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Trading regularity and fund performance: Evidence in uncertain markets

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Abstract

High trading regularity funds outperform low trading regularity funds more during periods of low market returns and greater market and economic uncertainty. Their trading also has strong return predictability on stock returns during periods of greater uncertainty. They trade more around news events, and their news related trading predicts stock return stronger during periods of greater uncertainty. They also profit from liquidity provision in highly uncertain market environment. Overall our evidence suggests that high trading regularity funds trade more frequently during periods of high uncertainty when information production and processing skill is more valuable and when the demand for liquidity is high.

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1. Introduction.

Institutions have become the majority shareholders of the US equity market over the past few decades, and institutional trades represent the lion share of active trading. While whether institutions in general add value to investors remains an open debate, the literature has long argued that at least some institutions have skills and add value to investors[1].

If a subset of managers is informed or possesses superior skills, a closely related issue is how they take advantage of their skills. On the one hand, they are likely to trade more often to take advantage of their skills. On the other hand, signals are noisy and trading is costly, more trading could lead to poorer performance. The empirical evidence on the relation between trading frequency and performance remains mixed too[2]. Yan and Zhang (2009) find that both short-term institutional holdings and trading predict future stock returns, but those of long-term institutions do not. Pastor, Stambaugh and Taylor (2015) show that the mutual fund turnover predicts future fund returns. However Lan, Moneta and Wermers (2015) argue that the long-term institutional holdings and trading predict long-run future stock returns. Cremers and Pareek (2015) provide evidence that short-term trading is related to stock return anomalies such as momentum, reversal, and share issuance. Using Ancerno data, Chakrabarty, Moulton, and Trzcinka (2017) find that a majority of short-term institutional trades lose money. Busse, Tong, Tong, and Zhang (2019) however shows that institutional trading regularity (how frequently they trade), and not necessarily the holding period of those trades, is positively related to fund performance, and they attribute the outperformance to high trading regularity funds trade more to take advantage of their information advantage and liquidity provision.

While most of the existing studies focus on the unconditional relation between fund performances and fund turnover/trading regularity for the entire sample period, there are good reasons to expect different trading patterns and fund performance under different market conditions. First, when the market is down or highly uncertain, the volatility of individual stocks would increase as well. Sophisticated investor could adopt strategies trying to time the

1 Jensen (1968), Elton, Gruber, Das, and Hlavka (1993), Malkiel (1995), Gruber (1996), Carhart (1997), Pastor and Stambaugh (2002), and Fama and French (2010), among others, find that active funds on average underperform passive benchmarks after fees. On the other hand, a number of studies have shown that at least some fund managers are skilled and their trading adds value, see, for example, Wermers(2000), Cohen, Coval, and Pastor (2005), Kacperczyk, Sialm, and Zheng (2005), (2008), Cohen, Coval, and Pastor (2005), Cremers and Petajisto (2009), Yan and Zhang (2009), Spiegel, and Zhang (2008), Amihud and Goyenko (2013), among others.

2 Earlier work on the relation between fund turnover and performance include Grinblatt and Titman (1989) , Chen, Jagadeesh and Wermers (2000) (positive), and Carhart (1997) (negative).

market return or volatility. While earlier research show little evidence that mutual funds market timing ability, Using portfolio level data Jiang, Yao and Yu (2006) show that some funds do show positive market timing ability. In addition, when the market is highly volatile, the information environment can become complicated. More noises and false information could prevent real value relevant information to get across. It requires true skills to perform well in this market. Indeed, Loh an Stulz (2018) show that analysts works harder and provides more valuable service during down and highly uncertain markets. Sun, Wang, Zheng (2019) show that hedge funds performance is only persistent following weak hedge funds markets but not after strong markets. If some institutional investors are more skilled at collecting and processing information from highly noisy signals, we would expect that they trade more frequently during volatile markets to take advantage of their skills and profit more from their trading relative to steady markets. On the other hand, the adverse market conditions could prove to be too costly to trade even for sophisticated investors, and for those who do trade, the performance would be poor.

In this paper, we empirically examine how institutional trading regularity affects the fund performance and stock prices under different market conditions. Following Busse et. al. (2019), we use Ancerno data to construct the institutional trading regularity measure as the ratio of the number of trades by the fund on a given day to the number of unique stocks traded by the fund. (More details are described in the data section.)

We use three proxies to capture the various the various aspects of the market conditions. We use the aggregate stock market return (from Ken French's website) to measure the general market performance. We classify a quarter in our sample period into bad/normal/good market periods if the market return during that quarter falls into the bottom/middle/top tercile over the entire sample period. Similarly, we use the VIX index from CBOE to capture the level of stock market uncertainty. The VIX index, often referred to as the fear index, is calculated using the mid-quote prices of the S&P 500 call and put options. VIX has been considered a popular measure for investors overall uncertainty about the market[3]. We classify a sample quarter into one of low/normal/high market uncertainty quarter, if the average VIX index in that quarter falls into the bottom/middle/top tercile. While the information environment can be noisier when the financial markets are down and/or volatile, the increase the uncertainty in the real economy

[3] (see, for example, Chung and Chuwonganant (2014) and Bhagwat, Dam, and Harford (2016))

can also make information production and processing more difficult, and potentially higher demand for liquidity in the financial market. To this end, we use the economic political uncertainty index (EPU) in Baker, Bloom, and Davis (2016), which proxies for economic policy related uncertainty[4]. We then define the low/normal/high economic uncertainty the same way as the other two proxies.

Consistent with Busse et. al. (2019), we find that high trading regularity funds outperform low trading regularity funds, and their trading predict future stock returns. Furthermore, we show that during down markets and periods with greater uncertainty, the outperformance of the high trading regularity funds is greater. For example, when the market condition is measured by VIX, the DGTW-adjusted returns for high regularity funds are 1.49% higher than those for the low trading regularity funds during the high uncertainty periods, while the outperformance during the low uncertainty periods is only 0.59% per quarter. The diff-in-diff measure is statistically significant at the 5% level. The results are similar for the value-weighted fund returns, and for alternative market uncertainty measures. The Fama-Macbeth regressions results are consistent with the portfolio based approaches.

Furthermore, we regress the daily stock return on the previous day's trading by the five trading regularity quintiles, and by their interaction with the market condition. Consistent with Busse, et al. (2019), the trading of the top two highest trading regularity quintiles of funds positively predict next day stock return, while the trading of the lower quintiles do not. Interestingly, the interaction between the market uncertainty and high regularity trading significantly predict stock returns, suggesting that the effect of high regularity trading on stock returns are greater during the periods with greater market uncertainty.

Why does the effect of trading regularity stronger during greater uncertainty? One possibility is that during uncertain markets, the information environment is nosier. It is therefore more difficult to extract real information from noisy signals. If mangers at high regularity funds are more informed or have better skills processing information compared to those at low trading regularity funds, their advantage would be greater during down and high uncertainty market periods, when signals are noisier and more difficult to process. They take advantage of that by trading more frequently. It could also be because they are trading more

[4] Previous studies that use the EPU index include Gulen and Ion (2016), Kim and Kung (2017), and Loh and Stulz (2018).

frequently to provide liquidity, when demand for liquidity is greater during higher market uncertainty.

Busse et. al. (2019) show that the trading by the high trading regularity funds before the earnings announcement can predict SUE and earnings announcement news, but the trading by the low trading regularity funds cannot. While earnings announcements contains important information about stock prices, abundance of other sources of information at both the firm and macro level could affect the stock prices. To examine the informational advantage of high trading regularity funds under different market conditions, we utilize news data from the Thomson Reuters News Analytics (TRNA), which includes the news releases on the Reuters Data Feed (RDF). Each day, the TRNA database contains a unique sentiment score ranging between -1(negative) and 1(positive) for each firm mentioned in a news article. We calculate for each firm and each a news sentiment score by taking a relevance weighted average of the sentiment of all news that mentioned the firm on that day.[5]

Hendershott, DmitryLivdan and Norman (2015) show that news sentiment predicts the next-day stock return. We show that this return predictability is stronger during market downturns and higher market uncertainty. The interaction term between news sentiment score and the market condition proxies are positive and statistically significant for all three proxies of the market condition. Moreover, We find that high trading regularity traders trade more than low trading regularity traders and especially so during bad market. Further analysis suggests that the increased trading activity of high regularity traders during bad market is attributed to their trading at days surrounding news announcements.

We further examine the effect of the news-related (non-news-related) trading by high (low) trading regularity funds during different market conditions. Indeed, for news-related trades, the high trading regularity funds perform better low regularity funds, especially during bad markets. Their new-related trades also predict next-day stock return stronger during bad markets. However, news related trades do not explain all the outperformance of high trading regularity funds. We show that even for non-news related trades, high trading regularity funds perform better during high market uncertainty. This suggest that they could be either providing liquidity when liquidity demand is high, or they process more private information (or public information not included in the data set).

5 More details of the construction of the daily news sentiment score is described in the data section.

Our results suggest that that they do provide liquidity. For non-news related trades, we decompose institutional trades into contrarian trades and momentum trades. The trading of high trading regularity funds perform better for their contrarian trades, and especially during bad markets. However, even for the momentum trades, high trading regularity funds outperform those of low trading regularity funds during bad times. This may suggest that these funds may have private information (or information not covered by our news article data.)

Our paper makes several contributions to the literature on the institutional investments. First, we document the asymmetrical relative performance between the high trading regularity funds and low trading regularity funds in various market conditions. Our evidence highlights the importance of the market condition in examining the informativeness of institutional trading, and directly link market condition to the role of institutional trading regularity. We show that some funds trade more frequently to exploit the adverse market conditions relative to other funds. Second, we provide direct evidence on the sources of the outperformance of those funds. High trading regularity funds trade more to take advantage of their skills in processing public information, especially during market down turns and high market they uncertainty, and to profit from liquidity provision, when the demand for liquidity is particularly high during high uncertainty periods. We also extent the literature on news sentiment by showing that news sentiment scores predict returns stronger in more uncertain markets, suggesting that news are more valuable during periods of higher uncertainty.

The remainder of the paper proceeds as follows. Section 2 describes the data and summary statistics. Section 3 presents the main results on how high trading regularity funds and low trading regularity funds perform differently under different market conditions. Section 4 examines possible sources of performance difference. Section 5 concludes the paper.

2. Data and Methodology

A. Data and Summary Statistics

We obtain information on institutional trade from ANcerno Ltd., a transaction cost analysis provider that serves the institutional money management industry.6 Our sample spans an 11-year sample period from January 1, 1999, to December 31, 2009. For each trade execution, the ANcerno database assigns a masked identity code for the institution, a masked identity code for the fund within the institution, the CUSIP and ticker for the stock, the stock price at the time of order placement, the date of execution, the execution price, the number of shares executed, the direction of the execution (buy or sell), and commissions paid. Compared with the Thomson Reuters holdings data, a major advantage for the ANcerno dataset is that it provides detailed fund trading activity including specific entry and exit dates and transaction prices, which allows researchers to capture round-trip trades within the calendar quarter and to precisely measure performance (see Puckett and Yan (2011) and Busse et al. (2018)).

In order to reduce the price impact, the trading desk of buy-side institutions usually break up a large order into several trades or among several brokers. In the ANcerno dataset, the allocation to each broker is defined as a "ticket," and each ticket may further result in several executions. Following Busse et al. (2018), we evaluate trades at the ticket level, rather than focusing separately on the trades that comprise the ticket.

The ANcerno database covers an extensive set of intuitional investors and the trades they placed. The database are responsible for approximately 115 million trades placed by 843 institutions and 5,277 different funds within those institutions, involving more than $42.6 trillion and 1,417 billion shares.[7] Following Busse et al. (2018), we restrict our sample to common stocks and drop fund-quarters that have a number of trades or a number of stocks traded at 1% extreme values at both ends.8 We also delete funds which cannot be reliably tracked to their institutions.

