Information Choices and Dynamic Institutional Trading Cycles[*]

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Abstract:

Using the transaction-level institutional trading data from Ancerno, we study the preference of information sources for different types of institutional investors. We measure the trade performance over the dynamic trading cycles classified by strategies of stock market anomalies. We decompose the trade performance of institutional investors into anomaly timing and selection. We find evidence that institutional investors tend to exploit firm-management related anomalies. Our study shows that institutional investors time the anomaly as they investors pay more attention to that news.

JEL Classification:

Keywords: Institutional investors, market anomaly, attention allocation, asset pricing, return measurement, market timing, stock selection.

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1. Introduction

In the U.S. common equity market, institutional investors hold a significant portion of shares, leading to numerous studies examining their trading skills. To assess institutional investors' asset management skills effectively, researchers often break them down into market timing and stock selection abilities, employing methods such as multiple regression and characteristic-based performance measures (Treynor and Mazuy, 1966; Ferson and Warther, 1996; Grinblatt and Titman, 1993; Daniel et al., 1997; Kacperczyk, Slaim, and Zheng KSZ, 2005).

In the past decade, many studies attempted to capture institutional investors' cumulative market timing and stock selection skills using quarterly holding data from the SEC. However, Chen et al. (2000) and Kothari and Warner (2001) pointed out that institutional trading records are a more potent and straightforward tool for measuring these skills. Based on the theoretical frameworks of KSZ (2005), Da Zhi (2011), and Kacperczyk, Van-Nieuwerburgh, and Veldkamp (KNV, 2014, 2016) on institutional investment skills, our study aims to timely and accurately understand the types of information institutional investors pay attention to and how their market timing and stock selection skills vary over time.

Market timing involves aligning an investor's portfolio with a benchmark portfolio, requiring a broad understanding of the benchmark components. In contrast, stock selection ability involves accurately predicting the future return of individual stocks, demanding in-depth knowledge of specific companies. To achieve successful market timing and stock selection, investment managers must undergo two steps. First, they allocate their limited attention to numerous information sources dynamically, leading to dynamic trading skills. KNV (2016) supports this finding, showing that investment managers focus more on market aggregate information during recessions and individual stock information during expansions. Second, investment managers assimilate the chosen information and generate their own investment beliefs, which influence their portfolio adjustments through active trading strategies. The ability to make sound judgments on market timing and stock selection based on the chosen information set varies widely among investment managers (KNV, 2014).

The sources of information impacting a stock's future return are abundant, ranging from macroeconomic-level data like market liquidity and volatility to firm-specific information like earnings announcements. Recent studies also reveal that investors can anticipate certain information releases, leading to news-driven abnormal returns before the information becomes public (Cieslak et al., 2019; Linnainmaa and Zhang, 2018).

The sources of information that have an impact on a stock's future return are undoubtedly overabundant. Managers can acquire macroeconomic-level information to enhance their market timing ability. The macroeconomic-level information includes market liquidity and volatility (Busse, 1999; Cao et al. 2013), market aggregate performance (KNV, 2014), economic fundamentals like gross productivity (KNV, 2016), and macro announcement such as FOMC (Lucca and Moench, 2015; Cieslak et al. 2019). Investors also learn about the direction and magnitude of a stock return deviating from its benchmark from firm-specific information such as earning announcements (eg. Ball and Brown, 1968). Recent studies also discover that investors are able to move ahead of certain information releases and thus result in news-driven abnormal returns ahead of the information schedule. (Cieslak et al, 2019; Linnainmaa and Zhang, 2018)

To evaluate the trading skill of institutional investors, we consider the performance of 11 prominent anomaly portfolios extensively examined by Stambaugh et al. (2012) as our benchmark. We display the detailed components of 11 anomalies in section 2. These 11 anomalies are either well discovered before our sample period, or detected during our sample period but supported by abnormal historical portfolio returns starting from a long time before our sample, which suggests that in the past, some institutional investors used these anomalies to generate abnormal return quietly as their secret weapon. Mclean and Pontiff (2016) pointed out that the abnormal performance of some market anomalies fell sharply after the anomaly-related academic journal was published. Their findings proved that investors in the market are generally smart enough to learn from academic journals. We find that all the 11 market anomalies included in our study have volatile but overall significant positive long-minus-short returns during our sample period, indicating that some skillful investors (often institutional investors) were still distinguishable from other institutional investors and individual investors. From the perspective of information acquisition, to benefit from these 11 market anomalies requires investors to absorb firm-specific information from fundamental releases, news announcements, and past performance and then draw an accurate depiction of each firm's future.

Our study contributes to understanding institutional investors' investment beliefs regarding market anomalies. Previous studies have shown mixed findings on whether institutional investors trade alongside market anomaly strategies. While many studies suggest that institutional trades often follow with positive future returns (Grinblatt et al., 1995; Chen et al., 2000), Edelen et al. (2016) demonstrate that institutional investors play a role in correcting the mispricing of market anomaly strategies in the long term. To capture the timely information choice and accurate performance measure of institutional investors, we place all the experiments on Ancerno data, an immense database consisting of daily and intraday transaction records of institutional investors. A detailed introduction of our data is in section 2. Following the empirical method in Barber and Odean (2008),and Kadan et al. (2018), we test whether our sample institution had took in advantage of those 11 market anomalies. Our results show that institution investors on average traded corresponding to what is suggested by the PERF anomalies, however, they had a dispersive attitude toward the MGMT anomalies and on average they trade opposite to MGMT long-minus-short strategies. We provide an explanation to these phenomenon. By observing that institutional investors' buying behavior for MGMT short quintile and selling behavior for PERF long quintile happens much more on the news day, we believe that institutional investors are good at taking the advantage of the abnormal demand for stocks around news day to secure trade performance or arbitrage for extra benefit.

To evaluate institutional investors' trading performance, we follow the evaluation method introduced by Puckett and Yan (2011) on Ancerno data to compute the trade performance on our selected interval. We adjust the trade performance using the empirical framework of KSZ (2005) to obtain the anomaly-timing ability and within-anomaly-group stock selection ability. Engelberg et al. (2018) reported that anomaly returns amplify remarkably during news-intensive time intervals, especially around earnings announcement dates. Our result shows that institutional investors possess skills to absorb information from earning announcement and time the abnormal return from MGMT anomalies trading strategy around such informative period. The fundamental information acquired from the earning announcement date also surves as complement for institutional investors to pick the stocks within similar past performance as in PERF anomalies.

Our study also contribute to the choice of information resources made by institutional investors. We first obtain the skill advantage of clustered managers with similar attributes in size and trade frequency. Then we observe that their performance composition vary fiercely through news concentration period. In general, institutional investors have diversified skill advantages on timing and picking, and they tend to balance both tasks of trading on the news intensive days.

The remaining content is organized as follows. Section 2 describes the sources and summary statistics of our sample data, Section 3 conducts stock-level analysis of aggregate institutional investors' trading activities. Section 4 conducts manager-level analysis on managers' information choice and dynamic trading skills. Section 5 concludes with our main results.

