately. A month is defined as earnings announcement month for a stock if there is an earnings announcement during the month. The table reports the average of the statistics across all firms for EA month and non-EA month as well as their differences and t-statistics. The sample period is from January 1998 to March 2015.

	EA Month	Non-EA Month	EA − Non-EA
Numbers of Stocks	9,220	9,220	
|ΔMFO| (%)	0.420	0.393	0.027 (3.01)
Number of MF trades	15.842	15.940	-0.099 (-0.72)
MF trade size (%)	0.050	0.046	0.003 (2.96)
MF trade size ($mil)	0.673	0.641	0.032 (2.42)

Table IV: Earnings Information and Mutual Fund Trading

Each quarter, stocks are assigned to quintiles based on FE using the breakpoints of the previous quarter in Panel A or cumulative abnormal returns over the three-day announcement window (CAR [-1, 1]) in Panel B. We calculate the mean and median mutual fund demand (ΔMFO) of stocks in each quintile. The time horizons include the month prior to earnings announcement (EAM[-1]), the two-month period including the month prior to and the month of earnings announcement (EAM [-1, 0]), and the two-month period following the earnings announcement (EAM[1, 2]). The table reports the time series averages of the mean and median ΔMFO. The table also reports the differences in ΔMFO between the top and bottom FE and EAR quintiles, as well as their Newey-West t-statistics. The sample period is from January 1998 to March 2015.

Panel A: Mutual Fund Demand (ΔMFO %) of FE Quintiles

FE Quintile	Mean			Median		
	EAM[-1]	EAM [-1, 0]	EAM[1, 2]	EAM[-1]	EAM [-1, 0]	EAM[1, 2]
1	0.243	0.441	0.366	0.060	0.149	0.095
2	0.292	0.526	0.457	0.104	0.247	0.183
3	0.349	0.634	0.542	0.144	0.329	0.250
4	0.331	0.599	0.528	0.128	0.305	0.234
5	0.277	0.488	0.457	0.079	0.196	0.167
Q5-Q1	0.034	0.048	0.092	0.018	0.047	0.072
NW-t	(3.152)	(3.223)	(7.286)	(4.808)	(4.911)	(6.311)

Panel B: Mutual Fund Demand (ΔMFO %) of CAR[-1, 1] Quintiles

CAR Quintile	Mean			Median		
	EAM[-1]	EAM [-1, 0]	EAM[1, 2]	EAM[-1]	EAM [-1, 0]	EAM[1, 2]
1	0.324	0.580	0.484	0.111	0.259	0.185
2	0.273	0.485	0.427	0.086	0.214	0.159
3	0.270	0.481	0.427	0.084	0.195	0.147
4	0.292	0.515	0.433	0.101	0.246	0.173
5	0.344	0.645	0.595	0.126	0.335	0.272
Q5-Q1	0.020	0.064	0.111	0.014	0.075	0.087
NW-t	(2.590)	(3.946)	(6.661)	(3.206)	(5.070)	(8.583)

Table V: Earnings Information and the Change of the Number of Mutual Fund Owners

Each quarter, stocks are assigned to quintiles based on FE using the breakpoints of the previous quarter in Panel A or cumulative abnormal returns over the three-day announcement window (CAR [-1, 1]) in Panel B. We calculate the mean and median change of the number of mutual fund owners (Δ#MF) of stocks in each quintile. The time horizons include the month prior to earnings announcement (EAM[-1]), the two-month period including the month prior to and the month of earnings announcement (EAM [-1, 0]), and the two-month period following the earnings announcement (EAM[1, 2]). The table reports the time series averages of the mean and median Δ#MF. The table also reports the differences in Δ#MF between the top and bottom FE and EAR quintiles, as well as their Newey-West t-statistics. The sample period is from January 1998 to March 2015.

