Trading Regularity and Fund Performance

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We construct a new measure of trading regularity, capturing the extent to which investors trade on a regular basis. Institutional investors that regularly trade outperform those that trade less regularly. The performance of funds that regularly trade persists for at least a year. Among those who trade most regularly, larger funds perform relatively worse, because they incur higher transaction costs associated with their larger trades. Institutions that regularly trade generate superior performance, in part, by behaving as contrarians and by trading more aggressively on information. By contrast, we find no relation between trading regularity and performance among index funds. (*JEL* G11, G14, G23)

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Trading represents one of the core activities undertaken by money management companies as they execute their investment strategies. To the extent that traders can capitalize on time-varying opportunities in the stock market, trading has the potential to enhance fund performance. For instance, an investment fund can generate greater returns by trading regularly on earnings announcements rather than periodically making wholesale portfolio changes after stock prices more fully reflect recent news (see, e.g., Campbell, Ramadorai, and Schwartz 2009). As another example, stock and market-level liquidity vary within the trading day and across longer spans of time, as

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the market absorbs an endless stream of news. A portfolio manager might trade regularly to exploit temporary pockets of liquidity that affect the costs associated with his trades.

In this paper, we examine the relation between the degree to which a fund trades regularly and performance for a large sample of institutional investors. As we discuss in detail later, we compute the extent to which a fund trades regularly by 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, marking the ratio as zero on a day with no trades, and we then average this daily ratio across time. As such, our measure of trading regularity distinguishes between funds that trade daily, for example, and those that trade less regularly, such as weekly.

Ex ante, it may be reasonable to expect a negative or insignificant relation to exist between the extent to which institutional investors trade regularly and the performance of their trades for three main reasons. First, price-sensitive news disseminates quickly, such that it would be difficult to consistently outperform by trading on publicly available information. Second, if institutions that trade regularly trade more in aggregate than institutions that trade sporadically, then institutions that regularly trade would be expected to generate greater total transaction costs. Third, evidence among retail investors (e.g., Barber and Odean 2000) suggests a strong negative relation between net performance and the extent to which investors turn over their portfolios.

Conversely, other rationale is consistent with a positive relation between trading regularity and performance. First, the empirical asset pricing literature identifies a plethora of anomalies consistent with abnormal returns for properly timed trades (see, e.g., Harvey, Liu, and Zhu 2016). Recent work by Novy-Marx and Velikov's (2016) suggests that these anomalies deliver abnormal returns for investors who actively manage their transaction costs. Second, in contrast to the retail investor sample of Barber and Odean (2000), we examine the activity of professional traders. Compared to retail investors, professionals might have greater ability to exploit opportunities that arise in the stock market. Moreover, the resources accessible to professional traders would likely allow them to incorporate the types of cost mitigation strategies described by Novy-Marx and Velikov's (2016).

We find a strong positive correlation between intraquarterly investment performance and the extent to which institutional investors regularly trade. Net of transaction costs, funds that regularly trade earn greater returns and abnormal returns from their trades than less regular funds. Performance increases across the first four quintiles of funds sorted based on trading regularity before declining at the highest quintile. For instance, funds in the highest trading regularity quintile (transacting 1.66 trades per stock per day, on average) produce a statistically significant, net abnormal return of 0.55% from trade entry until the end of the quarter, where we adjust performance via the Daniel et al. (DGTW, 1997) characteristic benchmark. Funds in the second-highest trading regularity quintile, which transact 1.00 trades per stock per day on average, produce a statistically significant, net abnormal return of 0.75% from trade entry until the quarter-end.[1] By contrast, funds in the lowest trading regularity quintile transact 0.12 trades per stock per day, generating an insignificant net abnormal return of –0.18%. Ex ante, our evidence suggests that the tendency to regularly trade proxies for skill, possibly attributable to the ability of these funds to exploit short-lived opportunities. Inference is unaffected based on alternative measures of trading regularity, including the number of days a fund trades during the quarter and the extent to which a fund's quarterly dollar trading volume is evenly distributed across the quarter's trading days.

In contrast to our findings across the entire sample of funds, we find no correspondence between performance and the extent to which index funds regularly trade. Given their emphasis on low tracking error, index funds would be expected to have less discretion than actively managed funds in choosing when and how they invest. As such, index funds represent an ideal control group for our analysis, because they should not generate performance the same way actively managed funds do. We find this to be true.