6 Previous studies that use ANcerno data include Goldstein et al. (2009), Chemmanur, He, and Hu (2009), Goldstein, Irvine, and Puckett (2011), Puckett and Yan (2011), Busse, Green, and Jegadeesh (2012), Chakrabarty et al. (2017), Busse et al. (2016), Jame (2017), and Busse et al. (2018).

7 According to Puckett and Yan (2011), ANcerno institutions account for an estimate 10% of all institutional trading volume. See Puckett and Yan (2011), Anand et al. (2012), and Busse et al. (2018) for additional details on this dataset.

8 Our results are qualitatively similar if we keep observations in which the number of stocks or trades is at the 1% extremes.

We present the summary statistics for the ANcerno trading data in panel A of Table 1 presents. After imposing the above filters, the total number of different stocks within the trade data ranges from 3,968 in 2009 to 6,142 in 2000. The total number of trade tickets increases dramatically from 3.19 million in 1999 to 11.01 million in 2009. In our sample, an average fund trades 310 times on 74 unique stocks each quarter in 1999, while it places 763 trades on 106 stocks per quarter in 2009.

We use three methods to split our sample period into three states: bad market, medium market, and good market. We rank all quarters by aggregate market returns from Kenneth French's website[9], VIX from CBOE, or the economic policy uncertain index (EPU) in Baker, Bloom, and Davis (2016) (from www.policyuncertainty.com). A quarter is categorized as a bad (good) market period if the aggregate market returns rank in the bottom (top) tercile, or if the VIX or EPU is in the top (bottom) tercile, otherwise it is defined as a medium market period.

We use the trading regularity measure in Busse et al. (2018) to capture the extent to which funds regularly trade, e.g., trading each day rather than each week. A fund that closely monitors the market and actively searches for time-varying trading opportunities would be expected to trade more regularly than a more passive investor who mainly trade to periodically rebalance his portfolio or address cash flow imbalances.

Following Busse et al. (2018), we compute the extent to which a fund trades regularly by first taking the ratio of the number of trades by the fund on a given day to the number of unique stocks traded by the fund. If a fund places no trades on a particular day, the fund's trading regularity measure on that day is marked as zero. We then take the average of its daily trading regularity measure across the quarter to obtain a fund's quarterly trading regularity measure.[10]

Table 1, Panel B reports aggregate fund trading activity for quintiles of funds sorted by trading regularity during good and bad market conditions. At the end of each quarter, we divide all funds into 5×5=25 groups based on their current quarter trading dollar volume and trading regularity. We then aggregate all funds that have the same regularity ranking across all trading volume quintiles and obtain 5 portfolios of trading regularity.

For funds in each trading regularity portfolio, we measure their aggregate trading activity by taking the ratio of the total number of trades placed and the number of unique stocks

9 http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

10 See Busse et al. (2018) for a detailed discussion of the trading regularity measure.

traded on each day. We present the averages of the ratios for each trading regularity quintile during periods of good and bad market condition respectively. As shown in Panel B2, for example, during periods of high VIX, funds in the highest trading regularity quintile trade on average 2.22 times on each stock, while funds in the lowest trading regularity quintile only trade 0.38, rendering a statistically significant difference of 1.84. During periods of low VIX, funds in the highest trading regularity trade 0.23 (statistically significant) times less on each stock than they do during high VIX periods. In contrast, funds in the lowest trading regularity group trade slightly more than they do during periods of low VIX. The gap in trading activity between funds in the highest and lowest trading regularity group is 1.84 during periods of high VIX and it is statistically significantly bigger than the gap between the two groups of funds during periods of low VIX, which is 1.59. The results suggest that funds in the highest trading regularity group are even more active compared funds in the lowest trading regularity group during bad market. We find similar patterns when market condition is measured by EPU in Panel B3. However, when market condition is measured by aggregate market returns in panel B1, although funds in the highest trading regularity quintile trade more times on each stock than funds in the lowest trading regularity quintile in both market conditions, the gaps in trading activity between the two groups of traders during bad or good market are not statistically different.

We utilize news data from the Thomson Reuters News Analytics (TRNA), which includes the news releases on the Reuters Data Feed (RDF). The TRNA database contains information on the time of the news story, the firms mentioned in the story, the relevance of the news article for each firm, and a unique sentiment score ranging between -1 and 1 for each firm mentioned in the article. A sentiment score that is equal to 1 (-1) suggests that the news story mentioned the firm in a positive (negative) tone, while a zero score means a neutral tone. We calculate a daily news sentiment score for each firm by taking a relevance weighted average of the sentiment of all news that mentioned the firm each day. To aging the dates of the news stories with institutional trading, the news stories appearing after 4 pm are assigned to the following date.

In addition to the transaction data from ANcerno, we obtain data on stock returns, share prices, trading volume, and shares outstanding from CRSP and book value of equity from Computstat.

B. Fund Performance

Similar to Puckett and Yan (2011) and Busse et al. (2018), we measure fund performance following as follows. For each fund, all trades within each quarter are separated into buys and sells. For each buy or sell, we calculate the holding-period return from the execution date (using the execution price) until the end of the quarter, accounting for stock splits, dividends, and, in certain analyses, commissions. Performance of each trade is measured using raw returns and abnormal returns. To compute abnormal returns, we subtract the DGTW benchmark return over the same holding period. For each fund, we calculate the weighted average of the performance of all trades. We use two ways of weighting. We weight each trade equally, and we weight by the dollar size of the trade. We refer to this latter weighting approach as principal weighting. We then compute average performance for buys and sells separately using the above two weighting schemes. Finally, we calculate the difference between the average performances of buys and sells, which captures the intra-quarter performance of the trades placed by a fund in a given quarter.

3. Main results

Busse et. al. (2019) show that funds with high trading regularity outperform those with low trading regularity. They relate the outperformance in part to their informational advantage and partly by liquidity provision. As we discuss in the introduction, the information environment and investors' liquidity needs can be different under different market conditions. We next examine whether the performance difference between high and low trading regularity funds is different during different market conditions.

Table 2 reports the results. Panel A reports the results for the market conditions are defined over the market returns. A quarter is defined as a good market period if the average market returns during the quarter is in the top (bottom) tertile. We report the equal-weighted and principal-weighted raw returns (A1 and A2), and DGTW-adjusted returns (A3 and A4). The general message is that high trading regularity funds outperforms low trading regularity funds more during bad (uncertain) market periods. In Panel A1 where the market condition is measured by the average market return during the quarter, the quarterly equal-weighted raw return of the low trading regularity funds during the bad market periods is -0.82%, while that for the quintile 4 is 0.96%, and for the high regularity funds (quintile 5) is 0.40%. The equal-weighted return difference between quintile 4 and quintile 1 is 1.78%, and that for the quintile 5 and quintile 1 is 1.22%, both statistically significant at the 5% level. This is consistent with Busse et. al. (2019) for all market conditions. On the other hand, during the good market periods, the equal-weighted return difference between quintile 4 and quintile 1 is -0.03%, and that for quintile 5 and quintile 1 is 0.05%, neither of which is statistically significant at the 10% level. Moreover, the difference in the return difference between the bad and good market periods is 1.81% (quintile 4 vs quintile 1) and 1.17% (quintile 5 vs quintile 1), both statistically significant at the 5% level. The results for the Principal-weighted raw returns are similar. In Panel A2, The principal-weighted return difference between quintile 4 and quintile 1 is 1.08%, and that for the quintile 5 and quintile 1 is 0.68%, both statistically significant at the 5% level. However, during the good market periods, the principal-weighted return difference between quintile 4 and quintile 1 and that for quintile 5 and quintile 1 are both statistically insignificant. Moreover, the difference in the principal-weighted return difference between the bad and good market periods is 1.42% (quintile 4 vs quintile 1), statistically significant at the 5% level, and 0.74% (quintile 5 vs quintile 1), significant at the 10% level.

The results for DGTW-adjusted returns reported in Panel A3 and A4 are consistent with raw returns. In Panel A3 for equal-weighted portfolio returns, during the bad market periods, the DGTW-adjusted return difference between quintile 4 and quintile 1 is 1.80%, and that for the quintile 5 and quintile 1 is 1.35%, both statistically significant at the 5% level. During good market periods, those DGTW-adjusted return differences are however significantly lower at 0.42%, and 0.43%, respectively. The difference in the DGTW-adjusted return difference between the bad and good market periods is 1.39% (quintile 4 vs quintile 1) and 0.92% (quintile 5 vs quintile 1), both statistically significant at the 5% level. The results in Panel A4 for Principal-weighted DGTW-adjusted portfolio returns are again consistent. The principal-weighted DGTW-adjusted return difference between quintile 4 and quintile 1 is 1.29%, and that for the quintile 5 and quintile 1 is 0.96%, both statistically significant at the 5% level; while those return difference are neither economically nor statistically significant during the good market periods. Moreover, the difference in the principal-weighted DGTW-adjusted return difference between the bad and good market periods is 1.13% (quintile 4 vs quintile 1), statistically significant at the 5% level, and 0.72% (quintile 5 vs quintile 1), significant at the 10% level.

The results are consistent when the market condition is measured by VIX (Panel B) and by EPU (Panel C). In Panel B1 the quarterly equal-weighted raw return of the low trading regularity funds (quintile 1) during the periods with higher market uncertainty is -0.48%, while that for the quintile 4 is 0.90%, and for the high regularity funds (quintile 5) is 0.57%. The equal-weighted return difference between quintile 4 and quintile 1 is 1.83%, and that for the quintile 5 and quintile 1 is 1.05%, both statistically significant at the 5% level. On the other hand, during the periods with lower market uncertainty, the equal-weighted return difference between quintile 4 and quintile 1 is 0.33%, and that for quintile 5 and quintile 1 is 0.09%, neither of which is statistically significant at the 10% level. Moreover, the difference in the return difference between the bad and good market periods is 1.05% (quintile 4 vs quintile 1), statistically significant at the 10%, and 0.96% (quintile 5 vs quintile 1), statistically significant at the 5% level. Results for DGTW-adjusted equal-weighted returns are qualitatively similar. In Panel B3 for equal-weighted portfolio returns, during periods with greater market uncertainty, the DGTW-adjusted return difference between quintile 4 and quintile 1 is 1.45%, and that for the quintile 5 and quintile 1 is 1.09%, both statistically significant at the 5% level. During good market periods, those DGTW-adjusted return differences are however significantly lower at 0.40%, and 0.21%, respectively. The difference in the DGTW-adjusted return difference between the high and low market uncertainty periods is 1.05% (quintile 4 vs quintile 1) and 0.88% (quintile 5 vs quintile 1), both statistically significant at the 5% level. The results for principal-weighted returns in B2 and B4 are also consistent with those for equal-weighted returns. Results in Panel C are similar with EPU as the uncertainty proxy. For equal-weighted raw return, the quarterly return difference between quintile 5 and quintile 1 is 1.44% during the high uncertainty periods, and significant at the 5% level. The corresponding return difference in low uncertainty is 0.26%, and statistically insignificant. The difference in difference in return between the high and low uncertainty periods is 1.06%, and significant at the 10% level. The results for principal-weighted returns and DGTW-adjusted returns are similar, although the difference-in-difference measure are noisier, statistically insignificant.

Overall Table 2 shows that high trading regularity funds outperform low trading regularity funds mostly during market downturns and during periods with greater market uncertainty. The performance difference could however be driven by fund and stock level factors other than trading regularity, and these factors could have different magnitude and have different impact during under different market conditions. We hence conduct fund-quarter level panel regression analysis of quarterly fund level equal-weighted (EW) or principle-weighted (PW) DGTW-adjusted performance on the trading regularity, and a number of fund and stock level control variables. The control variables include the previous quarter fund performance, the logarithm of the previous quarter fund aggregate volume, and the average value of characteristics of all stocks traded by the fund in the current quarter (book-to-market ratio, logarithm of market capitalization, the lagged 12-month return, turnover, idiosyncratic volatility, Amihud's illiquidity, the lagged one-day return, and herding). This regression setup is consistent with Busse et. al. (2019). The innovation is that we include in the independent variables a measure of the market condition, the interaction between the trading regularity and the market condition. If high trading regularity funds outperform low trading regularity funds more during market downturns and more volatile markets, the coefficients on the interaction term would be negative when the market condition is measured by the market returns, and negative when it is measured by VIX or EPU.