Panel A: Change of the Number of Mutual Fund Owners (Δ#MF) of FE Quintiles

	Mean			Median		
FE Quintile	EAM[-1]	EAM [-1, 0]	EAM[1, 2]	EAM[-1]	EAM [-1, 0]	EAM[1, 2]
1	1.221	2.271	2.147	0.435	1.014	0.949
2	2.166	4.136	3.918	1.232	2.616	2.435
3	2.817	5.543	5.416	1.841	4.058	3.971
4	2.292	4.576	4.690	1.333	3.101	3.232
5	1.547	3.157	3.542	0.717	1.674	2.058
Q5-Q1	0.327	0.885	1.395	0.283	0.659	1.109
NW-t	(5.427)	(6.519)	(7.237)	(3.658)	(5.357)	(6.838)

Panel B: Change of the Number of Mutual Fund Owners (Δ#MF) of CAR[-1, 1] Quintiles

	Mean			Median		
CAR Quintile	EAM[-1]	EAM [-1, 0]	EAM[1, 2]	EAM[-1]	EAM [-1, 0]	EAM[1, 2]
1	1.958	3.690	3.332	1.043	2.123	1.862
2	2.063	3.848	3.782	1.065	2.290	2.217
3	2.003	3.745	3.764	1.014	2.188	2.261
4	2.129	4.219	4.296	1.167	2.565	2.775
5	2.068	4.441	4.809	1.145	2.797	3.239
Q5-Q1	0.111	0.751	1.477	0.101	0.674	1.377
NW-t	(3.847)	(8.818)	(10.259)	(2.441)	(5.718)	(8.947)

Table VI: Mutual Fund Trading and Future Earnings Information

Each quarter, we perform Fama-MacBeth regressions of the rank of analyst forecast error (FE) on the mutual fund demand based on all trades in the previous month (ΔMFO_{t-1m}) and mutual fund demand based on large trades and small trades separately in the previous month ($\Delta MFO(L)_{t-1m}$ and $\Delta MFO(S)_{t-1m}$) as well as various control variables. A trade for a given stock is classified as large if the trade size is in the top tercile during a month and small otherwise. Control variables include market capitalization (SIZE), book to market ratio (B/M), lagged returns ($LRET_{[t-1m,t]}$, $LRET_{[t-6m,t-1m]}$, $LRET_{[t-12m,t-6m]}$), the Amihud illiquidity ratio (ILLIQ), idiosyncratic volatility (IVOL), and leverage (LEV). For details on variable definitions, please refer to Table II. The table reports time series average of coefficient estimates of quarterly regressions and their Newey-West t-statistics. ** and * indicate significance at the 1% and 5% level, respectively. The sample period is from January 1998 to March 2015.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔMFO_{t-1m}	4.670**	2.813**	1.320	0.913			
	(4.56)	(2.57)	(1.53)	(0.99)			
$\Delta MFO(L)_{t-1m}$					0.677**	0.434**	0.348**
					(5.41)	(3.43)	(2.85)
$\Delta MFO(S)_{t-1m}$					0.856	0.521	-0.133
					(0.93)	(0.52)	(-0.15)
FE_{Qt-1}		0.195**	0.187**	0.184**		0.194**	0.184**
		(9.83)	(9.00)	(8.88)		(9.80)	(8.87)
$LRET_{[t-1m,t]}$			4.538**	4.338**			4.318**
			(3.96)	(3.64)			(3.67)
$LRET_{[t-6m,t-1m]}$			2.335**	2.470**			2.446**
			(3.24)	(3.75)			(3.75)
$LRET_{[t-12m,t-6m]}$			0.379	0.312			0.271
			(0.81)	(0.70)			(0.62)
SIZE				-1.099			-1.060
				(-1.70)			(-1.64)
B/M				0.745**			0.745**
				(3.32)			(3.33)
IVOL				1.410			1.436
				(0.82)			(0.84)
ILLIQ				-2.863			-2.806
				(-1.92)			(-1.89)
LEV				1.903			1.886
				(1.69)			(1.67)
Intercept	0.500**	0.404**	0.405**	0.400	0.499**	0.403**	0.399**
	(80.86)	(33.98)	(31.45)	(23.40)	(80.27)	(33.90)	(23.34)
N	2885	2445	2330	2330	2885	2445	2330
Adj. R^2 (%)	0.039	3.901	4.153	4.505	0.113	3.924	4.517

Table VII: Mutual Fund Trading and Future Earnings Information – High and Low Turnover Funds

Each quarter, we separate mutual funds into high turnover and low turnover funds according to median fund turnover and calculate demand based on large trades and small trades separately for each subsample of funds in the previous month. We perform Fama-MacBeth regressions of the rank of analyst forecast error (FE) on demand of large trades and small trades in the previous month ($\Delta MFO(L)_{t-1m}$ and $\Delta MFO(S)_{t-1m}$) by high turnover funds and low turnover funds separately. The control variables are the same as those in Table VI. The table reports time series average of coefficient estimates of quarterly regressions and their Newey-West t-statistics. ** and * indicate significance at the 1% and 5% level, respectively. The sample period is from January 1998 to March 2015.