2. Data and Summary Statistics

a. Data

We obtain the institutional transaction records from Ancerno data (also called the Abel Noser data). Ancerno data provides detailed institutional investors' daily trading information, e.g., the side of trading, execution price, trading volume, tax, and commission fees. Each institutional client of Ancerno is uniquely identified by the institutional number ($clientcode$) and the fund number ($clientmgrcode$) Institutional investors included in Ancerno data can be mainly divided into three categories: plan sponsors, investment managers, and brokers. Data on monthly stock price, number of shares outstanding, and cumulative adjustment factor for stock spilt are obtained from the Center for Research in Security Prices (CRSP), we obtain the earning announcement date and extensive financial data from Compustat North America to construct the anomaly factors. Our study focuses on common stocks listed in major stock exchanges in the U.S. market. We restrict our sample to those with the CRSP share code of 10 or 11 and exchanged codes of 1, 2, or 3. Our study timeframe starts from 1 January 1999 to 30 September 2011.

We further obtain firm-level news coverage data for our sample stock from Ravenpack Edge 1.0, we collect the Ravenpack Entity ID, timestamp, topic, group, and relevance score of news to entity firm. The Ravenpack data starts from January 2000 and we limit our sample from 1 January 2000 to 30 September 2011 when the variables from Ravenpack are taken into consideration. Following Baradehi et al. (2021), we focus on the equity news from Dow Jones

Newswire with a relevance score high than 75. We then transfer the timestamp of each news from the UTC timezone to the EST timezone where NYSE, AMEX, and NASDAQ locate in and find the closest trading date for each news. Finally, we map the Ravenpack Entity ID to CUSIP and then GVKEY and PERMNO with the help of the company taxonomy file provided by Ravenpack and the linking procedure introduced in WRDS. We could successfully match 4.5 million news records from Ravenpack.

b. Ancerno

Ancerno data has the following advantages. First, Ancerno data has assigned unique ID for each institution and each fund within the same institution. Second, compared with the research the proxy the institutional trading via quarterly 13F holding file (e.g., KSZ, (2005)), Ancerno data proffers the higher- frequency intra-quarter trading data that empower us to generate new insights. Puckett and Yan (2011) document that certain institutional investors possess a positive abnormal trading performance on intra-quarter round-trip trading, which is undetectable in quarterly holding data. Third, Ancerno data provides more accurate record of the stock price when the trade is executed. As institutional investors execute buy or sell orders during active trading sessions, the trade price may be different than the closing price. Hence, the holding-based method that utilized the adjusted closing price to evaluate the institutional investor's performance omit the difference between intra-day price and closing price. By utilizing Ancerno data, the trade performance can be evaluated based on the execution price. Fourth, as highlighted by Chemmanur et al.(2009), Ancerno data is widely appliable in academic research for investigating the institutional trading behavior around firm news and seeking the focal point of institutional attention (eg. Jegadeesh and Tang 2010; Ben-Rephael, Da and Israelsen, 2017)

Following Hu et al. (2018), we construct our sample institutional trading data on U.S. common equity and keep the trading records made by plan sponsors and investment managers. We terminate our sample on 30 September 2011, as a key institution identifier was eliminated by Ancerno afterward. We then combine the intra-day trading records with daily trading records since the timestamp provided by Ancerno data may not be trustable (Anand et al. 2013). We further require the execution price of daily trades to exceed $1 to get rid of the noise and delete those trades with a suspicious execution price that is either 30% higher than the daily high or 30% lower than the daily low, this step, in total, eliminate less than 1% of our total trading records. Our processing procedure is similar to Chakrabarty et al. (2017).

[Table 2.1]

Panel A of Table 2.1 report the annual descriptive statistics of Ancerno data. We could reliably track 1076 different institutions and 116582 different funds within these institutions in our sample period. It is worth mentioning that Ancerno will regularly change the identifiers of their institutional clients for privacy and timeliness reason, see Hu, McLean, Pontiff, and Wang (2014) for more information. The version of Ancerno data we use has updated the fund identifiers (clientcode and clientmgrcode) so that we track much more funds than Puckett and Yan (2011). The growth of Ancerno's clients aligns with the U.S. economy. Compared to 1999, the dollar volume and share volume of trade almost doubled in 2006. The number of transactions recorded by Ancerno jumped from 5.14 million in 1999 to 28.37 million in 2006. However, many institutional investors could not survive the global financial crisis. The number of Ancerno's clients and trading activities decreased sharply from 2007 to 2009.

Panel B of Table 2.1 reports the distribution of annual trading volumes and the size per trade made by plan sponsors and investment managers respectively. The size per trade made by investment managers is around 15 times that of plan sponsors. This phenomenon illustrates that investment managers generally trade more actively than plan sponsors. The mean annual trading volume and size per trade for both plan sponsors and investment managers far exceed that of the 75th percentile, indicating that among Ancerno's institutional clients, a very small number of clients have an extremely large transaction volume. Compared with investment managers, the distribution of plan sponsors' annual average trading volume is more dispersed.

c. Anomalies

To examine the relationship between institutional investors' performance and stock characteristics, we first construct the 11 monthly anomalies factors following Stambaugh and Yuan (2012) at the end of each month. Then, following Stambaugh and Yuan (2017), we group the monthly anomalies factors into two clusters and construct the anomaly portfolios.

The anomalies factors include (i) $failure\ profibatility$ estimated by a dynamic logit model considering both accounting and equity market variables, (ii) the $O\ score$ proposed by Ohlson (1980) measuring the profitability of bankruptcy via a static model through accounting variables, (iii) $net\ stock\ issues$ as the growth rate of the split-adjusted number of share outstanding in the prior fiscal year, (iv) $composite\ equity\ issues$ as the amount of equity a firm issues or retires in exchange for cash or services in the prior fiscal year, (v) $total\ accruals$ estimated by the changes in non-cash working capital mins the depreciation expense scaled by average total assets across the previous two fiscal years, (vi) $net\ operating\ assets$ measured as the difference between operating assets and operating liabilities scaled by total assets, (vii) $momentum$ proxied as the equally weighted average return on six portfolios formed based on the ranking of cumulative returns from month $t-7$ to $t-2$, (viii) $gross\ profitability\ premium$ as the ratio of gross profits to total assets, (ix) $asset\ growth$ as the growth rate of total assets in the prior fiscal year, (x) $return\ on\ assets$

measured by the ratio of quarterly earnings to the prior quarter's assets, and (xi) $investmen\ to\ assets$ as the annual change in property, plant, and equipment plus the annual change in inventories scaled by the lagged book value of the assets.

We then formulate the anomaly portfolios based on the eleven anomaly factors. Following Stambaugh and Yuan (2017), we begin with forming the two monthly composite anomaly factors, $MGMT$ and $PERF$, related to firm's management and performance, respectively. The first composite anomaly cluster, $MGMT$, includes six anomaly factor: $net\ stock\ issues$, $composite\ equity\ issues$, $total\ accruals$, $net\ operating\ assets$, $asset\ growth$, and $investment\ to\ assets$. The second composite anomaly factor, $PERF$, includes five anomaly factor: $failure\ profitability$, $O\ score$, $momentum$, $gross\ profitability\ premium$, and $return\ on\ assets$. The monthly anomaly portfolio is constructed as follows. We first compute the ranking of each anomaly factor for each stock and average the rankings across the anomaly factors within the same composite anomaly cluster to obtain the stock-month composite anomaly score. For a stock to have a valid monthly composite anomaly score, we require at least three of the anomalies are available within the composite anomaly cluster. We sort the stocks into quintile portfolios based on composite anomaly scores at the end of each month.