Table 3 reports the results. When market condition is measured by the market returns, consistent with Busse et. al. (2019), the coefficient on the trading regularity is significantly positive. More interestingly, the coefficient on the interaction term between the trading regularity and the market condition is negative. When fund performance is measured as EW returns, the coefficient is -0.012, statistically significant at the 5% level. When the fund performance is measured as PW returns, the coefficient is -0.007, albeit not statistically significant. When the market condition is measured by VIX, the coefficient on the interaction term is positive, again consistent with our expectation. For EW fund performance measure, the coefficient 0.011, statistically significant at the 5% level, and for PW fund performance measure, the coefficient is 0.007, statistically significant at the 10% level. When the market condition is measured by EPU, the coefficient on the interaction term is also positive, but statistically insignificant. The coefficient on the control variables are generally consistent with those reported in Busse et. al. (2019). Overall, the results in Table 3 are consistent with those reported in Table 2: high trading regularity funds outperform low trading regularity funds more during the market downturns and more volatile markets.

We next examine how the trading of the high/low trading regularity funds affect stock return differently under different market conditions. To this end, we regress daily abnormal market adjusted return of the stock on the prior day net trading volume of funds in each of the five trading regularity quintiles, a dummy variable of Bad(Mid) market, the interaction term between the fund quintile trading volume and the market condition dummy, and control variables. The net trading volume is calculated as the total shares bought minus the total shares sold by funds in the same quintile divided by the shares outstanding. Bad (Mid) market is a dummy variable equal to 1 if the market returns in a quarter rank in the top (middle) tercile in the sample period, and zero otherwise. The control variables include the stock's lag one-day market adjusted return and trading volume and stock fixed effects.

Table 4 reports the regression results. Consistent with Busse et. al. (2019), unconditionally the trading of low trading regularity funds (T1 and T2) does not significantly predict next day stock returns, while the trading of high trading regularity funds (T3 to T5) predict future stock returns. Interestingly, the coefficients on the interaction term between trading volume and bad market dummy are significant, and especially so for the interaction between the trading volume of the high trading regularity funds and the bad market dummy. And the effect is stronger when the market condition is defined by VIX and EPU. This suggests that the effects of more frequent trading is stronger not necessarily when the market is doing poorly per se, but when the market is more volatile, in which the information environment is more uncertain, and those managers who trade more frequently may have more informational advantage towards those who trade less. We further examine this possibility next.

4. Sources of outperformance: Information vs liquidity provision

Busse et. al. (2019) show that part of the reasons that high trading regularity funds outperform low trading regularity funds is because of their informational advantage and their liquidity provision trades. For example, they show that the trading of high trading regularity funds can predict future earnings surprises and earnings announcement returns. Given our discussion earlier, this predictive power could be stronger during uncertain markets. While earnings announcement is an important source of information in investment decision, there are many other sources of information that investors trade upon. To include more sources of information, we utilize news data from the Thomson Reuters News Analytics (TRNA), which includes the news releases on the Reuters Data Feed (RDF). We then follow (JFE) and calculate a daily news sentiment score for each of the firm in the sample. The details of the TRNA data and the calculation of the sentiment score is described in the data section.

We first examine whether news sentiment have greater predictive power for stock returns during market downturns and market periods with greater uncertainty. We regress daily abnormal market adjusted return of the stock on the contemporaneous news sentiment, measures of market conditions, and control variables. Consistent with earlier analysis, to measure market conditions, we construct Bad (Mid) market dummy variables. The Bad market dummy equals 1 if the market returns (VIX, EPU) in a quarter rank in the bottom (top, top) tercile in the sample period, and zero otherwise. The Mid market dummy equals 1 if the market returns (VIX, EPU) in a quarter rank in the middle (middle, middle) tercile in the sample period, and zero otherwise. The control variables include the stock's lag one-day market adjusted return and trading volume and stock fixed effects.

Table 5 reports the results. Consistent with (JFE paper), news sentiment significantly predict next-day stock returns. The coefficient of the news sentiment is 0.005, and statistically significant at the 1% level. More importantly, the coefficient of the interaction term between news sentiment and Bad market is significantly positive, suggesting that during low market return periods and more volatile markets, the return predictability of the news sentiment is stronger. This is true for all three proxies for the market condition, with the coefficient 0.002, 0.002, and 0.001, for market returns, VIX, and EPU, respectively, all statistically significant at the 1% level. The results suggest that news have greater impact on stock returns during low return and more uncertain market periods.

As we show in Table 5 that news sentiment predicts return stronger during bad market periods. High trading regularity funds could outperform more during uncertain market periods because they are more skilled and process public news better than low trading regularity funds. If so, they would have more trading around news events during uncertain market periods relative to less uncertain market periods. We examine this hypothesis next. Specifically we examine funds trading around news days and no-news days separately, and in both low return (high uncertainty) markets and high return (low uncertainty) markets. We define a stock-day is as a news day if there is at least one news announcement about the stock within the [-3, 3] day window, and it is denoted as a no-news day otherwise. On each day, we calculate the ratio of total number of trades divided by total number of unique stocks traded by all funds in each regularity group. Table 6 reports the results. Panel A reports the results when the market condition is defined by low/high market returns. In Panel A.1 when the trading is around news events, the average trading regularity measure for high trading regularity funds are significantly higher than that for low regularity funds, consistent with previous findings. And this difference is statistically significant for both market conditions. Interestingly, comparing the trading around news days between bad markets versus good markets, the trading of high regularity funds is significantly more during the low return markets than that during the high return markets. The trading regularity measure of the quintile 5 funds is 3.02 during the bad return periods, and that during the good market return period is 1.55, the difference statistically significant at the 1% level. Moreover, the trading regularity difference between high trading regularity funds and low trading regularity funds is also higher during the bad market periods than during the good market periods, and the difference in difference statistically significant at the 1% level.

Results in Panel B are qualitatively similar, where the market condition is defined by VIX and EPU, respectively. In Panel B1 where the trading is around the news days, the difference in trading regularity measure for high regularity funds between the high VIX periods and the low VIX periods is 0.64, and statistically significant at the 1% level. On the other hand, the difference in in trading regularity measure for low regularity funds (fund quintile 1) between the high VIX periods and the low VIX periods is virtually 0, and statistically insignificant. The difference in difference measure of the trading regularity across high/low trading regularity quintiles in high/low VIX periods is 0.64, also statistically significant at the 1% level. In Panel B2 where the trading is not around news events, the difference in trading regularity measure for high regularity funds between the high VIX periods and the low VIX periods is much smaller at 0.18, and statistically insignificant. While the difference in difference measure remains statistically significant, the magnitude is much smaller at 0.17.

The results in Panel C where the market condition is defined over EPU is similar. In Panel C1 where the trading is around the news days, the difference in trading regularity measure for high regularity funds between the high EPU periods and the low EPU periods is 0.60, and statistically significant at the 1% level. On the other hand, the difference in in trading regularity measure for low regularity funds (fund quintile 1) between the high EPU periods and the low EPU periods is much lower at 0.03. The difference in difference measure of the trading regularity across high/low trading regularity quintiles in high/low EPU periods is 0.53, also statistically significant at the 1% level. In Panel C2 where the trading is not around news events, the difference in trading regularity measure for high regularity funds between the high EPU periods and the low EPU periods is smaller at 0.11, and the difference in difference measure also becomes smaller at 0.08.

Overall the results reported in Table 6 show that high regularity funds trade more around public news events during periods with low market returns and higher market uncertainty. As we show in Table 5 that news sentiment predicts stronger during periods of low market returns and greater market uncertainty, our results is consistent with high trading regularity funds outperform low regularity funds partially because their superior ability in processing public news relative to low regularity funds.

We next directly examine whether news related trades perform better. To this end, we repeat the portfolio sorting approach in Table 2. As in Table 2, we then calculate for each fund the average DGTW-adjusted performance in each quarter. The EW and PW DGTW-adjusted performance for funds in each trading regularity quintile during different market conditions is reported. The innovation here is that we calculate fund performance for all news related trades and no news related trades separately. Table 7 reports the results. As in Table 2, we report the results for both bad and good markets. For news related trades, the performance difference between the high and low trading regularity funds are significant for bad markets, but not for good markets. This result is robust across all measures of market uncertainty. For example, when the uncertainty is proxied by VIX, the quarterly DGTW-adjusted EW return difference between quintile 5 and quintile 1 is 1%, statistically significant at the 5% level, while the corresponding return is 0.37, and statistically insignificant. However, the return difference remains significant for the non-news related trades. This suggest that the news related trades cannot fully the return difference.

To further examine the information channel, we conduct regression analysis of next-day stock return on high (low) trading regularity measures. As in Table 3, we regress daily abnormal market adjusted returns of the stock on the prior day net trading volume of funds in each of the five trading regularity quintiles, measures of market conditions, the interaction between the trading regularity and market conditions dummy variable, and the same set of control variables included in Table 3. The market condition dummy is also defined the same way as in Table 3. We conduct the regression analysis over different sample samples of news days and no-news days. A stock-day is defined as a news day if there is at least one news announcement about the stock within the [-3, 3] day window, and it is denoted as a no news day otherwise. Table 8 reports the results. Panel A reports the results for the sample of news days, and Panel B reports the results for the sample of no-news days. The main message is that while during news days the trading of high trading regularity funds during periods of low market returns and high market uncertainty predicts stock returns better, the same is true during no-news days. Specifically, in Panel A for the news-days sample, the coefficient on the interaction term of the trading of high regularity funds and bad market is 0.001, and statistically significant at 5% level for all three proxies of the market condition, average market return, VIX, and EPU. On the other hand, in Panel B for the no-news days sample, the results are qualitatively the same. These results suggest that while public news-related trades during periods of low market returns and high uncertainty can partially explain high trading regularity funds' superior performance during those market conditions, non-public-news related trades also play important roles in explaining the outperformance.

One source of the outperformance of high trading regularity funds in no-news related trades could be profits from liquidity provision. Busse et. al. (2019) show that unconditionally liquidity provision is an important source of the outperformance of high trading regularity funds over low trading regularity funds. As we argue earlier, under different market condition, investors' needs for liquidity can be different. When the market is down, or when the level of the market uncertainty is high, investors would have greater demands for liquidity. High trading regularity funds may be especially better at providing liquidity during bad market through their frequent trading, and hence realize better performance. We next examine liquidity provision under different market conditions of funds by examining their contrarian trades versus momentum trading for no-news related news.

The sample includes only no news related trades when there is not any news announcements about the stock within the [-3, 3] day window of the trade. We further separate all no-news related trades into momentum and contrarian trades by trade directions. If a trade is in the same direction as the stock's prior one day return, it is labeled as a momentum trade. A contrarian trade is defined otherwise. We then calculate for each fund the average DGTW-adjusted performance of all momentum and contrarian trades in each quarter the same as in Table 2. The EW and PW DGTW-adjusted performance of all momentum and contrarian trades for funds in each trade regularity quintile during different market conditions are reported in Table 9.