	Demand by High Turnover Funds			Demand by Low Turnover Funds		
	(1)	(2)	(3)	(1)	(2)	(3)
$\Delta MFO(L)_{t-1m}$	1.678**	1.139**	0.949**	-0.216	-0.119	-0.070
	(7.46)	(5.27)	(4.27)	(-1.11)	(-0.55)	(-0.33)
$\Delta MFO(S)_{t-1m}$	1.637	0.352	-0.643	0.944	0.165	0.343
	(1.02)	(0.21)	(-0.51)	(0.64)	(0.11)	(0.23)
FE_{Qt-1}		0.194**	0.184**		0.195**	0.184**
		(9.79)	(8.86)		(9.82)	(8.87)
$LRET_{[t-1m,t]}$			4.286**			4.342**
			(3.64)			(3.66)
$LRET_{[t-6m,t-1m]}$			2.418**			2.486**
			(3.71)			(3.81)
$LRET_{[t-12m,t-6m]}$			0.277			0.306
			(0.63)			(0.69)
SIZE			-1.052			-1.106
			(-1.63)			(-1.71)
B/M			0.749**			0.742**
			(3.32)			(3.30)
IVOL			1.382			1.449
			(0.81)			(0.84)
ILLIQ			-2.829			-2.862
			(-1.88)			(-1.91)
LEV			1.826			1.890
			(1.65)			(1.66)
Intercept	0.499**	0.403**	0.399**	0.500**	0.404**	0.400**
	(81.59)	(34.11)	(23.43)	(82.38)	(34.13)	(23.42)
N	2885	2445	2330	2885	2445	2330
Adj. R^2 (%)	0.115	3.917	4.505	0.082	3.905	4.507

Table VIII: Analyst Revision around Earnings Announcements

Each quarter, for each firm we calculate the average number of analyst revisions (#REV) and average analyst revision (REV) during the month prior to earnings announcement (EAM[-1]), the month of earnings announcement (EAM[0]), and the two months following earnings announcement (EAM[1] and EAM[2]). We then calculate the average number of analyst revisions and average analyst revisions for all stocks and stocks in each FE quintile. #REV is defined as the total number of analyst revisions of earnings forecast during the same period as the dependent variable. REV is defined as average revisions. This table reports the time series averages of the number of analyst revisions and average analyst revision of earnings forecasts for all stocks and stocks in each FE quintile. The sample period is from January 1998 to March 2015.

Panel A: Number of Analyst Revisions (#REV)

FE Quintile	EAM[-1]	EAM[0]	EAM[1]	EAM [2]
All Stocks	1.129	0.966	0.525	1.122
1	0.817	0.609	0.408	0.769
2	1.323	1.175	0.596	1.337
3	1.450	1.359	0.650	1.458
4	1.223	1.039	0.554	1.210
5	0.830	0.655	0.415	0.835

Panel B: Average Revision (REV)

FE Quintile	EAM[-1]	EAM[0]	EAM[1]	EAM [2]
All Stocks	-0.006	-0.005	-0.003	-0.005
1	-0.012	-0.010	-0.005	-0.009
2	-0.005	-0.005	-0.002	-0.005
3	-0.003	-0.002	-0.001	-0.004
4	-0.004	-0.002	-0.002	-0.004
5	-0.006	-0.004	-0.002	-0.005

Table IX: Mutual Fund Trading and Future Earnings Information: The Role of Analysts

Each quarter, we perform Fama-MacBeth regressions of the rank of analyst forecast error (FE) on the mutual fund demand based on large trades and small trades in the previous month ($\Delta MFO(L)_{t-1m}$ and $\Delta MFO(S)_{t-1m}$) as well as various control variables. The demand is calculated for all funds and separately for high turnover mutual funds and low turnover mutual funds. Other than those in Table VI, the control variables include analyst coverage (COV), the number of analyst revisions (#REV), and average revision (REV). COV is the number of analysts covering the stock during the previous quarter. #REV is defined as the total number of analyst revisions of earnings forecast during the same period as the dependent variable. REV is defined as average revision of earnings forecasts for the next quarter. For details on variable definitions, please refer to Tables II and Tables VI. The table reports time series average of coefficient estimates of quarterly regressions and their Newey-West t-statistics. ** and * indicate significance at the 1% and 5% level, respectively. To preserve space, coefficients of firm characteristics (FCs), namely SIZE, B/M, IVOL, ILLIQ and LEV, are not reported. The sample period is from January 1998 to March 2015.