[Table 2.2]

Table 2.2 reports the returns of the composite anomaly portfolios formed based on the ranking of the eleven anomaly factors. As shown in Panel A, the excess returns generally follow an increasing trend across the anomaly portfolios sorted based on the quintile of composite anomaly scores. Both the long-short strategies based on $MGMT$ and $PERF$ generates positive returns of 0.46% and 1.08% per month, respective, with significant return found in long-short portfolio based on $MGMT$ score. Panel B reports the Fama-French three-factor alphas. The alphas are increased generally monotonically across portfolios. We observe positive and highly significant alpha for long-short strategy formed based on both $MGMT$ and $PERF$ score at the level of 0.46% and 1.33%, respectively. Our findings are overall consistent with Guo, Li, and Wei (2020), where the long-short strategy formed based on $PERF$ score generates higher excess return and alpha than the long-short strategy formed based on $MGMT$ score. Our results further implicates that the anomaly factors contain useful information related to future returns.

d. Amplifying Effect on News Day

Engelberg et al. (2018) point out that the anomaly returns amplify multiple times on the news day, especially for earning announcement date. Stocks within the shortest quintile of composite anomaly have abnormally lower returns while stocks within the longest quintile have abnormally larger returns. We display this phenomenon in our sample universe of stocks and anomalies in Table 2.3.

[Table 2.3]

Table 2.3 reports the coefficient of regression results separately for MGMT anomalies in columns 1-4 and PERF anomalies in columns 5-8. In column 3, we see that the coefficient for the smallest quintile of MGMT anomalies is -0.037 while the coefficient on earning announcement date is -0.072, which means that stock returns on the shortest side of MGMT anomalies are 2 times smaller on earning announcement date than usual. The amplifying effect on the longest side of MGMT anomalies is not significantly detected. In column 7, we observe a conspicuous amplifying effect on both the short side and the long side of anomalies. Our result is robust to add the stock-level control variables such as past return, volatility, and the market trading volume as in Engelberg et al. (2018).

3. Stock-Level Analysis

In this section, we present the research methodology and empirical evidence for our major findings. We conduct the stock-level analysis by aggregating institutional investors' trading behavior on each trading date. Following the approach of Kadan, Michaely, and Moulton (2018), we construct measures of institutional daily trading imbalance and volume on the number of shares. We scale the daily trading measures with CRSP average trading volume for the past year (around 252 trading days, we require at last half of data observed). The daily institutional trading measures for stock i on date j over all the institutional investor j are expressed as follows:

$$Volume_{i,t} = \frac{\sum_j Share\ \ Bou\ \ \ \ _{i,j,t} + Shares\ Sold_{i,j,t}}{CRSP\ Avg\ Trading\ Volume\ on\ stock\ i\ over\ t{-}252\ to\ t{-}1} \tag{1}$$

$$Imbalance_{i,t} = \frac{\sum_j Sha\ \ \ \ Bough\ _{i,j,t} - Share\ \ Sold_{i,j,t}}{CRSP\ Avg\ Trading\ Volume\ on\ stock\ i\ over\ t{-}252\ to\ t{-}1} \tag{2}$$

The aggregate trading imbalance gauges the net institutional demand on a given stock and the aggregate trading volume proxies for attention allocated and action taken by institutional investors. For robustness check, we also prepare the trading measures that replace the CRSP average trading volume by the number of shares outstanding at date t as is applied in Jegadeesh and Tang (2010) to capture the proportion of shares traded by institutional investors.

3.1 Institutional trade on different anomaly group

We conduct the following baseline regression to explore the true attention and demand of institutional investors on different anomaly groups of stocks:

$$Imbalance(Volume)_{i,t} = a + b * MGMT(PERF)\ quintile_{i,t-1} + \varepsilon_{i,t} \tag{3}$$

Where trading imbalance and volume are calculated as equation (1) and (2), MGMT quintile and PERF quintile is the anomaly group that the stock belongs to. We are interested in the extreme quintile of anomaly, thus we combine quintile 2,3,4 into a baseline quintile and report the average and t-statistic of coefficient. It is worth mentioning that we are cautious to include some common control variables like size, bm, and mom because they are already priced in the anomaly group, thus including these variables may have an overwhelming effect on the coefficient. Imbalance is winsored at 1% and 99% level, and volume is winsored at 99% level because it is positive-defined. the base panel of our regression is orthogonalized by our sample stock universe and all the trading date in CRSP DSF. The days without institutional trading in our sample is filled by 0 and hence have limited effects on our major result.

[Table 3.1]

In table 3.1, we find that institutional investors have opposite investment belief on two kinds of anomaly strategies. Insititution have positive net demand on the long tail of PERF anomaly group. However, institution tend to enter the short position of MGMT anomaly group. Our result is consistent with the major finding of Edelene et al. (2016), who document their major result in table 4 that institution investor are net buyers for management-related anomaly like NOA, IA, BM but still maintain in the long postion for performance-related anomaly such as Oscore, MOM and Gross Profitability.

3.2 Institutional trade on anomaly portfolio in news interval

Engelburg et al. (2018) conduct analysis on 97 market anomalies and find that the anomaly return is many times larger on news arrival days than normal days. This abnormal return interval generally starts from three days before news arrival to three days after. We thus test if institutional investors acquire information on the firm news and incorporate them with their original belief on the anomaly groups of stocks.

We first check the distribution of news arrival among different anomaly groups of stock. We label a trading date as news arrival date if more than 1 firm-related news sourced from Dow Jones newswire. In addition, we identify if a piece of news is related to firms' business affaire by the variable, TOPIC, in Ravenpack. Nearly 99% of firm-related news are business related. We then follow the definiton made by DeHaan et al. (2022) on finance-related news to identify the subgroup of financial news from business news. Among 4.3 million of business news we collect 1.3 million of financial news related to a firm. We set the quintile 1 as baseline quintile and report the mean and t statistics of daily difference of relevant news, business news and finance news between other quintile and the baseline quintile in table 3.2.

[Table 3.2]

It is clear to see that the short tail of MGMT stocks and long tail of PERF stocks receive better media coverage and consequently these stocks could attract more investors. The distribution of news also help us explain our findings in Table 3.1. With more media coverage, institutional investors are easily attracted by the short tail of MGMT group and long tail of PERF group and make their moves based on their choice of information/

We then run the following regression to explore if institutional investors change their beliefs on news day. Compared with regression in equation (2), we add a dummy variable that indicates whether the trading date has news arrival from one day before to one day after the trading date, and an intersection term between news interval dummy and the anomaly group. We report the mean and t-statistic in Table 3.3. Our major finding is still consistent if we define the news interval from two days before to two days after news arrival

$$Imbalance_{i,t} = a + b * MGMT(PERF)\ quintile_{i,t-1} + c * News\ Interval_{i,t}$$

$$+d * MGMT(PERF)\ quintile_{i,t-1} * News\ Interval_{i,t} + \varepsilon_{i,t} \quad (4)$$

[Table 3.3]

We continue to observe the phenomenon that institutional investors have a net demand for the short tail of MGMT and long tail of PERF anomalies. News arrivals amplify this effect for MGMT anomalies, as we observe an even larger gap between the net trade imbalance and turnover of the short tail and long tail. Our findings provide evidence that institutional investors absorb information to enhance their understanding of firms' management conditions. Regarding the PERF anomaly, institutional investors exhibit a weaker response to news. One explanation is that the PERF anomaly strategy generates a larger return and alpha than the MGMT anomaly strategy, as shown in Table 2.2. Skillful institutional investors have already mastered similar trading skills used in the PERF strategy. However, news arrivals for PERF anomaly stocks lead to an increase in demand from individual investors, providing opportunities for institutional investors to realize their returns by net supplying PERF Q5 stocks on news arrival dates.