Panel A to C report the results where the market condition is proxied by average market returns, VIX, and EPU, respectively. A few patterns emerge. When we compare the contrarian trades versus momentum trades, high trading regularity funds' contrarian trades' perform better than momentum trades. This is true for both the bad and good market conditions. However, the contrarian trades of the high trading regularity funds tend to do even better during bad market conditions. This is especially true when the market condition is proxied by market uncertainty. For example, when the market condition is proxied by VIX, during the high VIX periods, the EW DGTW-adjusted return of the high regularity funds' contrarian trades is 1.38%, while that for the low regularity fund is 0.33%. The difference is 1.05%, and significant at the 5% level. During the low VIX periods, the EW DGTW-adjusted return of the high regularity funds' contrarian trades is smaller at 0.73% compared to that during the VIX periods, and the difference of 0.65% is significant at the 10% level. The return difference between the high and low trading regularity funds during the low VIX period is 0.68%, lower than corresponding return difference during the high VIX period by 0.37%, albeit statistically insignificant. For no-news related momentum trades, the corresponding returns are generally lower. During high VIX periods, the EW DGTW-adjusted return for the high regularity funds' momentum trades is 0.12, and that for the low regularity funds' momentum trades is -0.67, both smaller than the corresponding returns returns for the contrarian trades. The return difference between high and low trading regularity funds is smaller at 0.79%, albeit still marginally significant at the 10% level. During low VIX period the return differences between high and low regularity fund's momentum trades are no longer significant.

The results for the PW returns and for those where the market conditions are proxied by EPU and average market returns are similar, although the effects somewhat smaller. The overall evidence in Table 9 suggests that contrarian trading in the no-news related trades of the high trading regularity funds contributes to the their outperformance during periods of low market returns and high uncertainty, consistent with them profiting from liquidity provision. However, even for momentum trading in the no-news related trades, high trading regularity funds perform better than low regularity funds during periods of low market returns and higher market uncertainty, which suggest liquidity provision is not the only source of trading profits for non-public news related trades. It is possible that some of those trades are private information driven as well.

5. Conclusions

Busse et. al. (2019) show that High trading regularity funds outperform low trading regularity funds. In this paper, we provide evidence that this outperformance largely occurs during periods of low market returns and high uncertainty, in term of both financial and economic uncertainty. During periods when the average market return is within the lower third of the whole sample period, the EW DGTW-adjusted quarterly return for the quintile of funds with the most frequent trades is …. Higher relative to that for the quintile with the least frequent trades. The corresponding return difference is , and , when the market condition is measured by VIX or economic policy uncertainty (EPU), respectively. On other hand, during periods of high market returns and low uncertainty, the return difference between high trading regularity funds and low trading regularity funds are statistically and economically insignificant.

We explore a number of possible reasons to explain the above evidence. During market downturns and uncertain markets, high regularity funds who are skilled at processing information from noises are especially valuable, and they trade frequently to take advantage of their informational skills. In addition, during uncertain markets, investors are more risk averse, and their demand for liquidity could be particularly high upon any news shock, and high trading regularity funds could profit from enhanced liquidity provision. It is also possible during uncertain markets it is easier for these skilled funds to retain private information.

Using news sentiment scores as comprehensive measure of public information, we show that 1) news sentiment predicts stock returns stronger during periods of low market returns and high market uncertainty. 2) During periods of high uncertainty, The trades of high trading regularity funds are significantly more news related relative to those of the low trading regularity funds. During periods of low market uncertainty on the other hand, the effect is less significant. 3) On the performance of news related trades, we find mixed evidence. While news related trades of high trading regularity funds predict future stock returns stronger during periods of high market uncertainty, the no-news related trades of the same funds also predict stock returns better in high uncertainty environments.

Combined, these results suggest that high trading regularity funds do take advantage of their skills in processing public news by trading more frequently, especially during highly uncertain markets when news are more valuable among a lot of noises. On the other hand, the outperformance of the no-news related trades suggest that high trading regularity funds profit from other sources as well. One possibility is that they trade frequently to provide market liquidity, and do more so during uncertain markets, when the demand is liquidity is especially high. Consistent with this hypothesis, the contrarian trading of high trading regularity funds outperforms that of the low trading regularity funds, especially during high uncertainty markets. However, even for momentum trades, high trading regularity funds outperform low regularity funds, in periods of both high and low uncertainty markets. This could be because the high trading regularity funds trade frequently because they are privately informed or because they are trading on news that is not covered in our news sentiment score data.

Overall, we show that the superior performance of high trading regularity funds over low trading regularity funds largely occur during periods of low market returns and high market uncertainty. Our evidence is consistent with high trading regularity funds trade frequently because of their informational advantage, and their ability to provide liquidity to the market. They do so more during market downturns and highly uncertain market periods, when information is more valuable and when the market demands for liquidity is especially high.

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Table 1. Descriptive Statistics

This table presents descriptive statistics of institutional trading data obtained from ANcerno Ltd. The sample period is from January 1, 1999 to December 31, 2009. The sample includes only common stocks. Panel A presents descriptive statistics from the ANcerno data each year of our sample period. We report the total number of unique stocks traded by all funds in our sample as well as the average number of unique stocks traded by each fund in each quarter. We also present the total number of trades placed by all funds and the average number of trades placed by each fund in each quarter. The total trading volume in shares and dollars are also presented. Trading regularity is defined, for each fund each quarter, as the average of daily ratios of the number of trades divided by the number of unique stocks traded. In Panel B, at the end of each quarter, we divide all funds into 5×5=25 portfolios based on their current quarter trading dollar volume and trading regularity. We then aggregate all funds that have the same regularity ranking within each trading volume quintile and obtain 5 portfolios of trading regularity. On each day, we calculate the total number of trades divided by total number of unique stocks traded by all funds in each regularity group. The daily averages of the ratios in periods of good market and bad market are presented. We also report the difference of the ratios between good and bad market. A quarter is defined as a good (bad) market period if the average market returns rank in the top (bottom) tercile, or if the average VIX or Economic Policy Uncertainty (EPU) is in the bottom (top) tercile in our sample period. *t*-statistics are reported in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Trade Statistics by Year

Year	Funds	Institutions	Stocks		Trades		Volume		Regularity
			Total	Average	Total ($x10^6$)	Average	Shares ($x10^9$)	Dollars ($x10^{12}$)	
1999	1871	354	6126	74.08	3.19	310.4	42	1.88	0.68
2000	1762	343	6142	87.55	4.44	403.9	61.2	2.76	0.71
2001	1817	358	5324	82.53	5.42	407.4	80.2	2.43	0.73
2002	1835	357	4968	82.34	5.86	421.9	99.5	2.4	0.74
2003	1592	310	4779	77.78	5.9	408.3	82.6	2.05	0.72
2004	1748	333	4786	84.22	7.18	482.8	109.1	3.1	0.76
2005	1445	302	4786	83.32	6.3	465.9	66.3	2	0.8
2006	1420	305	4692	89.91	7.38	544.6	74.1	2.33	0.86
2007	1352	293	4743	93.29	8.52	575.8	75.8	2.69	0.88
2008	1153	262	4314	102.06	9.4	681.8	81.6	2.3	0.9
2009	1284	306	3968	106.35	11.01	762.6	132.9	3.39	0.88

Table 1 continued.

Panel B. Trading Regularity under different market conditions

Regularity	Bad market	Good market	Bad-Good
B1. Trading regularity during low and high market returns			
1 (Low)	0.38***	0.37***	0.01
	(35.58)	(37.84)	(0.53)
2	0.47***	0.43***	0.04***
	(60.09)	(55.43)	(3.50)
3	0.70***	0.71***	-0.01
	(76.97)	(77.44)	(-0.93)
4	1.26***	1.25**	0.01
	(127.64)	(132.90)	(0.50)
5 (High)	2.15***	2.12***	0.04*
	(141.20)	(166.21)	(1.93)
4–Low	0.88***	0.88***	0.00
	(62.68)	(64.45)	(-0.05)
High–Low	1.77***	1.74***	0.03
	(95.27)	(106.28)	(1.20)
B2. Trading regularity during high and low VIX			
1 (Low)	0.38***	0.40***	-0.03*
	(39.64)	(37.23)	(-1.79)
2	0.49***	0.38***	0.10***
	(63.09)	(50.35)	(9.96)
3	0.76***	0.62***	0.14***
	(78.03)	(98.30)	(11.84)
4	1.27***	1.31**	-0.04***
	(127.88)	(148.17)	(-2.85)
5 (High)	2.22***	1.99***	0.23***
	(158.98)	(165.84)	(12.39)
4–Low	0.90***	0.91***	-0.01
	(66.89)	(63.28)	(-0.55)
High–Low	1.84***	1.59***	0.25***
	(107.44)	(98.90)	(10.75)

Table 1 continued.

Panel B continued.

Regularity	Bad market	Good market	Bad-Good
B3. Trading regularity during high and low EPU			
1 (Low)	0.39***	0.37***	0.02*
	(38.62)	(41.22)	(1.66)
2	0.45***	0.41***	0.05***
	(60.44)	(53.94)	(4.40)
3	0.73***	0.58***	0.16***
	(81.38)	(98.72)	(13.47)
4	1.26***	1.21**	0.05***
	(140.48)	(127.11)	(3.89)
5 (High)	2.24***	2.00***	0.24***
	(162.31)	(178.17)	(13.04)
4–Low	0.87***	0.84***	0.03
	(64.84)	(64.58)	(1.39)
High–Low	1.85***	1.64***	0.22***
	(104.66)	(108.26)	(9.06)

Table 2 Fund Performance for Univariate Sort by Trading Regularity under Different Market Conditions

This table presents average fund performance in quintiles sorted by contemporaneous trading regularity. The sample period is from January 1, 1999 to December 31, 2009. The sample includes only common stocks. For each fund, in each quarter, we define trading regularity as the average of daily ratios of the number of trades divided by the number of unique stocks traded. Performance is obtained for all trades placed by the fund. For each trade, we calculate the raw cumulative stock return from execution price until quarter end. We adjust the raw cumulative return by the DGTW benchmark return over the same period. For each fund in each quarter, we then compute equal-weighted (EW) or principal-weighted (PW) raw returns and DGTW-adjusted returns separately for buys and sells. Lastly, we take the difference in raw returns or DGTW-adjusted returns between buys and sells. In Panel A, we divide all funds into 5 quintiles at the end of each quarter based on their current quarter trading regularity. We then report equal-weighted and principle-weighted gross performance measured in raw returns (Panel A1 and A2) and DGTW-adjusted returns (Panel A3-A4) under good and bad market conditions for these quintiles. We also report the difference of the performance between good and bad market. A quarter is defined as a good (bad) market period if the average market returns rank in the top (bottom) tercile. In Panel B and C, similar performance statistics are presented over bad and good market condition defined by VIX or EPU. A particular quarter is defined as a good (bad) market period if the average VIX or EPU is in the bottom (top) tercile in our sample period. All returns are expressed in percent. *t*-statistics are reported in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Market condition defined by aggregate market return

Regularity	Bad market	Good market	Bad-Good
A1. Equal weighted raw returns			
1 (Low)	-0.82***	0.70***	-1.52***
	(-2.61)	(2.90)	(-3.95)
2	-0.35*	0.70***	-1.06***
	(-1.76)	(3.31)	(-3.49)
3	-0.10	0.51***	-0.62***
	(-0.45)	(2.92)	(-2.21)
4	0.96***	0.67***	0.29
	(3.29)	(4.41)	(0.84)
5 (High)	0.40*	0.75***	-0.35
	(1.76)	(4.48)	(-1.35)
4–Low	1.78***	-0.03	1.81***
	(3.32)	(-0.10)	(3.30)
High–Low	1.22***	0.05	1.17***
	(3.09)	(0.24)	(2.73)

A2. Principle weighted raw returns			
1 (Low)	-0.66*	0.70***	-1.36***
	(-1.88)	(3.52)	(-3.41)
2	-0.13	0.58***	-0.72**
	(-0.66)	(2.60)	(-2.19)
3	-0.18	0.35**	-0.54*
	(-0.70)	(2.04)	(-1.70)
4	0.42*	0.36	0.07
	(1.94)	(1.56)	(0.19)
5 (High)	0.02	0.63***	-0.61***
	(0.17)	(4.83)	(-3.16)
4–Low	1.08**	-0.34	1.42***
	(2.21)	(-1.33)	(2.76)
High–Low	0.68*	-0.06	0.74*
	(1.72)	(-0.31)	(1.76)

Table 2 continued.

Panel A continued.