We find persistence in the relative trade performance of the top two trading regularity quintiles, whereas the trade performance of the bottom two trading regularity quintiles does not persist. For example, within the top two trading regularity quintiles, the top performing quintile of funds generates approximately 66 basis points greater quarterly abnormal performance than the bottom performing quintile of funds for four quarters following the performance ranking, with the performance difference statistically significant each quarter. By contrast, similar performance differences among funds in the bottom two trading regularity quintiles are largely statistically insignificant. Furthermore, we find that the extent to which funds regularly trade strongly persists over time: funds that regularly trade during one quarter continue to regularly trade the next quarter and also four quarters later, though some of this persistence in trading regularity may be mandated by the firm rather than chosen by the fund.

Trading incurs transaction costs, and transaction costs attributable to price impact positively correlate with trade size. Since large funds require larger trades than smaller funds, the trades associated with large funds might be expected to generate greater transaction costs than the trades of smaller funds. However, compared to smaller funds, larger funds have greater resources to more effectively manage transaction costs, and they have greater incentives to do so. Nevertheless, we find a negative relation between the performance of funds and a proxy for the size of the fund. Moreover, smaller funds that regularly trade outperform larger funds that regularly trade. This result helps explain earlier findings in the literature of diseconomies of scale within some sectors of the money management industry. For example, Chen et al. (2004) find that larger mutual funds underperform smaller mutual funds, on average. Our

[1] Relatively high mean transaction costs for funds in the highest trading regularity quintile are one possible reason performance peaks at quintile four. We discuss transaction costs in greater detail later.

results suggest that one avenue through which diseconomies of scale manifests itself is via the trading opportunities investment managers are able to pursue. That is, given that larger funds trade larger orders, they are susceptible to greater price impact from their trades. Larger funds consequently realize lower net returns when they attempt to exploit short-term trading opportunities, or they may choose not to invest resources in a top-quality trading team and forgo such opportunities.

We also find that funds in the highest trading regularity quintile generate greater transaction costs than less regular funds, whereas the transaction costs of funds in the second-highest trading regularity quintile are comparable to the transaction costs of less regular funds. The transaction cost disadvantage of funds in the highest trading regularity quintile is one possible reason we consistently find that funds in the highest trading regularity quintile underperform funds in the next quintile. Our results are consistent with Novy-Marx and Velikov's (2016) conclusion that certain trading strategies have the capacity to produce abnormal returns net of transaction costs, but not indefinitely, as increasing transaction costs offset gains.

How do institutional investors that regularly trade generate abnormal performance? One possibility is that they act as contrarians by stepping in to buy stocks that have been beaten down or by selling stocks whose price has run up. Trading in this manner would be consistent with earning returns related to the reversal anomaly, like in Nagel (2012) and Jame (2017). Consistent with funds that regularly trade behaving as contrarians, we find particularly strong performance when these funds buy (sell) stocks with relatively low (high) recent returns.

Another possibility is that institutional investors that regularly trade either quickly respond to news or have some ability to forecast news. For example, earnings releases are scheduled announcements; investors know well in advance the date and time that a company plans to release its quarterly earnings. If funds that regularly trade have ability, on average, to forecast a stock's response to these announcements, we would expect a positive relation between the extent to which funds regularly trade and abnormal returns around earnings announcements, which is consistent with our findings.

Our measure of trading regularity differs from typical measures of trading activity, which often emphasize how quickly a portfolio turns over. We simply capture the extent to which funds trade on a regular basis. Consequently, funds classified as regular traders via our measure need not show relatively high portfolio turnover, as funds can regularly trade different stocks. Moreover, funds that trade with relatively high intensity but only on a small fraction of trading days need not be classified as regular traders via our measure.[2] By contrast, whereas funds that transact on a high fraction of trading days but without a

[2] The distribution of holding periods associated with the trades of sample funds indicates that our sample does not include "high-frequency trading" (HFT) firms, which are characterized by very frequent intraday trading and

large number of trades each day may not be considered highly active traders by typical notions of active trading, they could be classified as regular traders via our measure.