4. Manager-Level Analysis

4.1 Performance Measurement

The previous section holistically examines the transactional behavior of institutional investors. In this section, we differentiate each institutional investor based on their overall trading performance among all stocks. Using the long-minus-short performance benchmark for MGMT and PERF anomalies, we follow the framework of KSZ (2005) and apply the characteristic-based benchmark timing and stock selection decomposition of a fund's performance.

There are different ways to measure a fund's performance based on trading activity. We are aware of the dollar-weighted return measure (also known as IRR in Dichev and Yu, 2007; Hayley 2014), which distributes the total fund performance equally to each time unit and requires a considerable calculation process. There's also the round-trip trade performance applied by Puckett and Yan (2011) and Chakrabarty et al. (2017), but they produce conflicting major findings about funds' short-term performance. Additionally, Busse et al. (2020) attempted to link Ancerno data to 13F holding data and evaluate fund performance with daily holding-based measures. However, according to Puckett and Yan (2011)'s investigation, institutions in Ancerno data have larger fund size on average than the CRSP survivorship mutual fund database, and the percentage of an exact match between quarterly cumulative trades from Ancerno and quarterly holding changes from 13F is around 20%. Hence, even though Ancerno is regarded as a survivorship-biased free database, the final dataset consistent with 13F may not be.

We begin by measuring a fund manager's monthly trading performance. We accumulate the trades for each manager j and stock i since 1999. Then, for each month, we sum up the total inflow and outflow from both the trades and the liquidation of boundary positions. Our measure of trade performance follows the all-trade measure introduced in Puckett and Yan (2011) and has a similar philosophy of the dollar-weighted return defined by Dichev and Yu (2007). To handle the cumulative short position, we record the starting negative position as capital inflow and the ending negative position as capital outflow. Specifically, we measure fund manager j's performance on all stocks i within the interval t1 to t2 as follows:

We first accumulate all the numbers of shares traded and find the cumulative trade position CT at the start and end of our interesting interval t1-t2:

$$CT_{j,i,T} = \sum_{t \leq T} Trade_{i,j,t} \tag{5}$$

Then, we calculate the liquidation value of the cumulative trade position on the boundary of the return measurement interval and separate it by capital inflow and capital outflow (Similar to Puckett and Yan, 2011)

$$Position\ Inflow_{t1,t2} = |CT_{j,i,t1}| * I(CT_{j,i,t1} < 0) * P_{i,t1} + |CT_{j,i,t2}| * I(CT_{j,i,t2} > 0) * P_{i,t2}$$

$$Position\ Outflow_{t1,t2} = |CT_{j,i,t2}| * I(CT_{j,i,t2} < 0) * P_{i,t2} + |CT_{j,i,t1}| * I(CT_{j,i,t1} > 0) * P_{i,t1}$$

Afterward we sum up the inflow and outflow from trades within the interval:

$$Trade\ Inflow_{t1,t2} = \sum_{t1 \leq T \leq t2} Sell_T * Execution\ Price_T$$

$$Trade\ Outflow_{t1,t2} = \sum_{t1 \leq T \leq t2} Buy_T * Execution\ Price_T$$

Finally, we define the performance as:

$$R_{t1,t2} = \frac{(Trade\ Inflow_{t1,t2} + Position\ Inflow_{t1,t2})}{(Trade\ Ou\qquad_{t1,t2} + Position\ Outflow_{t1,t2})} - 1 \tag{6}$$

According to the above procedure, we prepare the fund j's overall performance in interval from t1 to t2, and each stock's trading return during this interval based on equation (6). The fund overall performance can be express as the capital outflow value-weighted of stocks' trading return. We winsor the fund-stock trade performance and fund-overall trade performance at 1% and 99% level because the trade performance contains observations with outlying magnitude under our valuation method that origins from the arbitrage of trade. We further exclude those funds with less than 15 stocks in the portfolio to eliminate the small-size fund. Our skill measures have a slight difference from that introduced in Puckett and Yan 2011 in the buy-and-hold performance across intervals. By maintaining the cumulative trade position of fund managers, we are able to detect the skill from the trade in previous intervals and hold until to the current intervals.

Then, we decompose the fund overall performance to anomaly-portfolio timing and within-anomaly-group stock selection performance as follow:

$$Anomaly\ Timing_{j,t1,t2} = \textstyle\sum_i outflow\ weight_{i,t1} * BR_{i,t1,t2} \tag{7}$$

$$Anomaly\ Selection_{j,t1,t2} = \textstyle\sum_i outflow\ weight_{i,t1} * (R_{i,t1,t2} - BR_{i,t1,t2}) \tag{8}$$

Where BR denotes the benchmark return of the quintile-sorting anomaly portfolio to where stock i belongs, R t1 t2 denotes the trade return of stock i in fund j for the interval with boundary t1 and t2. This trade return differs from stock returns in CRSP monthly security file because we take the short selling and exact execution price into consideration and thus our measurement of managers' trade performance is more close to the reality.

4.2 Dynamic Trading Skills

To verify whether the anomaly timing and stock selection skills are dynamic, we then prepare the monthly news concentration ratio, CR, to each manager-month observation:

$$CR_{j,t} = \sum_i outflow\ weight_{j,i,t} * News\_Arrival_{i,t} \tag{9}$$

Where outflow weight denotes the percentage of a stock's monthly capital flow to fund's overall monthly capital flow. News_Arrival is a dummy variable that indicate a stock has certain type of news within month t. we prepare the news concentration ratio for earning announcement, business news, non-business news and financial news. Then we run the following regressions and report the result in Table 4.1:

$$Performance\ Measures_{j,t} = a + b * CR_{j,t} + \varepsilon_{j,t} \tag{10}$$

Where $Performance\ Measures_{j,t}$ include anomaly timing and within anomaly stock selection and are calculated by equation (7) and equation (8). $CR_{j,t}$ measures news density and is calculated by equation (9). The panel regression is clustered at fund level with yearly fixed effect. Timing and selection are multiplied by 1000 for readability. We also consider the covariance measurement of managers' timing and picking skills as is applied in KSZ (2016) as robustness test.

a. Earning Annoucement

[Table 4.1]

Table 4.1 reports the coefficients and t-statistic of our performance measures on earning announcement concentration months. In columns (1) and (2) of Panel A, we find that, ideally, if managers' portfolio receive 1 more earning announcement for every stock during that month, the managers' timing performance on the MGMT trading strategy have around 19 bp positive abnormal performance but 7 bp negative performance on the stock-selection performance within the MGMT quintile significantly. As for the benchmark trading strategy generated by PERF anomalies in columns (3) and (4) of Panel A, managers will have remarkable 12 bp positive abnormal performance on the stock-selection performance. Hence, we find strong evidence that during months with concentrated earning announcement arrivals, investors have better timing ability on MGMT anomalies and stock selection performance on PERF anomalies. Our result are robustness for the covariance measures of trading skills and information choice in Panel B. We only show the empirical result by weight-averaged measures for brevity after then.