Regularity	Bad market	Good market	Bad-Good
A3. Equal weighted DGTW-adjusted returns			
1 (Low)	-0.83***	0.20	-1.03***
	(-3.71)	(0.94)	(-3.21)
2	-0.31	0.48***	-0.79***
	(-1.55)	(2.97)	(-3.13)
3	-0.12	0.32**	-0.44**
	(-0.64)	(2.51)	(-2.12)
4	0.97***	0.62***	0.36
	(4.39)	(5.47)	(1.40)
5 (High)	0.52***	0.63***	-0.11
	(3.31)	(4.25)	(-0.55)
4–Low	1.80***	0.42*	1.39***
	(5.72)	(1.90)	(3.62)
High–Low	1.35***	0.43**	0.92**
	(4.15)	(1.96)	(2.30)
A4. Principle weighted DGTW-adjusted returns			
1 (Low)	-0.74***	0.17	-0.91***
	(-2.95)	(0.70)	(-2.58)
2	-0.09	0.42***	-0.51**
	(-0.45)	(2.81)	(-2.09)
3	-0.11	0.18	-0.29
	(-0.64)	(1.59)	(-1.42)
4	0.55**	0.33**	0.22
	(2.44)	(2.54)	(0.84)
5 (High)	0.22**	0.40***	-0.19
	(2.02)	(2.96)	(-1.05)
4–Low	1.29***	0.16	1.13***
	(4.66)	(0.71)	(3.16)
High–Low	0.96***	0.24	0.72*
	(3.69)	(0.84)	(1.82)

Table 2 continued.

Panel B: Market condition defined by VIX

Regularity	Bad market	Good market	Bad-Good
B1. Equal weighted raw returns			
1 (Low)	-0.48	0.20	-0.68
	(-1.28)	(1.03)	(-1.59)
2	0.27	0.34**	-0.07
	(0.85)	(2.22)	(-0.19)
3	0.41*	0.33**	0.08
	(1.87)	(1.96)	(0.28)
4	0.90***	0.54***	0.36
	(2.95)	(3.66)	(1.04)
5 (High)	0.57**	0.30**	0.28
	(2.44)	(2.40)	(1.09)
4–Low	1.38**	0.33	1.05*
	(2.38)	(1.46)	(1.77)
High–Low	1.05***	0.09	0.96**
	(2.70)	(0.37)	(2.19)
B2. Principle weighted raw returns			
1 (Low)	-0.36	0.28	-0.64
	(-0.93)	(1.33)	(-1.47)
2	0.41	0.36**	0.04
	(1.50)	(2.04)	(0.14)
3	0.25	0.22	0.04
	(1.16)	(1.34)	(0.11)
4	0.49**	0.25*	0.23
	(2.10)	(1.68)	(0.65)
5 (High)	0.36**	0.08	0.27
	(2.30)	(0.68)	(1.28)
4–Low	0.85*	-0.02	0.88
	(1.69)	(-0.09)	(1.62)
High–Low	0.72*	-0.19	0.91**
	(1.93)	(-0.83)	(2.19)

Table 2 continued.

Panel B continued.

Regularity	Bad market	Good market	Bad-Good
B3. Equal weighted DGTW-adjusted returns			
1 (Low)	-0.54*	0.09	-0.62*
	(-1.78)	(0.50)	(-1.79)
2	0.02	0.34**	-0.32
	(0.08)	(2.17)	(-1.15)
3	0.21	0.27**	-0.06
	(1.06)	(2.21)	(-0.27)
4	0.91***	0.49***	0.42*
	(3.99)	(3.88)	(1.67)
5 (High)	0.55***	0.30**	0.25
	(3.46)	(2.52)	(1.33)
4–Low	1.45***	0.40*	1.05**
	(3.59)	(1.85)	(2.51)
High–Low	1.09***	0.21	0.88**
	(3.33)	(0.97)	(2.15)
B4. Principle weighted DGTW-adjusted returns			
1 (Low)	-0.45	0.13	-0.58
	(-1.43)	(0.69)	(-1.55)
2	0.20	0.35**	-0.15
	(0.98)	(2.19)	(-0.60)
3	0.13	0.23**	-0.11
	(0.81)	(1.99)	(-0.50)
4	0.54**	0.28**	0.26
	(2.42)	(2.30)	(1.00)
5 (High)	0.38***	0.13	0.25
	(3.07)	(1.25)	(1.48)
4–Low	0.99***	0.15	0.84**
	(2.84)	(0.60)	(2.21)
High–Low	0.83***	0.00	0.84**
	(3.06)	(-0.02)	(2.11)

Table 2 continued.

Panel C: Market conditions measured by EPU

Regularity	Bad market	Good market	Bad-Good
C1. Equal weighted raw returns			
1 (Low)	-0.43	0.27	-0.70
	(-1.08)	(1.29)	(-1.60)
2	0.05	0.16*	-0.11
	(0.16)	(1.73)	(-0.33)
3	0.40*	0.27	0.13
	(1.93)	(1.46)	(0.46)
4	1.01***	0.64***	0.37
	(3.69)	(2.95)	(1.07)
5 (High)	0.60**	0.53***	0.06
	(2.57)	(3.23)	(0.24)
4–Low	1.44**	0.37	1.06*
	(2.52)	(1.09)	(1.81)
High–Low	1.02***	0.26	0.76*
	(2.60)	(1.30)	(1.70)

Regularity	Bad market	Good market	Bad-Good
C2. Principle weighted raw returns			
1 (Low)	-0.35	0.16	-0.51
	(-0.89)	(0.82)	(-1.18)
2	0.18	0.03	0.15
	(0.74)	(0.16)	(0.43)
3	0.31	0.26	0.05
	(1.48)	(1.29)	(0.15)
4	0.56***	0.27	0.28
	(2.78)	(1.14)	(0.80)
5 (High)	0.38**	0.25	0.13
	(2.36)	(1.59)	(0.62)
4–Low	0.91*	0.12	0.80
	(1.88)	(0.35)	(1.51)
High–Low	0.74**	0.09	0.65
	(1.99)	(0.40)	(1.56)

Table 2 continued.

Panel C continued.

Regularity	Bad market	Good market	Bad-Good
C3. Equal weighted DGTW-adjusted returns			
1 (Low)	-0.49	0.03	-0.52
	(-1.55)	(0.23)	(-1.46)
2	-0.06	0.39***	-0.46*
	(-0.26)	(3.14)	(-1.66)
3	0.16	0.37***	-0.21
	(0.85)	(2.79)	(-0.94)
4	0.95***	0.66***	0.29
	(4.50)	(4.10)	(1.14)
5 (High)	0.56***	0.49***	0.07
	(3.53)	(3.18)	(0.36)
4–Low	1.43***	0.63***	0.81*
	(3.49)	(2.81)	(1.90)
High–Low	1.05***	0.46**	0.59
	(3.18)	(1.97)	(1.40)
C4. Principle weighted DGTW-adjusted returns			
1 (Low)	-0.41	-0.12	-0.29
	(-1.30)	(-0.61)	(-0.77)
2	0.11	0.28**	-0.17
	(0.53)	(2.09)	(-0.66)
3	0.11	0.39***	-0.29
	(0.67)	(2.64)	(-1.40)
4	0.51**	0.39***	0.12
	(2.39)	(2.85)	(0.45)
5 (High)	0.33***	0.25	0.07
	(2.66)	(1.56)	(0.42)
4–Low	0.93***	0.52	0.41
	(2.60)	(2.18)	(1.04)
High–Low	0.74***	0.38	0.36
	(2.60)	(1.21)	(0.89)

Table 3: Regression – Fund performance on trading regularity and measures of market conditions

This table presents estimation results from regressing fund performance on trading regularity and measures of market conditions. The sample period is from January 1, 1999 to December 31, 2009. The sample includes only common stocks. Each quarter, we define fund quarterly equal- (principal-) weighted DGTW-adjusted performance the same as in Table 2. For each fund, in each quarter, we define trading regularity as the average of daily ratios of the number of trades divided by the number of unique stocks traded. In each quarter, we calculate for each fund the average characteristics for all stocks it trades. These characteristics include stock market capitalization, book-to-market ratio, lag 12-month return, turnover, idiosyncratic volatility, and Amihud's illiquidity. All of these variables are based on data available at the end of the previous quarter. Lag 12-month return, turnover, idiosyncratic volatility, and Amihud's illiquidity are calculated using 12 months of data ending at the previous quarter's end. Lag one-day return is the mean of the past one-day return for each stock traded by the fund (multiplying by -1 for sell trades) in each quarter. We define fund herding for each fund, in each quarter, as the percentage of trades that are in the same direction as the net imbalance across all funds in the ANcerno dataset on the same day. A panel regression model with quarter fixed effects is estimated by regressing quarterly fund equal-weighted (EW) or principle-weighted (PW) DGTW-adjusted performance on funds' trading regularity and market conditions measured by market returns, VIX, or EPU. The control variables include lag quarter fund performance, logarithm of lag quarter fund aggregate volume, and the characteristics of stocks traded in the current quarter (book-to-market ratio, logarithm of market capitalization, lag 12-month return, turnover, idiosyncratic volatility, Amihud's illiquidity, lag one-day return, and herding). Lag fund aggregate volume represents the fund's aggregate trading volume across all stocks during the previous quarter. Heteroscedasticity robust *t*-statistics are reported in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Market conditions defined by:	Market returns		VIX		EPU	
	EW	PW	EW	PW	EW	PW
Intercept	0.041**	0.037**	0.086	0.069	0.02	0.022
	(2.50)	(2.12)	(1.33)	(1.01)	(0.99)	(1.08)
Regularity	0.003***	0.002***	0	0	0.001	0
	(3.44)	(2.85)	(0.27)	(0.02)	(0.62)	(0.28)
Regularity×Market conditions	-0.012**	-0.007	0.011**	0.008*	0.001	0.001
	(-1.98)	(-1.23)	(2.22)	(1.81)	(0.71)	(0.76)
Fund aggregate volume	0	0	0*	0*	0*	0*
	(1.62)	(1.60)	(-1.75)	(-1.70)	(-1.67)	(-1.65)
Lag performance	0.027***	0.041***	0.027***	0.041***	0.027***	0.041***
	(3.21)	(5.16)	(3.20)	(5.15)	(3.21)	(5.16)
Book-to-market ratio	0	0.001	0	0.001	0	0.001
	(0.14)	(0.70)	(0.11)	(0.68)	(0.14)	(0.69)
Market capitalization	-0.001***	-0.001**	-0.001***	-0.001**	-0.001***	-0.001**
	(-3.70)	(-2.49)	(-3.69)	(-2.48)	(-3.68)	(-2.47)
Turnover	-2.215	-1.572	-2.219	-1.574	-2.219	-1.575
	(-1.49)	(-1.01)	(-1.50)	(-1.01)	(-1.50)	(-1.01)
Idiosyncratic volatility	0.02	0.017	0.02	0.017	0.02	0.017
	(0.81)	(0.70)	(0.81)	(0.70)	(0.82)	(0.71)
Lag 12-month return	-0.001	0	-0.001	0	-0.001	0
	(-0.66)	(0.13)	(-0.66)	(0.13)	(-0.67)	(0.12)
Lag one-day return	-0.331***	-0.348***	-0.332***	-0.348***	-0.332***	-0.348***
	(-4.09)	(-4.14)	(-4.20)	(-4.16)	(-4.10)	(-4.15)
Illiquidity ratio	-0.008*	-0.011*	-0.008*	-0.011*	-0.008*	-0.011*
	(-1.66)	(-1.87)	(-1.68)	(-1.88)	(-1.68)	(-1.87)
Herd	0.004	0.003	0.004	0.003	0.004	0.003
	(0.54)	(0.45)	(0.54)	(0.45)	(0.54)	(0.45)
Market conditions	-0.134	-0.099	-0.002	-0.002	0	0
	(-0.79)	(-0.55)	(-0.85)	(-0.59)	(0.76)	(0.52)
R-squared	0.01	0.01	0.01	0.01	0.01	0.01