	Demand by All Funds		Demand by High Turnover Funds		Demand by Low Turnover Funds	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta MFO(L)_{t-1m}$	0.312*	0.358**	0.892**	0.910**	-0.092	-0.005
	(2.52)	(2.90)	(3.99)	(4.10)	(-0.43)	(-0.02)
$\Delta MFO(S)_{t-1m}$	-0.123	0.128	-0.750	-0.205	0.347	0.732
	(-0.14)	(0.16)	(-0.60)	(-0.18)	(0.24)	(0.52)
FE_{Qt-1}	0.183**	0.181**	0.183**	0.181**	0.183**	0.181**
	(8.83)	(8.73)	(8.82)	(8.72)	(8.83)	(8.73)
$LRET_{[t-1m,t]}$	4.362**	3.559**	4.341**	3.539**	4.386**	3.592**
	(3.70)	(3.08)	(3.67)	(3.05)	(3.69)	(3.08)
$LRET_{[t-6m,t-1m]}$	2.514**	2.141**	2.488**	2.118**	2.554**	2.191**
	(3.87)	(3.43)	(3.84)	(3.40)	(3.93)	(3.51)
$LRET_{[t-12m,t-6m]}$	0.316	0.141	0.326	0.153	0.350	0.180
	(0.72)	(0.33)	(0.74)	(0.36)	(0.79)	(0.42)
FCs	Yes	Yes	Yes	Yes	Yes	Yes
COV	7.052*	9.470**	7.047*	9.495**	7.310**	9.738**
	(2.52)	(3.00)	(2.52)	(3.00)	(2.60)	(3.06)
#REV		-0.770*		-0.779*		-0.767*
		(-2.15)		(-2.17)		(-2.13)
REV		6.696**		6.676**		6.680**
		(11.16)		(11.27)		(11.16)
Intercept	0.392**	0.393**	0.392**	0.393**	0.393**	0.393**
	(19.66)	(19.66)	(19.70)	(19.71)	(19.68)	(19.67)
N	2330	2329	2330	2329	2330	2329
Adj. R^2 (%)	4.580	5.024	4.569	5.011	4.572	5.014

Table X: Mutual Fund Trading and Earnings Response Coefficient

Each quarter, we perform Fama-MacBeth regressions of cumulative abnormal return during the earnings announcement window ($CAR_t[-1,1]$) on the decile rank of analyst forecast error (FE), its interaction with dummy variable $d^{|\Delta MFO(L)|}$, and various control variables. The dummy variable $d^{|\Delta MFO(L)|}$ is equal to 1 if the absolute value of ΔMFO(L) is higher than the median value of all stocks in the earnings announcement month and 0 otherwise. Mutual fund large trades and small trades (ΔMFO(L) and ΔMFO(S)) are defined the same as Table VI. Other than those in Table IX, the control variables include systematic risk (BETA), earnings persistence (AC_{CF}) and earnings uncertainty (σ_{CF}). BETA is the coefficient of the market return of the Fama-French 3-factor model estimated from daily returns over the quarter. AC_{CF} is the coefficient of the AR(1) term of EPS over the past eight quarters, and σ_{CF} is the standard error of the residual of the AR(1) model. The table reports time series average of coefficient estimates of quarterly regressions and their Newey-West t-statistics. ** and * indicate significance at the 1% and 5% level, respectively. To preserve space, coefficients of firm characteristics (FCs), namely SIZE, B/M, IVOL, ILLIQ and LEV, are not reported. The sample period is from January 1998 to March 2015.