Earing announcement contains much more abundant information about firms' management and operation than other firm news. Investors could clearly obtain their interesting fundamental ratio (such as Anomalies categorized by MGMT) from annual or quarterly earnings reports. Therefore, we are expected to observe the positive abnormal timing performance from the fundamental-based trading strategy for the investors. On the opposite, PERF anomalies encounter more with the market-based information such as return, volatility and liquidity. Earning announcement date also have temporary effect on the market (well known as PEAD) but majorly, the abundant fundamental information from earning announcement will serve as a substitution of information set in picking the stock within same market-based indicators (such as Anomalies categorized by PERF) and therefore we are expected to observe the positive abnormal stock selection performance on PERF trading strategy.

b. News Content

We further differentiate managers' choices on different types of news. We re-estimate the regression in equation (10) on the arrival of business news, non-business news, and finance news we've categorized and report the mean and t-statistic of their coefficients in Table 4.2.

[Table 4.2]

Our sample of the business-related news from Ravenpack is much larger in amount but less vital in context importance than earning annoucement. From Panel A of Table 4.2 we could ovserve that the business-related news contribute to the within-style stock selection performance, but such a broad set of information is hard to detect the preference of fund managers' investment style. In comparison, the subsample of finance news consists of fundamental-related news (eg. earnings and revenues) and market-related news (eg. stock price and credit rating). We observe a signficant performance from the timing of both the MGMT and PERF strategy on those finance news in Panel B of Table 4.2. It demonstrates that fund managers have a tendency to adjust the investment style timely toward these finance-related news. In sum, our investigation of the managers' trading performance on different kinds of news has provided strong evidence to the statement that different choice of information will contribute to the dynamic skills of trading.

c. Managers Group

In this section, we divide institutional investors into different groups to capture the common trading skill and information preference among similar investors. We sort each investors into quintile groups based on the size and frequency of trade. The trade size is measured by annual dollars of trade according to Chakrabarty et al. (2017) and is a good proxy for the size of fund's AUM. The trade frequency is prepared to potentially seperate the value investors from technical investors. We display the regression result of following equation in Table 4.3 and 4.4. $Qgroup_j$ is categorical variable of size or frequency quintile for fund j

$$Performance\ Measures_{j,t} = a + b * CR_{j,t} + c * Qgroup_j + d * CR_{j,t} * Qgroup_j + \varepsilon_{j,t} \quad (11)$$

[Table 4.3]

We observe adverse skill measures for managers in size quintiles on news-intensive month than usual. Columns (2) and (8) of the Table 4.3 show that generally, managers with small AUM size have higher timing ability on MGMT and PERF trading strategy. Column (5) and (11) of the Table 4.3 show that maanger with larger size have higher stock selection ability. These findings reconcile with KSZ (2014). But on the news-intensive month, we find contradict result from the coefficients of interaction term of news CR and quintile number, indicating that small managers concern more on stock picking while large managers concern more on the timing. We find no linear relationship between the skill performance and trade frequency of fund managers in Table 4.4. But the mean distribution of overall performance measures of managers in different trading frequency quintile in columns (2) (5) (8) and (11), is also not identical, even contrary to the mean distribution of interaction term in columns (3) (6) (9) and (12). We can therefore conclude that institutional investors owns different preference on sources of information and have different skillset on processing the information. Their dynamic trading skill possibily derives from the non-uniformly distributed arrival of firm-level news.

[Table 4.4]

5. Conclusion

By conducting stock-level analysis on aggregated institutional behavior, this paper concludes that institutional investors possess skills to choose information and take advantage of the anomaly return. Additionally, institutional investors have their own beliefs about firms, and they don't just herd into the long tail of anomaly strategies. With the help of the decomposition of each manager's trade performance, we enhance our conclusion that institutional investors have preferences toward different sources of information and, at the same time, their trading skills are dynamic in periods with different information densities.

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Table 2.1 Descriptive Statistics of Ancerno Data

Panel A of this table shows the descriptive statistics of Ancerno trading data. Our sample period start from Jan 1999 to Sep 2011. Institution is identified by CLIENTCODE in Ancerno data, trade frequency count the annual number of trades made by Ancerno clients. Panel B describe the distribution of average trade size and dollar amount per trade for plan sponsors and investment manager. Plan sponsor and investment manager are categorized by CLIENTMGRCODE in ancerno data.

Panel A: Year-by-year descriptive statistics

Year	# of institutions	# of stocks	share volumes (in billion)	trade frequency (in million)	dollar volume ($ in billion)
1999	379	6221	46.23	5.14	2060.20
2000	371	5966	62.62	6.48	2762.14
2001	398	5124	89.01	8.12	2698.91
2002	425	4747	112.19	10.48	2708.02
2003	400	4822	94.59	10.42	2350.50
2004	402	5017	91.77	12.72	2615.61
2005	376	4854	98.91	16.84	3059.52
2006	398	4737	120.04	28.37	3860.46
2007	377	4774	117.88	36.03	4160.89
2008	333	4382	138.67	30.25	3960.83
2009	316	4279	131.83	24.44	2833.76
2010	307	3961	98.72	24.85	2615.79
2011	259	3637	57.67	18.39	1771.64

Panel B1: Distribution of annual average size of trades (in thousand dollars)

			Percentile	
Buy	mean	25th	50th	75th
Plan Sponsor	39360.60	4.97	154.65	13276.99
Investment Manager	109078.62	41.44	161.58	2535.81

			Percentile	
Sell	mean	25th	50th	75th
Plan Sponsor	40247.71	6.34	148.40	13475.67
Investment Manager	102709.08	35.80	140.11	2011.86

Panel B2: Distribution of dollar amounts per trade (in thousand dollars)

			Percentile	
Buy	mean	25th	50th	75th
Plan Sponsor	162.55	0.22	0.86	38.25
Investment Manager	135.35	2.43	8.61	45.50

			Percentile	
Sell	mean	25th	50th	75th
Plan Sponsor	153.94	0.13	0.94	44.45
Investment Manager	126.75	2.43	9.00	46.35