Table 4: Regression – Stock returns on prior one day fund net trading and market conditions

This table presents a regression analysis relating daily stock abnormal returns to the prior day trading by funds in the ANcerno dataset during different market conditions. We regress daily abnormal market adjusted return of the stock on the prior day net trading volume of funds in each of the five trading regularity quintiles, measures of market conditions, and control variables. The net trading volume is calculated as the total shares bought minus the total shares sold by funds in the same quintile divided by the shares outstanding. In Column 1, Bad (Mid) market is a dummy variable equal to 1 if the market returns in a quarter rank in the bottom (middle) tercile in the sample period, and zero otherwise. In Column 2 and 3, Bad (Mid) market is a dummy variable equal to 1 if the VIX or EPU, respectively, in a quarter ranks in the top (middle) tercile in the sample period, and zero otherwise. The control variables include the stock's lag one-day market adjusted return and trading volume and stock fixed effects. We report the estimated coefficients and the associated heteroscedasticity robust *t*-statistics (in parentheses) from the panel regressions. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Market condition measured by:	Market returns	VIX	EPU
T1 net	-0.002	0.002	0.000
	(-1.51)	(1.12)	(-0.25)
T1 net×Bad market	0.006***	0.001	0.002
	(3.04)	(0.58)	(1.16)
T1 net×Mid market	0.001	-0.006***	-0.001
	(0.60)	(-2.80)	(-0.46)
T2 net	-0.001	0.000	-0.001
	(-1.49)	(0.64)	(-0.83)
T2 net×Bad market	0.001	-0.002**	-0.001
	(0.84)	(-1.97)	(-0.53)
T2 net×Mid market	0.000	-0.002*	0.000
	(-0.13)	(-1.75)	(-0.14)
T3 net	0.002***	0.001***	0.002***
	(4.30)	(3.73)	(4.92)
T3 net×Bad market	-0.001*	0.000	-0.001
	(-1.65)	(-0.47)	(-1.89)
T3 net×Mid market	0.000	0.000	-0.001
	(0.23)	(0.27)	(-1.34)
T4 net	0.001***	0.001***	0.001***
	(6.09)	(4.60)	(4.14)
T4 net×Bad market	0.000	0.001**	0.001**
	(1.58)	(2.36)	(2.52)
T4 net×Mid market	0.000	0.001**	0.001**
	(0.23)	(2.07)	(1.96)
T5 net	0.001***	0.001***	0.001***
	(9.66)	(4.89)	(8.30)
T5 net×Bad market	0.001***	0.001***	0.001***
	(3.74)	(6.91)	(4.69)
T5 net×Mid market	0.000	0.001***	0.000
	(-0.83)	(5.34)	(0.12)
Bad market	-0.004***	0.000***	-0.001***
	(-141.20)	(-7.62)	(-20.50)
Mid market	-0.002***	0.001***	-0.001***
	(-79.48)	(32.54)	(-36.93)
Lag one-day return	-0.081***	-0.081***	-0.080***
	(-356.16)	(-352.33)	(-352.10)
Lag one-day volume	0.001***	0.001***	0.001***

	(62.49)	(66.37)	(64.72)
R-squared	0.01	0.01	0.01

Table 5: Regression – Stock returns on news sentiment and market conditions

This table presents a regression analysis relating daily stock abnormal returns to the contemporaneous news sentiment during different market conditions. We regress daily abnormal market adjusted return of the stock on the contemporaneous news sentiment, measures of market conditions, and control variables. In Column 1, Bad (Mid) market is a dummy variable equal to 1 if the market returns in a quarter rank in the bottom (middle) tercile in the sample period, and zero otherwise. In Column 2 and 3, Bad (Mid) market is a dummy variable equal to 1 if the VIX or EPU, respectively, in a quarter ranks in the top (middle) tercile in the sample period, and zero otherwise. The control variables include the stock's lag one-day market adjusted return and trading volume and stock fixed effects. We report the estimated coefficients the associated heteroscedasticity robust *t*-statistics (in parentheses) from the panel regressions. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Market condition measured by:		
	Market returns	VIX	EPU
	(1)	(2)	(3)
News sentiment	0.005***	0.005***	0.005***
	(43.43)	(43.43)	(45.98)
Lag one-day news sentiment	0.000***	0.000***	0.000***
	(-3.30)	(-3.30)	(-3.49)
News sentiment×Bad market	0.002***	0.002***	0.001***
	(13.00)	(13.00)	(8.12)
News sentiment×Mid market	0.001***	0.001***	0.000***
	(7.45)	(7.45)	(1.59)
Bad market	0.000**	0.000**	-0.001***
	(1.79)	(1.79)	(-4.69)
Mid market	0.001***	0.001***	-0.001***
	(6.90)	(6.90)	(-5.31)
Lag one-day return	-0.018***	-0.018***	-0.018***
	(-19.92)	(-19.92)	(-19.83)
Lag one-day volume	0.000**	0.000**	0.000**
	(2.07)	(2.07)	(2.31)

Table 6 Trading regularity under different market conditions around news (no news) days

This table presents the aggregate trading regularity by funds in the ANcerno dataset on stock-days with news vs. without news during different market conditions. A stock-day is defined as a news day if there is at least one news announcement about the stock within the [-3, 3] day window, and it is denoted as a no news day otherwise. On each day, we calculate the total number of trades divided by total number of unique stocks traded by all funds in each regularity group. We present the daily averages of the ratios on news days and no news days in periods of good market and bad market. A quarter is defined as a good (bad) market period if the average market returns rank in the top (bottom) tercile (Panel A), or if the average VIX (Panel B) or EPU (Panel C) is in the bottom (top) tercile in our sample period. *t*-statistics are reported in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Market conditions defined by average market returns

Regularity	Bad market	Good market	Bad-Good
A1. News days			
1 (Low)	0.61***	0.57***	0.04**
	(34.29)	(39.72)	(1.98)
2	0.73***	0.64***	0.09***
	(55.23)	(53.52)	(5.09)
3	1.00***	0.97***	0.03*
	(95.15)	(87.33)	(1.94)
4	1.71***	1.66***	0.05***
	(146.00)	(140.04)	(2.95)
5 (High)	3.02***	2.77***	0.26***
	(98.59)	(135.18)	(7.28)
4–Low	1.09***	0.70***	0.00
	(52.47)	(76.80)	(0.18)
High–Low	2.41***	1.36***	0.21***
	(72.75)	(104.77)	(5.35)
A2. No news days			
1 (Low)	0.21***	0.20***	0.01
	(29.51)	(31.24)	(0.80)
2	0.29***	0.26***	0.03***
	(55.90)	(55.54)	(4.83)
3	0.47***	0.49***	-0.02***
	(78.98)	(79.34)	(-2.46)
4	0.91***	0.90***	0.01
	(149.35)	(156.28)	(1.04)
5 (High)	1.55***	1.55***	0.00
	(123.09)	(145.49)	(-0.31)
4–Low	0.70***	0.70***	0.00
	(71.15)	(76.80)	(0.10)
High–Low	1.34***	1.36***	-0.01
	(92.47)	(104.77)	(-0.66)

Table 6 continued.

Panel B: Market conditions defined by VIX

Regularity	Bad market	Good market	Bad-Good
B1. News days			
1 (Low)	0.60***	0.57***	0.03
	(39.60)	(37.64)	(1.57)
2	0.76***	0.51***	0.25***
	(60.39)	(49.07)	(14.76)
3	1.08***	0.78***	0.30***
	(102.42)	(96.57)	(22.41)
4	1.74***	1.60***	0.14***
	(141.50)	(144.71)	(8.51)
5 (High)	3.11***	2.48***	0.64***
	(114.38)	(152.14)	(19.03)
4–Low	1.13***	1.03***	0.11***
	(58.00)	(52.98)	(3.80)
High–Low	2.51***	1.91***	0.60***
	(84.42)	(86.66)	(15.67)
B2. No news days			
1 (Low)	0.21***	0.20***	0.01
	(34.04)	(32.63)	(0.57)
2	0.29***	0.23***	0.07***
	(59.63)	(50.59)	(10.35)
3	0.49***	0.44***	0.06***
	(80.45)	(95.24)	(7.27)
4	0.90***	0.97***	-0.06***
	(159.28)	(161.14)	(-7.91)
5 (High)	1.59***	1.41***	0.18
	(134.30)	(152.93)	(11.65)
4–Low	0.70***	0.77***	-0.07***
	(78.31)	(83.69)	(-5.29)
High–Low	1.38***	1.21***	0.17***
	(101.99)	(107.67)	(9.35)

Table 6 continued.

Panel C: Market conditions defined by EPU

Regularity	Bad market	Good market	Bad-Good
C1. News days			
1 (Low)	0.63***	0.56***	0.07***
	(40.35)	(42.75)	(3.11)
2	0.72***	0.61***	0.10***
	(58.70)	(48.26)	(6.14)
3	1.05***	0.79***	0.25***
	(97.78)	(89.95)	(18.19)
4	1.73***	1.56***	0.17***
	(140.74)	(144.21)	(10.42)
5 (High)	3.20***	2.60***	0.60***
	(113.56)	(124.59)	(17.70)
4–Low	1.10***	1.00***	0.10***
	(57.25)	(56.42)	(3.70)
High–Low	2.57***	2.04***	0.53***
	(83.59)	(83.44)	(13.63)
C2. No news days			
1 (Low)	0.22***	0.19***	0.03***
	(32.76)	(39.04)	(3.15)
2	0.27***	0.25***	0.03***
	(55.11)	(53.70)	(4.09)
3	0.49***	0.41***	0.08***
	(85.17)	(95.35)	(10.12)
4	0.90***	0.89***	0.01
	(158.09)	(144.32)	(1.50)
5 (High)	1.60***	1.49***	0.11***
	(136.63)	(141.50)	(7.06)
4–Low	0.69***	0.70***	-0.02
	(72.91)	(82.42)	(-1.22)
High–Low	1.38***	1.30***	0.08***
	(98.97)	(107.81)	(4.34)

Table 7 Performance of news and no news related trades

This table present the performance of news related and no news related trades placed by funds in the ANcerno dataset. Each quarter, we separate all trades placed by each fund in the sample into news related trades and no news related trades. A trade is defined as news related if there is a news announcement of the stock within the [-3, 3] day window of the trade, and it is defined as no news related otherwise. We then calculate for each fund the average DGTW-adjusted performance of all news related and no news related trades in each quarter as in Table 2. The EW and PW DGTW-adjusted performance of news and no news related trades for funds in each trading regularity quintile during different market conditions is reported. A quarter is defined as a good (bad) market period if the average market returns rank in the top (bottom) tercile (Panel A), or if the average VIX (Panel B) or EPU (Panel C) is in the bottom (top) tercile in our sample period. All returns are expressed in percent. *t*-statistics are reported in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Market conditions measured by aggregate market returns

Regularity	Bad market	Good market	Bad-Good
A1. Equal weighted DGTW-adjusted performance of news related trades			
1 (Low)	-0.71**	0.09	-0.80*
	(-2.16)	(0.26)	(-1.85)
2	-0.38*	0.53**	-0.91***
	(-1.89)	(2.47)	(-3.22)
3	-0.13	0.16	-0.28
	(-0.61)	(0.82)	(-1.12)
4	0.85***	0.54***	0.31
	(4.07)	(4.54)	(1.20)
5 (High)	0.51**	0.58***	-0.07
	(2.57)	(4.23)	(-0.30)
4–Low	1.56***	0.45***	1.11***
	(3.90)	(3.90)	(3.90)
High–Low	1.22***	0.49	0.73
	(2.96)	(1.30)	(1.33)

Regularity	Bad market	Good market	Bad-Good
A2. Equal weighted DGTW-adjusted performance of no news related trades			
1 (Low)	-0.57	0.25	-0.82*
	(-1.41)	(0.97)	(-1.92)
2	0.23	0.85***	-0.62
	(0.65)	(4.22)	(-1.56)
3	0.30	0.19	0.11
	(0.90)	(0.89)	(0.26)
4	1.31***	0.65***	0.67*
	(3.96)	(3.29)	(1.73)
5 (High)	0.86***	0.67***	0.18
	(5.18)	(3.53)	(0.68)
4–Low	1.89***	0.40	1.49***
	(5.65)	(1.07)	(3.11)
High–Low	1.43***	0.42	1.01**
	(3.65)	(1.16)	(2.00)

Table 7 continued.