	(1)	(2)	(3)	(4)
FE	6.979**	7.166**	7.170**	7.165**
	(10.56)	(10.22)	(10.22)	(10.20)
$d^{|\Delta MFO(L)|}$*FE	2.222**	2.281**	2.286**	2.279**
	(9.83)	(10.21)	(10.22)	(10.23)
$d^{|\Delta MFO|(L)|}$	-1.025**	-1.066**	-1.047**	-1.044**
	(-6.16)	(-5.89)	(-6.24)	(-8.16)
$LRET_{[t-1m,t]}$		-13.856**	-13.903**	-14.234**
		(-6.57)	(-6.62)	(-6.74)
$LRET_{[t-6m,t-1m]}$		-4.731*	-4.755*	-4.828*
		(-2.43)	(-2.46)	(-2.52)
$LRET_{[t-12m,t-6m]}$		-0.449	-0.503	-0.529
		(-0.45)	(-0.51)	(-0.54)
FCs		Yes	Yes	Yes
Beta		-0.135*	-0.121*	-0.124*
		(-2.19)	(-2.00)	(-2.04)
AC_{CF}		-0.039	-0.034	-0.036
		(-0.94)	(-0.80)	(-0.86)
σ_{CF}		-0.055	-0.058	-0.059
		(-1.06)	(-1.11)	(-1.10)
COV			-0.077	-0.095*
			(-1.58)	(-1.98)
#REV				0.103
				(1.10)
REV				1.814*
				(2.01)
Intercept	-3.432**	-3.006**	-2.945**	-2.938**
	(-8.63)	(-5.10)	(-4.73)	(-4.70)
N	2760	2391	2391	2391
Adj. R^2 (%)	8.552	10.039	10.061	10.081

Table XI: Mutual Fund Trading and Stock Price Discovery

Each quarter, we perform Fama-MacBeth regressions of cumulative abnormal return during the earnings announcement window in quarter t+1 to t+i ($CAR_{[t+1,\ t+i]}[-1, 1]$, i=1, 2, and 4) on cumulative abnormal return during the earnings announcement window in quarter t ($CAR_t[-1, 1]$), its interaction with dummy variable $d^{|\Delta MFO(L)|}$, and various control variables. The earnings announcement window includes the day prior to, the day of and the day after earnings announcement. The dummy variable $d^{|\Delta MFO(L)|}$ is equal to 1 if the absolute value of ΔMFO(L) is higher than the median value of all stocks in the earnings announcement month and 0 otherwise. The control variables are the same as those in Table IX. The table reports time series average of coefficient estimates of quarterly regressions and their Newey-West t-statistics. ** and * indicate significance at the 1% and 5% level, respectively. To preserve space, coefficients of firm characteristics (FCs), namely SIZE, B/M, IVOL, ILLIQ and LEV, are not reported. The sample period is from January 1998 to March 2015.

	CAR_{t+1}		$CAR_{[t+1,\ t+2]}$		$CAR_{[t+1,\ t+4]}$	
	(1)	(2)	(3)	(4)	(5)	(6)
CAR [-1,1]	2.218**	2.214**	3.047**	3.033**	4.489**	4.479**
	(4.49)	(4.49)	(3.49)	(3.47)	(4.58)	(4.54)
$d^{|\Delta MFO(L)|}$*CAR[-1,1]	-0.183**	-0.185**	-0.207*	-0.209*	-0.305*	-0.309*
	(-3.09)	(-3.10)	(-2.09)	(-2.09)	(-2.50)	(-2.52)
$d^{|\Delta MFO(L)|}$	2.360**	2.409**	4.179**	4.386**	5.937**	6.106**
	(9.13)	(6.60)	(5.28)	(5.71)	(5.60)	(5.99)
FE	-1.021	-0.971	3.100	3.117	5.479*	5.481*
	(-0.57)	(-0.52)	(1.58)	(1.53)	(2.31)	(2.26)
$LRET_{[t-1m,t]}$	-1.961	-1.741	-2.211	-1.854	-2.649	-2.267
	(-0.65)	(-0.59)	(-0.58)	(-0.50)	(-0.60)	(-0.53)
$LRET_{[t-6m,t-1m]}$	2.382	2.423*	1.781	1.886	1.926	2.081
	(1.87)	(1.97)	(0.85)	(0.91)	(0.73)	(0.80)
$LRET_{[t-12m,t-6m]}$	-0.419	-0.429	-1.154	-1.189	-1.917	-1.917
	(-0.52)	(-0.54)	(-0.85)	(-0.88)	(-1.25)	(-1.25)
FCs	Yes	Yes	Yes	Yes	Yes	Yes
COV		-2.271		-3.068		0.254
		(-0.49)		(-0.29)		(0.03)
#REV		8.248		8.789		4.903
		(1.92)		(1.91)		(1.67)
REV		-0.739		-2.100*		-2.504*
		(-0.84)		(-2.28)		(-2.52)
Intercept	3.106**	1.803	3.449*	1.341	4.480*	3.923
	(2.93)	(0.92)	(1.97)	(0.56)	(2.03)	(1.33)
N	2490	2490	2521	2521	2523	2523
Adj. R^2 (%)	0.878	0.913	0.919	0.949	1.012	1.069