Table 2.2: Anomaly Returns

This table shows the monthly average excess returns and the alphas for the long-short portfolios of the two composite anomaly portfolio from January 1999 to September 2011. The MGMT composite anomaly portfolio is formed based on the average ranking of net stock issues, composite equity issues, total accruals, net operating assets, asset growth, and investment to assets. The PERF composite anomaly portfolio is formed based on the average ranking of failure profitability, O score, momentum, gross profitability premium, and return on assets. Panel A reports the excess returns of the two anomaly portfolios within each quintile and between the extreme quintiles. Panel B reports the Fama-French three-factor alphas obtained by running the OLS regression: $R_t = a + bMKT_t + cHML_t + dSMB_t + \varepsilon$, where R_t is the strategy's excess return in month t. We report the value of a in the above regression in Panel B. The t-statistics in parentheses are based on Newey-West standard errors with optimal lag length.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Panel A: Excess Return						
MGMT	-0.23%	0.05%	0.13%	0.24%	0.23%	0.46%
	(-0.45)	(0.10)	(0.37)	(0.69)	(0.61)	(1.72)
PERF	-0.92%	0.20%	0.11%	0.15%	0.16%	1.08%
	(-0.98)	(0.32)	(0.24)	(0.38)	(0.42)	(1.50)
Panel B: Fama-French Three-factor Alphas						
MGMT	-0.30%	-0.03%	0.09%	0.18%	0.16%	0.46%
	(-2.41)	(-0.27)	(0.84)	(1.64)	(1.58)	(2.44)
PERF	-1.19%	0.01%	0.01%	0.09%	0.14%	1.33%
	(-2.51)	(0.02)	(0.08)	(0.74)	(1.19)	(2.43)

Table 2.3: Anomaly Returns on Earning Announcement Day

This table shows the daily returns of the stocks in our sample universe within different groups of composite anomalies from January 1999 to September 2011. The MGMT composite anomaly portfolio is formed based on the average ranking of net stock issues, composite equity issues, total accruals, net operating assets, asset growth, and investment to assets. The PERF composite anomaly portfolio is formed based on the average ranking of failure profitability, O-score, momentum, gross profitability premium, and return on assets. Columns 1-4 display the coefficients of stock returns on the extreme high-and-low MGMT anomaly quintiles, Earning announcement date, and the interaction effect between extreme high-and-low MGMT anomaly quintiles and earning announcement date. Columns 5-8 report the same coefficients for the composite PERF anomalies. Stock-level control variables include the sum of daily returns, squared daily returns as a measure of volatility, and the market trading volume for the stock in the past 10 days. Standard errors are clustered on firm-day level with t-statistics shown in parentheses. *,**,*** denote two-tail statistical signficance at the 10%, 5% and 1% level respectively

	1	2	3	4	5	6	7	8
Group	MGMT anomalies				PERF anomalies			
Anomaly short (Q1)	-0.038***	-0.013***	-0.037***	-0.012**	-0.179***	-0.153***	-0.174***	-0.149***
	(-7.22)	(-2.77)	(-7.02)	(-2.49)	(-19.33)	(-14.02)	(-18.80)	(-13.34)
Anomaly long (Q5)	0.007	-0.000	0.008*	0.000	0.040***	0.026***	0.037***	0.024***
	(1.64)	(-0.09)	(1.79)	(0.03)	(6.11)	(4.13)	(5.77)	(3.93)
EA			0.338***	0.304***			0.379***	0.335***
			(12.87)	(12.18)			(13.12)	(12.13)
Anomaly short * EA			-0.072**	-0.087***			-0.351***	-0.351***
			(-2.17)	(-2.74)			(-7.34)	(-7.70)
Anomaly long * EA			-0.047	-0.036			0.155***	0.153***
			(-1.54)	(-1.25)			(3.84)	(3.98)
return_past10days		6.391***		6.389***		6.287***		6.254***
		(56.05)		(56.04)		(55.05)		(55.20)
volatility_past10days		-0.646***		-0.646***		-0.616***		-0.620***
		(-3.85)		(-3.85)		(-3.31)		(-3.27)
volume_past10days		0.000*		0.000*		0.000		0.000
		(1.66)		(1.65)		(1.61)		(1.58)
Constant	0.015	-0.022	0.010	-0.027	0.028	-0.007	0.022	-0.012
	(0.85)	(-1.27)	(0.58)	(-1.52)	(1.45)	(-0.38)	(1.17)	(-0.67)
Observations	14,984,990	14,977,950	14,984,990	14,977,950	11,857,311	11,455,787	11,857,311	11,852,457
R-squared	0.000	0.054	0.000	0.054	0.000	0.054	0.001	0.054
Double FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 3.1: Trading imbalance and Turnover on different anomaly group

This table shows the result of regression: $Imbalance(Volume)_{i,t} = a + b * MGMT(PERF)\ quintile_{i,t-1} + \varepsilon_{i,t}$. Column (1) and (2) report the result for trading imbalance, which is defined as the net trade imbalance scaled by average CRSP trading volume for past year. Column (3) and (4) report the regression result for trading volume scaled by acerage CRSP trading volume for pas year. Rows contains the coefficients and their t-statistic for MGMT extreme quintile and then PERF extreme quintile. T-statistic is reported in parenthesis with double-way clustered. Imbalance is winsored at 1% and 99% level, Volume is winsored at 99% level. Imbalance and volume are multiplied by 1000 for readability.

	(1)	(2)	(3)	(4)
	Imbalance		Volume	
MGMT Q1	0.758***		4.074***	
	(3.03)		(2.78)	
MGMT Q5	-0.568**		-15.397***	
	(-2.29)		(-10.76)	
PERF Q1		-3.604***		-48.548***
		(-12.91)		(-28.16)
PERF Q5		0.352		7.164***
		(1.19)		(3.87)
Constant	3.310***	3.310***	93.441***	93.441***
	(16.78)	(16.78)	(69.95)	(69.95)
Observations	13,400,204	13,400,204	13,537,206	13,537,206
R-squared	0.000	0.000	0.001	0.001
Double FE	YES	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.2: News distribution on Anomaly Group

This table shows the difference in number of news day among each group of Anomaly. The 1st quintile is set as the baseline. Column (1) and (4) includes all ravenpack news with relevance score larger than 75, Column (2) and (5) select news with topic "business", and Column (3) and (6) select financial news according to Dehaan et al. (2022) definition. T-statistic with double way clustered is reported in parenthesis.

	(1)	(2)	(3)	(4)	(5)	(6)
Anomaly Group		Management			Performance	
News type	Relevant	Business	Finance	Relevant	Business	Finance
Baseline Q1	0.143***	0.143***	0.033***	0.107***	0.107***	0.028***
	(67.36)	(67.21)	(62.17)	(55.47)	(55.32)	(44.85)
Q2 - Q1	0.002	0.002	0.002***	0.026***	0.026***	0.006***
	(1.15)	(1.14)	(4.11)	(11.66)	(11.66)	(11.26)
Q3 - Q1	0.000	0.000	0.002***	0.040***	0.040***	0.008***
	(0.16)	(0.15)	(3.98)	(14.11)	(14.12)	(11.26)
Q4 - Q1	0.002	0.002	0.003***	0.053***	0.053***	0.009***
	(0.85)	(0.84)	(4.93)	(16.55)	(16.59)	(10.91)
Q5 - Q1	-0.009***	-0.009***	0.001*	0.078***	0.078***	0.011***
	(-2.63)	(-2.65)	(1.76)	(15.76)	(15.82)	(9.94)
Observations	12,216,929	12,216,929	12,216,929	9,683,826	9,683,826	9,683,826
R-squared	0.000	0.000	0.000	0.005	0.005	0.000
Double FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.3: Trading imbalance and Turnover on different anomaly group at news interval

This table shows the mean and T-statsitic of the coefficients from the regression:
$Imbalance_{i,t} = a + b * MGMT(PERF)\ quintile_{i,t-1} + c * News\ Interval_{i,t} + d * MGMT(PERF)\ quintile_{i,t-1} * News\ Interval_{i,t} + \varepsilon_{i,t}$. Column (1) and (2) report the result for trading imbalance, which is defined as the net trade imbalance scaled by average CRSP trading volume for past year. Column (3) and (4) report the regression result for trading volume scaled by acerage CRSP trading volume for pas year. Rows contains the coefficients and their t-statistic for MGMT extreme quintile and then PERF extreme quintile. Coefficients on dummy variables indicating the 3-day interval around news arrivals together with intersection term is reported. T-statistic is reported in parenthesis with double-way clustered. Imbalance is winsored at 1% and 99% level, Volume is winsored at 99% level. Imbalance and volume are multiplied by 1000 for readability.