Panel A continued.

Regularity	Bad market	Good market	Bad-Good
A3. Principle weighted DGTW-adjusted performance of news related trades			
1 (Low)	-0.65*	0.11	-0.76
	(-1.90)	(0.28)	(-1.57)
2	-0.05	0.54**	-0.58**
	(-0.29)	(2.38)	(-2.09)
3	-0.07	0.12	-0.19
	(-0.31)	(0.84)	(-0.77)
4	0.59***	0.18	0.41
	(2.60)	(0.92)	(1.25)
5 (High)	0.25**	0.35***	-0.10
	(2.15)	(3.64)	(-0.46)
4–Low	1.24***	0.07	1.17**
	(3.60)	(0.19)	(2.35)
High–Low	0.90**	0.24	0.66
	(2.57)	(0.55)	(1.19)
A4. Principle weighted DGTW-adjusted performance of no news related trades			
1 (Low)	-0.63*	0.17	-0.80**
	(-1.77)	(0.78)	(-2.02)
2	0.02	0.76***	-0.74*
	(0.07)	(3.83)	(-1.92)
3	0.15	0.08	0.07
	(0.48)	(0.44)	(0.17)
4	0.74**	0.56***	0.18
	(2.00)	(3.03)	(0.47)
5 (High)	0.56***	0.50**	0.07
	(3.19)	(2.55)	(0.26)
4–Low	1.37***	0.39	0.98**
	(5.19)	(1.06)	(2.13)
High–Low	1.20***	0.32	0.87*
	(4.35)	(0.97)	(1.91)

Table 7 continued.

Panel B: Market conditions measured by VIX

Regularity	Bad market	Good market	Bad-Good
B1. Equal weighted DGTW-adjusted performance of news related trades			
1 (Low)	-0.52	0.05	-0.57
	(-1.34)	(0.24)	(-1.30)
2	-0.01	0.32**	-0.33
	(-0.03)	(2.28)	(-1.06)
3	0.20	0.28**	-0.08
	(1.02)	(2.01)	(-0.31)
4	0.71***	0.48***	0.23
	(3.22)	(3.76)	(0.90)
5 (High)	0.57***	0.34**	0.23
	(3.19)	(2.27)	(1.00)
4–Low	1.24**	0.43*	0.80
	(2.57)	(1.65)	(1.59)
High–Low	1.09**	0.29	0.80
	(2.45)	(1.05)	(1.49)
B2. Equal weighted DGTW-adjusted performance of no news related trades			
1 (Low)	-0.42	0.28	-0.70
	(-1.07)	(1.22)	(-1.59)
2	0.45	0.36	0.09
	(1.26)	(1.52)	(0.21)
3	0.36	0.09	0.27
	(1.09)	(0.35)	(0.65)
4	1.23***	0.56***	0.66*
	(3.72)	(2.73)	(1.72)
5 (High)	0.75***	0.33**	0.42*
	(3.67)	(2.05)	(1.66)
4–Low	1.65***	0.28	1.36***
	(4.02)	(0.83)	(2.73)
High–Low	1.17***	0.05	1.12**
	(2.75)	(0.19)	(2.20)

Table 7 continued.

Panel B continued.

Regularity	Bad market	Good market	Bad-Good
B3. Principle weighted DGTW-adjusted performance of news related trades			
1 (Low)	-0.38	0.11	-0.49
	(-0.94)	(0.50)	(-1.00)
2	0.27	0.39***	-0.12
	(1.43)	(2.64)	(-0.42)
3	0.20	0.23*	-0.03
	(1.18)	(1.73)	(-0.12)
4	0.46*	0.27**	0.19
	(1.95)	(2.22)	(0.57)
5 (High)	0.46***	0.15	0.30
	(3.14)	(1.23)	(1.45)
4–Low	0.84*	0.16	0.68
	(1.88)	(0.54)	(1.31)
High–Low	0.84**	0.04	0.79
	(2.09)	(0.17)	(1.45)
B4. Principle weighted DGTW-adjusted performance of no news related trades			
1 (Low)	-0.53	0.26	-0.79*
	(-1.51)	(1.01)	(-1.95)
2	0.26	0.33	-0.07
	(0.78)	(1.37)	(-0.16)
3	0.15	0.01	0.13
	(0.46)	(0.06)	(0.31)
4	0.75**	0.38*	0.37
	(2.11)	(1.90)	(0.98)
5 (High)	0.56***	0.08	0.48*
	(2.91)	(0.56)	(1.86)
4–Low	1.27***	0.11	1.16**
	(3.79)	(0.32)	(2.50)
High–Low	1.09***	-0.18	1.27***
	(3.28)	(-0.66)	(2.82)

Table 7 continued.

Panel C: Market conditions measured by EPU

Regularity	Bad market	Good market	Bad-Good
C1. Equal weighted DGTW-adjusted performance of news related trades			
1 (Low)	-0.61	-0.22	-0.39
	(-1.59)	(-0.79)	(-0.89)
2	-0.10	0.36*	-0.46
	(-0.40)	(1.66)	(-1.51)
3	0.12	0.19	-0.07
	(0.64)	(0.85)	(-0.25)
4	0.89***	0.69***	0.20
	(4.14)	(3.91)	(0.77)
5 (High)	0.54**	0.53***	0.01
	(3.39)	(3.07)	(0.05)
4–Low	1.49***	0.90***	0.59
	(3.20)	(3.03)	(1.17)
High–Low	1.15***	0.74*	0.40
	(2.76)	(1.93)	(0.73)
C2. Equal weighted DGTW-adjusted performance of no news related trades			
1 (Low)	-0.18	0.38*	-0.56
	(-0.44)	(1.73)	(-1.26)
2	0.65*	0.65***	0.00
	(1.83)	(3.81)	(0.00)
3	0.52*	0.47*	0.05
	(1.65)	(1.85)	(0.13)
4	1.35***	0.63**	0.72*
	(4.34)	(2.21)	(1.88)
5 (High)	0.81***	0.74***	0.07
	(4.44)	(3.48)	(0.25)
4–Low	1.53***	0.26	1.27**
	(3.58)	(0.79)	(2.51)
High–Low	1.00**	0.37	0.63
	(2.28)	(1.08)	(1.18)

Table 7 continued.

Panel C continued.

Regularity	Bad market	Good market	Bad-Good
C3. Principle weighted DGTW-adjusted performance of news related trades			
1 (Low)	-0.51	-0.31	-0.19
	(-1.29)	(-0.87)	(-0.40)
2	0.20	0.35	-0.15
	(1.02)	(1.47)	(-0.51)
3	0.20	0.27	-0.07
	(1.14)	(1.42)	(-0.30)
4	0.51**	0.41	0.10
	(2.17)	(1.47)	(0.30)
5 (High)	0.32***	0.27	0.05
	(3.32)	(1.35)	(0.22)
4–Low	1.02**	0.72**	0.29
	(2.27)	(1.97)	(0.57)
High–Low	0.83**	0.59	0.24
	(2.16)	(1.24)	(0.43)
C4. Principle weighted DGTW-adjusted performance of no news related trades			
1 (Low)	-0.36	0.27	-0.63
	(-0.99)	(1.25)	(-1.53)
2	0.46	0.54***	-0.07
	(1.40)	(3.06)	(-0.19)
3	0.26	0.44*	-0.19
	(0.87)	(1.78)	(-0.46)
4	0.81**	0.44**	0.36
	(2.35)	(2.25)	(0.97)
5 (High)	0.52**	0.50**	0.02
	(2.49)	(2.16)	(0.08)
4–Low	1.16***	0.17	0.99**
	(3.47)	(0.51)	(2.10)
High–Low	0.88**	0.23	0.65
	(2.42)	(0.61)	(1.35)

Table 8: Regression – Stock returns on prior day fund net trading on news and no news days

This table presents a regression analysis relating daily stock abnormal returns to the prior day trading by funds in the ANcerno dataset over news and no news days during different market conditions. A stock-day is defined as a news day if there is at least one news announcement about the stock within the [-3, 3] day window, and it is denoted as a no news day otherwise. We regress daily abnormal market adjusted return of the stock on the prior day net trading volume of funds in each of the five trading regularity quintiles, measures of market conditions, and control variables in the subsamples of news days (Panel A) and no news days (Panel B). The net trading volume is calculated as the total shares bought minus the total shares sold by funds in the same quintile divided by the shares outstanding. Bad (Mid) market is a dummy variable equal to 1 if the market returns in a quarter rank in the top (middle) tercile in the sample period, and zero otherwise. The control variables include the stock's lag one-day market adjusted return and trading volume and stock fixed effects. We report the estimated coefficients and the associated heteroscedasticity robust *t*-statistics (in parentheses) from the panel regressions. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Stock returns on prior one day fund net trading and market conditions in news days

	Market condition measured by:		
	Market returns	VIX	EPU
T1 net	-0.003*	0.001	-0.002
	(-1.95)	(0.53)	(-1.09)
T1 net×Bad market	0.007***	0.001	0.003
	(2.64)	(0.41)	(1.01)
T1 net×Mid market	0.002	-0.007***	0.001
	(0.72)	(-2.61)	(0.41)
T2 net	-0.001	0.000	0.000
	(-1.39)	(0.25)	(-0.36)
T2 net×Bad market	0.000	-0.004***	-0.002*
	(-0.23)	(-2.76)	(-1.70)
T2 net×Mid market	0.000	-0.002	-0.001
	(-0.07)	(-1.25)	(-0.91)
T3 net	0.001*	0.001*	0.002***
	(1.87)	(1.80)	(2.85)
T3 net×Bad market	-0.001	-0.001	-0.001*
	(-0.97)	(-0.79)	(-1.92)
T3 net×Mid market	0.000	0.001	-0.001
	(0.42)	(0.77)	(-1.01)
T4 net	0.001***	0.001***	0.001**
	(3.66)	(2.94)	(2.35)
T4 net×Bad market	0.000	0.001	0.001**
	(1.08)	(1.23)	(2.02)
T4 net×Mid market	0.000	0.001	0.000
	(-0.10)	(1.40)	(0.82)
T5 net	0.001***	0.000**	0.001***
	(3.49)	(2.29)	(2.87)
T5 net×Bad market	0.001**	0.001***	0.001***
	(2.44)	(3.24)	(2.61)
T5 net×Mid market	0.000	0.001**	0.000
	(-0.38)	(2.15)	(0.49)

Bad market	-0.004***	0.000***	-0.001***
	(-76.42)	(-2.78)	(-12.42)
Mid market	-0.002***	0.001***	-0.001***
	(-45.68)	(11.03)	(-13.81)
Lag one-day return	-0.024***	-0.023***	-0.023***
	(-52.14)	(-49.44)	(-49.45)
Lag one-day volume	0.000***	0.000***	0.000***
	(9.94)	(10.37)	(10.10)
News sentiment	0.005***	0.006***	0.006***
	(109.62)	(110.83)	(110.50)

Table 8 continued.