Table XII: Trading on Earnings News and Fund Performance

Each quarter, mutual funds are assigned to quintiles based on the covariance between their trades and subsequent analyst forecast error ($\Delta MFO_{mt-1}*FE_{mt}$). The covariance is calculated based on all mutual fund trades (Panel A) and based on only large mutual fund trades (Panel B). A trade for a given stock is classified as large if the trade size is in the top tercile during a month and small otherwise. We calculate the average fund returns of each quintile in quarter t+1 to t+4 ($RET_{[t+1, t+i]}$, i=1, 2, and 4). The table reports the timer series averages of the mean of fund returns (in percentage). The differences in fund returns between the top, middle and bottom quintiles, the differences in three-factor alphas and four-factor alphas between the top and bottom quintiles, as well as their Newey-West t-statistics are also reported. The sample period is from January 1998 to March 2015.

Panel A: Funds are Sorted based on Covariance between All Trades and Forecast Errors

Quintile	Gross Fund Returns			Net Fund Returns		
	$Q_{[t+1]}$	$Q_{[t+1, t+2]}$	$Q_{[t+1, t+4]}$	$Q_{[t+1]}$	$Q_{[t+1, t+2]}$	$Q_{[t+1, t+4]}$
			Fund Returns			
1	2.136	4.224	8.739	1.846	3.636	7.529
2	1.881	3.792	7.557	1.607	3.236	6.423
3	1.954	3.919	7.560	1.683	3.369	6.436
4	2.189	4.526	9.003	1.907	3.954	7.833
5	2.245	4.762	9.616	1.955	4.172	8.398
Q1-Q3	0.181	0.305	1.179	0.163	0.266	1.094
NW-T	(1.26)	(1.12)	(2.31)	(1.01)	(0.90)	(2.16)
Q5-Q3	0.290	0.843	2.056	0.271	0.803	1.962
NW-T	(1.90)	(2.52)	(2.96)	(1.23)	(1.84)	(2.37)
Q5-Q1	0.109	0.538	0.877	0.109	0.536	0.868
NW-T	(1.15)	(1.97)	(1.65)	(0.83)	(1.84)	(1.55)
			Three-Factor Alphas			
Q5-Q1	0.077	0.454	0.868	0.077	0.452	0.856
NW-T	(0.52)	(1.60)	(2.03)	(0.52)	(1.60)	(2.03)
			Four-Factor Alphas			
Q5-Q1	0.086	0.406	0.932	0.086	0.403	0.918
NW-T	(0.56)	(1.39)	(2.11)	(0.56)	(1.38)	(2.11)

Panel B: Funds are Sorted based on Covariance between Large Trades and Forecast Errors

Quintile	Gross Fund Returns			Net Fund Returns		
	$Q_{[t+1]}$	$Q_{[t+1,\ t+2]}$	$Q_{[t+1,\ t+4]}$	$Q_{[t+1]}$	$Q_{[t+1,\ t+2]}$	$Q_{[t+1,\ t+4]}$
			Fund Returns			
1	2.057	4.178	8.601	1.768	3.593	7.400
2	2.054	4.152	8.085	1.778	3.595	6.961
3	2.017	4.067	8.389	1.743	3.512	7.249
4	2.090	4.316	8.690	1.812	3.754	7.540
5	2.329	4.898	9.577	2.038	4.305	8.357
Q1-Q3	0.040	0.111	0.212	0.025	0.081	0.151
NW-T	(0.29)	(0.42)	(0.44)	(0.18)	(0.31)	(0.34)
Q5-Q3	0.312	0.830	1.188	0.295	0.793	1.109
NW-T	(2.89)	(5.63)	(4.85)	(2.70)	(5.01)	(4.30)
Q5-Q1	0.272	0.719	0.977	0.270	0.712	0.957
NW-T	(2.54)	(2.38)	(2.10)	(2.52)	(2.37)	(2.08)
			Three-Factor Alphas			
Q5-Q1	0.263	0.657	0.973	0.261	0.651	0.956
NW-T	(2.18)	(2.58)	(2.36)	(2.18)	(2.57)	(2.34)
			Four-Factor Alphas			
Q5-Q1	0.304	0.690	1.005	0.303	0.683	0.987
NW-T	(2.48)	(2.62)	(2.35)	(2.48)	(2.60)	(2.33)