	(1)	(2)	(3)	(4)
VARIABLES	Imbalance		Volume	
MGMT Q1	0.342		5.165***	
	(1.15)		(3.68)	
MGMT Q5	-0.244		-11.137***	
	(-0.84)		(-7.31)	
PERF Q1		-3.650***		-38.791***
		(-11.23)		(-23.67)
PERF Q5		1.167***		8.268***
		(3.06)		(4.39)
3-day interval of relevant news	0.394*	0.836***	45.307***	45.703***
	(1.76)	(3.42)	(30.86)	(29.87)
MGMT Q1 * 3-days news interval	0.937***		-3.651**	
	(2.65)		(-2.17)	
MGMT Q5 * 3-days news interval	-0.434		-2.419	
	(-1.18)		(-1.43)	
PERF Q1 * 3-days news interval		0.378		-13.166***
		(0.95)		(-6.77)
PERF Q5 * 3-days news interval		-1.905***		-13.101***
		(-4.43)		(-7.04)
Constant	3.420***	3.710***	77.016***	86.143***
	(16.00)	(15.85)	(63.63)	(60.40)
Observations	11,904,955	9,360,761	12,033,710	9,461,827
R-squared	0.000	0.000	0.009	0.013
Double FE	YES	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.1: Performance measures on different information-concentration month

This table shows the result of regression for equation (10) . Columns (1) to (4) report the regression result for MGMT timing, MGMT picking, PERF timing and PERF picking on EA concentration ratio. Column (5) to (8) report the regression result for the covariance measures of skills and earning announcement as robustness check. Timing and Selection measures is defined from equation (7) and (8). EA Concentration is defined by equation (9). Covariance measures replace the weighted average in equation (7), (8), and (9) by calculating the covariance of monthly outflow weight with trade performance or information choice. Our sample start from Jan 1. 1999 to Sep 30. 2011. Funds with less than 15 stocks are excluded. T-statistic is reported in parenthesis with fixed effect on manager and trading year. Timing and Selection measures are multiplied by 1000 for readability.

Panel A. Weight average measure of skills on information-concentrated month

	(1)	(2)	(3)	(4)
VARIABLES	MGMT_TIMING	MGMT_PICKING	PERF_TIMING	PERF_PICKING
EA Concentration	1.893***	-0.701***	0.148	1.168***
	(12.85)	(-5.56)	(1.15)	(10.36)
Constant	5.307***	-4.440***	6.458***	-5.533***
	(84.82)	(-82.95)	(117.75)	(-115.50)
Observations	1,391,233	1,391,233	1,391,233	1,391,233
R-squared	0.144	0.119	0.135	0.116
Double FE	YES	YES	YES	YES

Panel B. Covariance measure of skills on information-concentrated month

	(5)	(6)	(7)	(8)
VARIABLES	MGMT_TIMING	MGMT_PICKING	PERF_TIMING	PERF_PICKING
EA Concentration (COV)	0.270***	-2.145***	-2.213***	2.108***
	(9.66)	(-8.42)	(-47.04)	(7.81)
Constant	0.001***	-0.113***	-0.001***	-0.113***
	(15.71)	(-206.96)	(-13.05)	(-195.84)
Observations	1,391,056	1,391,043	1,389,319	1,389,203
R-squared	0.077	0.101	0.098	0.110
Double FE	YES	YES	YES	YES

Table 4.2: Performance measures on information-concentration month sourced from different type of news

This table shows the result of regression for equation (10) . Panel A reports the coefficients of performance measures on the concentration ratio of Dow Jones Business News. Business news is collected in Ravenpack with news group= "Business" and relevance score over 75. Panel B reports the coefficients of performance measures on the concetration ratio of Dow Jones Finance-related news. Finance news is a subsample from business news and categorized if news subgroup is within "Earnings, Revenues, stock prices, assets, credit, credit ratings, dividends" followed filters in deHaaN et al. (2022). Columns (1) to (4) report the regression result for MGMT timing, MGMT stock selection, PERF timing, and PERF stock selection respectively. Timing and Selection measures is defined from equation (7) and (8) CR is defined by equation (9) and calculated based on business news and finance news respectively. T-statistic is reported in parenthesis with fixed effect on manager and trading year. Timing and Selection measures are multiplited by 1000 for readability.

	(1)	(2)	(3)	(4)
Panel A. Business News				
VARIABLES	MGMT_TIMING	MGMT_PICKING	PERF_TIMING	PERF_PICKING
Business	-31.721***	15.747***	-24.424***	12.194***
	(-32.57)	(19.03)	(-28.67)	(16.51)
Constant	36.033***	-19.453***	29.572***	-16.484***
	(38.63)	(-24.55)	(36.25)	(-23.31)
Observations	1,363,669	1,363,669	1,363,669	1,363,669
R-squared	0.144	0.119	0.135	0.114
Double FE	YES	YES	YES	YES
Panel B. Finance News				
VARIABLES	MGMT_TIMING	MGMT_PICKING	PERF_TIMING	PERF_PICKING
Finance (subsample of business)	4.974***	-0.851***	2.339***	2.097***
	(17.98)	(-3.62)	(9.66)	(9.99)
Constant	2.214***	-3.792***	4.572***	-6.276***
	(11.26)	(-22.70)	(26.57)	(-42.08)
Observations	1,363,669	1,363,669	1,363,669	1,363,669
R-squared	0.144	0.118	0.134	0.114
Double FE	YES	YES	YES	YES

Table 4.3: Performance measures on information-concentration month sourced from different type of news

This table shows the result of regression for equation (11) for quintile managers group sorted by trade size. Panel A reports the coefficients of performance measures toward MGMT portfolio benchmark. Panel B reports the coefficients of performance measures toward PERF portfolio benchmark. Columns (1) (4) (7) and (10) is the baseline regression result displayed already in Table 4.1. Columns (2) (5) (8) and (11) report the difference in mean of performance measures with the baseline quintile. Columns (3) (6) (9) and (12) report the interaction effect of EA concentration and size quintile. T-statistic is reported in parenthesis with fixed effect on the manager and trading year. Timing and Selection measures are multiplited by 1000 for readability.