Panel B: Stock returns on prior one day fund net trading and market conditions in no news days

	Market condition measured by:		
	Market returns	VIX	EPU
T1 net	0.000	0.002	0.001
	(-0.23)	(0.81)	(0.63)
T1 net×Bad market	0.004	0.002	0.002
	(1.43)	(0.53)	(0.62)
T1 net×Mid market	0.000	-0.004	-0.004
	(-0.02)	(-1.49)	(-1.26)
T2 net	-0.001	0.000	-0.001
	(-1.28)	(0.42)	(-1.32)
T2 net×Bad market	0.002	-0.001	0.001
	(1.26)	(-0.64)	(0.51)
T2 net×Mid market	0.000	-0.002	0.001
	(-0.20)	(-1.50)	(0.90)
T3 net	0.001***	0.002***	0.002***
	(3.07)	(3.05)	(3.77)
T3 net×Bad market	-0.001	0.000	-0.001
	(-1.00)	(-0.33)	(-1.25)
T3 net×Mid market	0.000	0.000	-0.001
	(0.73)	(-0.14)	(-0.78)
T4 net	0.001***	0.001***	0.001***
	(4.60)	(3.20)	(3.09)
T4 net×Bad market	0.000	0.001*	0.001*
	(1.02)	(1.91)	(1.66)
T4 net×Mid market	0.000	0.001	0.001*
	(0.26)	(1.42)	(1.80)
T5 net	0.002***	0.001***	0.002***
	(8.97)	(3.79)	(7.96)
T5 net×Bad market	0.001**	0.002***	0.001***
	(2.36)	(5.53)	(3.27)
T5 net×Mid market	0.000	0.001***	0.000
	(-0.38)	(4.59)	(-0.38)
Bad market	-0.004***	0.000	0.000***
	(-116.48)	(-0.93)	(-11.50)
Mid market	-0.002***	0.001***	-0.001***
	(-66.23)	(33.48)	(-33.92)
Lag one-day return	-0.101***	-0.100***	-0.100***
	(-380.62)	(-377.78)	(-377.56)
Lag one-day volume	0.001***	0.001***	0.001***
	(66.82)	(70.22)	(69.11)

Table 9 Performance of no news related trades: momentum vs. contrarian trades

This table present the performance of momentum vs. contrarian trades placed by funds in the ANcerno dataset. The sample includes only no news related trades when there is not any news announcements about the stock within the [-3, 3] day window of the trade. We further separate all no news related trades into momentum and contrarian trades by trade directions. If a trade is in the same direction as the stock's prior one day return, it is labeled as a momentum trade. A contrarian trade is defined otherwise. We then calculate for each fund the average DGTW-adjusted performance of all momentum and contrarian trades in each quarter as in Table 2. The EW and PW DGTW-adjusted performance of all momentum and contrarian trades for funds in each trading regularity quintile during different market conditions is reported. A quarter is defined as a good (bad) market period if the average market returns rank in the top (bottom) tercile (Panel A), or if the average VIX (Panel B) or EPU (Panel C) is in the bottom (top) tercile in our sample period. All returns are expressed in percent. *t*-statistics are reported in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Market condition measured by aggregate market returns

Regularity	Bad market	Good market	Bad-Good
A1. Equal weighted DGTW-adjusted performance of no news related momentum trades			
1 (Low)	-0.71**	0.09	-0.80*
	(-2.16)	(0.26)	(-1.85)
2	-0.38*	0.53**	-0.91***
	(-1.89)	(2.47)	(-3.22)
3	-0.13	0.16	-0.28
	(-0.61)	(0.82)	(-1.12)
4	0.85***	0.54***	0.31
	(4.07)	(4.54)	(1.20)
5 (High)	0.51**	0.58***	-0.07
	(2.57)	(4.23)	(-0.30)
4–Low	1.56***	0.45***	1.11***
	(3.90)	(3.90)	(3.90)
High–Low	1.22***	0.49	0.73
	(2.96)	(1.30)	(1.33)
A2. Equal weighted DGTW-adjusted performance of no news related contrarian trades			
1 (Low)	-0.57	0.25	-0.82*
	(-1.41)	(0.97)	(-1.92)
2	0.23	0.85***	-0.62
	(0.65)	(4.22)	(-1.56)
3	0.30	0.19	0.11
	(0.90)	(0.89)	(0.26)
4	1.31***	0.65***	0.67*
	(3.96)	(3.29)	(1.73)
5 (High)	0.86***	0.67***	0.18
	(5.18)	(3.53)	(0.68)
4–Low	1.89***	0.40	1.49***
	(5.65)	(1.07)	(3.11)
High–Low	1.43***	0.42	1.01**
	(3.65)	(1.16)	(2.00)

Table 9 continued.

Panel A continued.

Regularity	Bad market	Good market	Bad-Good
A3. Principle weighted DGTW-adjusted performance of no news related momentum trades			
1 (Low)	-0.65*	0.11	-0.76
	(-1.90)	(0.28)	(-1.57)
2	-0.05	0.54**	-0.58**
	(-0.29)	(2.38)	(-2.09)
3	-0.07	0.12	-0.19
	(-0.31)	(0.84)	(-0.77)
4	0.59***	0.18	0.41
	(2.60)	(0.92)	(1.25)
5 (High)	0.25**	0.35***	-0.10
	(2.15)	(3.64)	(-0.46)
4–Low	1.24***	0.07	1.17**
	(3.60)	(0.19)	(2.35)
High–Low	0.90**	0.24	0.66
	(2.57)	(0.55)	(1.19)

Regularity	Bad market	Good market	Bad-Good
A4. Principle weighted DGTW-adjusted performance of no news related contrarian trades			
1 (Low)	-0.63*	0.17	-0.80**
	(-1.77)	(0.78)	(-2.02)
2	0.02	0.76***	-0.74*
	(0.07)	(3.83)	(-1.92)
3	0.15	0.08	0.07
	(0.48)	(0.44)	(0.17)
4	0.74**	0.56***	0.18
	(2.00)	(3.03)	(0.47)
5 (High)	0.56***	0.50**	0.07
	(3.19)	(2.55)	(0.26)
4–Low	1.37***	0.39	0.98**
	(5.19)	(1.06)	(2.13)
High–Low	1.20***	0.32	0.87*
	(4.35)	(0.97)	(1.91)

Table 9 continued.

Panel B: Market condition measured by VIX

Regularity	Bad market	Good market	Bad-Good
B1. Equal weighted DGTW-adjusted performance of no news related momentum trades			
1 (Low)	-0.67*	0.16	-0.83
	(-1.56)	(0.54)	(-1.60)
2	-0.61	-0.02	-0.60
	(-1.15)	(-0.06)	(-1.09)
3	-0.18	-0.05	-0.13
	(-0.43)	(-0.20)	(-0.28)
4	0.68**	0.46*	0.22
	(2.02)	(1.71)	(0.44)
5 (High)	0.12	0.08	0.04
	(0.52)	(0.40)	(0.12)
4–Low	1.35***	0.29	1.06
	(2.72)	(0.67)	(1.64)
High–Low	0.79*	-0.08	0.87
	(1.80)	(-0.22)	(1.45)

B2. Equal weighted DGTW-adjusted performance of no news related contrarian trades			
1 (Low)	0.33	0.05	0.28
	(0.61)	(0.34)	(0.47)
2	0.94**	0.68***	0.25
	(2.19)	(2.83)	(0.35)
3	1.10***	0.41*	0.69
	(3.35)	(1.65)	(1.43)
4	1.93***	0.72***	1.21***
	(5.84)	(3.21)	(2.59)
5 (High)	1.38***	0.73***	0.65*
	(6.28)	(4.06)	(1.80)
4–Low	1.60***	0.67***	0.93
	(3.18)	(3.22)	(1.50)
High–Low	1.05**	0.68***	0.37
	(2.18)	(3.50)	(0.63)

Table 9 continued.

Panel B continued.

Regularity	Bad market	Good market	Bad-Good
B3. Principle weighted DGTW-adjusted performance of no news related momentum trades			
1 (Low)	-0.87**	0.15**	-1.02**
	(-2.09)	(0.45)	(-2.00)
2	-0.80	-0.12	-0.68
	(-1.58)	(-0.38)	(-1.30)
3	-0.50	-0.16	-0.34
	(-1.31)	(-0.61)	(-0.72)
4	0.33	0.15	0.18
	(0.97)	(0.53)	(0.37)
5 (High)	-0.01	-0.23	0.22
	(-0.05)	(-1.02)	(0.65)
4–Low	1.20***	0.00	1.20*
	(2.69)	(0.00)	(1.91)
High–Low	0.86**	-0.38	1.24**
	(2.49)	(-1.07)	(2.31)

B4. Principle weighted DGTW-adjusted performance of no news related contrarian trades			
1 (Low)	0.19	0.01	0.18
	(0.36)	(0.03)	(0.32)
2	0.86**	0.67**	0.19
	(2.16)	(2.56)	(0.22)
3	1.05***	0.33	0.72
	(3.13)	(1.19)	(1.43)
4	1.46***	0.57**	0.88*
	(4.07)	(2.45)	(1.68)
5 (High)	1.23***	0.55***	0.68*
	(5.47)	(3.06)	(1.75)
4–Low	1.27**	0.57**	0.70
	(2.50)	(2.55)	(1.17)
High–Low	1.04**	0.55***	0.50
	(2.05)	(2.98)	(0.87)

Table 9 continued.

Panel C: Market condition measured by EPU

Regularity	Bad market	Good market	Bad-Good
C1. Equal weighted DGTW-adjusted performance of no news related momentum trades			
1 (Low)	-0.45	-0.16	-0.29
	(-1.15)	(-0.44)	(-0.54)
2	-0.45	0.03	-0.48
	(-0.89)	(0.11)	(-0.88)
3	-0.04	0.23	-0.26
	(-0.09)	(0.80)	(-0.56)
4	0.78**	0.19	0.59
	(2.34)	(0.39)	(1.19)
5 (High)	0.14	0.46**	-0.33
	(0.63)	(2.26)	(-0.97)
4–Low	1.23**	0.34	0.89
	(2.56)	(0.66)	(1.37)
High–Low	0.58	0.62	-0.04
	(1.35)	(1.43)	(-0.06)
C2. Equal weighted DGTW-adjusted performance of no news related contrarian trades			
1 (Low)	0.88	0.36	0.53
	(1.46)	(1.63)	(0.92)
2	1.30**	1.70***	-0.40
	(2.56)	(2.71)	(-0.55)
3	1.21***	0.91***	0.30
	(3.37)	(3.40)	(0.63)
4	2.02***	1.18***	0.84*
	(7.22)	(3.12)	(1.76)
5 (High)	1.51***	1.20***	0.31
	(6.41)	(3.58)	(0.81)
4–Low	1.13**	0.82**	0.31
	(1.99)	(2.36)	(0.50)
High–Low	0.63	0.85**	-0.22
	(1.21)	(2.29)	(-0.38)

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Table 9 continued.

Panel C continued.

Regularity	Bad market	Good market	Bad-Good
C3. Principle weighted DGTW-adjusted performance of no news related momentum trades			
1 (Low)	-0.65*	-0.22	-0.43
	(-1.74)	(-0.56)	(-0.81)
2	-0.58	-0.09	-0.49
	(-1.16)	(-0.40)	(-0.93)
3	-0.36	0.14	-0.51
	(-1.02)	(0.49)	(-1.07)
4	0.27	-0.21	0.48
	(0.75)	(-0.48)	(1.00)
5 (High)	-0.12	0.11	-0.23
	(-0.47)	(0.47)	(-0.67)
4–Low	0.92**	0.00	0.91
	(2.05)	(0.01)	(1.44)
High–Low	0.53	0.32	0.21
	(1.52)	(0.73)	(0.35)
C4. Principle weighted DGTW-adjusted performance of no news related contrarian trades			
1 (Low)	0.73	0.25	0.48
	(1.31)	(1.13)	(0.88)
2	1.15**	1.89**	-0.74
	(2.39)	(2.11)	(-0.84)
3	1.10***	1.02***	0.08
	(3.18)	(3.22)	(0.15)
4	1.58***	1.05***	0.53
	(4.63)	(2.95)	(1.00)
5 (High)	1.23***	1.07***	0.16
	(4.91)	(3.11)	(0.39)
4–Low	0.85*	0.80**	0.06
	(1.68)	(2.20)	(0.09)
High–Low	0.51	0.83**	-0.32
	(1.04)	(2.34)	(-0.56)