Panel A. MGMT Timing and Picking

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES		MGMT_TIMING			MGMT_PICKING	
EA Concentration	1.893***		4.063***	-0.701***		2.174***
	(12.85)		(12.80)	(-5.56)		(7.82)
SIZE Q2		-2.017***	-0.179		1.659***	1.100***
		(-15.90)	(-0.92)		(14.93)	(6.41)
SIZE Q3		-3.284***	-1.524***		3.016***	3.447***
		(-24.61)	(-7.50)		(25.80)	(19.36)
SIZE Q4		-3.761***	-3.567***		3.861***	5.687***
		(-26.51)	(-17.33)		(31.07)	(31.55)
SIZE Q5		-4.105***	-4.062***		2.996***	5.463***
		(-28.97)	(-19.75)		(24.13)	(30.31)
SIZE Q2 * EA Concentration			-5.540***			1.625***
			(-12.39)			(4.15)
SIZE Q3 * EA Concentration			-5.310***			-1.333***
			(-11.52)			(-3.30)
SIZE Q4 * EA Concentration			-0.607			-5.531***
			(-1.35)			(-14.06)
SIZE Q5 * EA Concentration			-0.165			-7.440***
			(-0.37)			(-18.94)
Constant	5.307***	8.522***	7.179***	-4.440***	-6.968***	-7.680***
	(84.82)	(87.12)	(50.06)	(-82.95)	(-81.31)	(-61.15)
Observations	1,391,233	1,407,402	1,407,402	1,391,233	1,407,402	1,407,402
R-squared	0.144	0.127	0.127	0.119	0.076	0.077
Double FE	YES	YES	YES	YES	YES	YES

Panel B. PERF Timing and Picking

	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES		PERF_TIMING			PERF_PICKING	
EA Concentration	0.148		1.284***	1.168***		5.108***
	(1.15)		(4.61)	(10.36)		(20.53)
SIZE Q2		-2.424***	-0.782***		2.008***	1.772***
		(-21.79)	(-4.55)		(20.19)	(11.54)
SIZE Q3		-4.018***	-2.829***		3.761***	4.739***
		(-34.34)	(-15.87)		(35.95)	(29.74)
SIZE Q4		-4.516***	-4.839***		4.507***	6.751***
		(-36.30)	(-26.81)		(40.52)	(41.85)
SIZE Q5		-4.777***	-5.161***		3.683***	6.625***
		(-38.43)	(-28.61)		(33.14)	(41.08)
SIZE Q2 * EA Concentration			-4.895***			0.600*
			(-12.48)			(1.71)
SIZE Q3 * EA Concentration			-3.545***			-3.028***
			(-8.77)			(-8.38)
SIZE Q4 * EA Concentration			1.012**			-6.849***
			(2.57)			(-19.46)
SIZE Q5 * EA Concentration			1.187***			-8.934***
			(3.02)			(-25.41)
Constant	6.458***	9.618***	9.184***	-5.533***	-7.945***	-9.618***
	(117.75)	(112.12)	(73.03)	(-115.50)	(-103.59)	(-85.56)
Observations	1,391,233	1,407,402	1,407,402	1,391,233	1,407,402	1,407,402
R-squared	0.135	0.117	0.117	0.116	0.072	0.072
Double FE	YES	YES	YES	YES	YES	YES

Table 4.4: Performance measures on information-concentration month sourced from different type of news

This table shows the result of regression for equation (11) for quintile managers group sorted by trade frequency. Panel A reports the coefficients of performance measures toward MGMT portfolio benchmark. Panel B reports the coefficients of performance measures toward PERF portfolio benchmark. Columns (1) (4) (7) and (10) is the baseline regression result displayed already in Table 4.1. Columns (2) (5) (8) and (11) report the difference in mean of performance measures with the baseline quintile. Columns (3) (6) (9) and (12) report the interaction effect of EA concentration and frequency quintile. T-statistic is reported in parenthesis with fixed effect on the manager and trading year. Timing and Selection measures are multiplited by 1000 for readability.

Panel A. MGMT Timing and Picking

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES		MGMT_TIMING			MGMT_PICKING	
EA Concentration	1.893***		-1.598***	-0.701***		1.280***
	(12.85)		(-5.16)	(-5.56)		(4.72)
FREQ Q2		0.495***	-1.624***		-0.429***	2.173***
		(4.08)	(-8.58)		(-4.04)	(13.11)
FREQ Q3		0.777***	0.002		-1.066***	-3.493***
		(6.17)	(0.01)		(-9.66)	(-20.23)
FREQ Q4		-0.028	-1.381***		-0.575***	-0.290*
		(-0.23)	(-7.15)		(-5.33)	(-1.71)
FREQ Q5		-1.553***	-2.845***		-0.083	1.822***
		(-12.75)	(-14.76)		(-0.78)	(10.80)
FREQ Q2 * EA Concentration			6.389***			-7.835***
			(14.59)			(-20.43)
FREQ Q3 * EA Concentration			2.351***			7.290***
			(5.15)			(18.24)
FREQ Q4 * EA Concentration			4.073***			-0.863**
			(9.12)			(-2.21)
FREQ Q5 * EA Concentration			3.891***			-5.726***
			(8.65)			(-14.54)
Constant	5.307***	5.951***	6.478***	-4.440***	-4.231***	-4.656***
	(84.82)	(68.84)	(48.25)	(-82.95)	(-55.86)	(-39.60)
Observations	1,391,233	1,407,402	1,407,402	1,391,233	1,407,402	1,407,402
R-squared	0.144	0.127	0.127	0.119	0.076	0.077
Double FE	YES	YES	YES	YES	YES	YES

Panel B. PERF Timing and Picking

VARIABLES	(7)	(8)	(9)	(10)	(11)	(12)
		PERF_TIMING			PERF_PICKING	
EA Concentration	0.148		-2.571***	1.168***		2.249***
	(1.15)		(-9.47)	(10.36)		(9.27)
FREQ Q2		0.371***	-0.925***		-0.544***	1.112***
		(3.49)	(-5.57)		(-5.72)	(7.49)
FREQ Q3		0.744***	0.129		-1.281***	-3.896***
		(6.73)	(0.74)		(-12.96)	(-25.20)
FREQ Q4		-0.106	-1.234***		-0.629***	-0.510***
		(-0.98)	(-7.28)		(-6.51)	(-3.37)
FREQ Q5		-1.702***	-2.993***		-0.037	1.758***
		(-15.93)	(-17.71)		(-0.39)	(11.64)
FREQ Q2 * EA Concentration			3.905***			-4.977***
			(10.16)			(-14.49)
FREQ Q3 * EA Concentration			1.855***			7.873***
			(4.63)			(22.01)
FREQ Q4 * EA Concentration			3.392***			-0.357
			(8.66)			(-1.02)
FREQ Q5 * EA Concentration			3.890***			-5.395***
			(9.86)			(-15.30)
Constant	6.458***	6.611***	7.464***	-5.533***	-4.656***	-5.405***
	(117.75)	(87.17)	(63.36)	(-115.50)	(-68.66)	(-51.34)
Observations	1,391,233	1,407,402	1,407,402	1,391,233	1,407,402	1,407,402
R-squared	0.135	0.116	0.116	0.116	0.070	0.072
Double FE	YES	YES	YES	YES	YES	YES