Our analysis relates to prior analyses that examine trading activity both among individuals and institutions. Barber and Odean (2000) document poor performance among active retail investors, largely driven by high transaction costs. Their evidence contrasts with our evidence of positive performance among institutional investors. However, their focus on portfolio turnover emphasizes an investor's aggregate trading relative to his portfolio size, whereas we emphasize the extent to which funds regularly trade. Several other papers, including Odean (1999) and Barber and Odean (2001, 2002), also find evidence that suggests that retail investors make poor trading decisions, on average, and generate below market returns. Similarly, Barber et al. (2009) and Barber et al. (2014) find evidence of poor overall trading ability among a unique sample of retail investors in Taiwan.

Our evidence of positive performance associated with institutional stock trades relates to Chen et al. (2000) analysis of mutual funds, where the authors find evidence of skill in trades that they infer by comparing consecutive snapshots of quarterly portfolio holdings. Yan and Zhang (2009) find that the change in the quarterly portfolio holdings of short-term institutions predicts future stock returns, which they attribute to an information advantage. Relative to samples that infer trades from changes in portfolio holdings, our sample of actual trade data from ANcerno provides the advantage of exact entry and exit dates and times, which allows for precision in trade performance computation and transparency with respect to a fund's intraquarterly round-trip trades. The importance of this latter advantage is evident in light of Puckett and Yan (2011) finding that trades that cannot be inferred from portfolio holdings generate positive abnormal performance.

In another recent paper, Chakrabarty, Moulton, and Trzcinka (2017) use ANcerno data to examine the performance of the short-duration trades of institutions (e.g., positions held for less than 90 days), providing insight into their short-term trading ability. Chakrabarty, Moulton, and Trzcinka (2017) find that a majority of short-term institutional trades lose money. In rationalizing Chakrabarty, Moulton, and Trzcinka (2017) findings of poor short-term performance with our findings of positive relative performance for funds that regularly trade, it is important to note that our measure of trading regularity is not closely inversely correlated with a fund's mean holding period. As confirmed by the data, our measure tends to capture funds trading regularly but on different stocks, such that the mean holding period of stocks held by funds that regularly trade is not unusually short. For instance, we find the median holding period of the quintile of funds in the highest trading regularity

very short intraday holding periods. HFT firms trade both regularly and actively. See Brogaard, Hendershott, and Riordan (2014).

quintile in our sample averages 220 days, greatly exceeding the shorter holding periods emphasized by Chakrabarty, Moulton, and Trzcinka (2017) and only marginally lower than the 243-day median across the full sample of funds. Moreover, only 22% of the trades of the funds in the highest trading regularity quintile are held for 90 days or less.[3] Consequently, Chakrabarty, Moulton, and Trzcinka's (2017) finding that short-duration trades perform poorly need not imply that funds that regularly trade underperform, as the vast majority of the trades of funds that regularly trade are not of short duration. Also, in most of our analysis, we utilize Puckett and Yan (2011) methodology for tracking trades, which differs from the approach used by Chakrabarty, Moulton, and Trzcinka (2017).[4] When we apply Chakrabarty, Moulton, and Trzcinka (2017) approach, consistent with their results, we find that trades with shorter holding periods show poorer performance on average than those with long holding periods. Nonetheless, a positive relation between performance and our measure of trading regularity exists after controlling for the holding period of the trade and also across subsamples of short-duration trades.

Our analysis also relates to the mutual fund literature that examines the cross-sectional relation between portfolio turnover and performance, including Carhart (1997), who finds a negative relation, and Wermers (2000), who finds a positive relation. More recently, Pástor, Stambaugh, and Taylor (2017) examine the time-series relation between fund turnover and performance, finding a positive relation, such that changes in turnover predict future performance among individual funds and also for the mutual fund industry in aggregate, consistent with the idea that funds trade more when better opportunities exist. Compared to the mutual fund literature that examines the broad relation between standard turnover measures and overall performance, our trade data allow for greater precision in tying trading activity to the performance of specific trades, so that we can better pin down some of the drivers of performance, including contrarian behavior and information related to earnings. However, since the ANcerno data do not include fund turnover or portfolio holdings, we are unable to determine from the data fund trading activity relative to fund total assets. Lastly, our study relates to Lan et al. (2015) and Cremers and Pareek (2016). Lan et al. find evidence of superior long-term performance for long-term holdings. Cremers and Pareek (2016) show outperformance in high active share funds that trade infrequently. Both papers use quarterly holdings data to estimate trading and investment horizon. By contrast, our intraday data reports actual trades that we use to precisely estimate trading regularity and short-term performance. In addition, unlike Cremers and Pareek (2016), who measure fund

3 Across all trades, Chakrabarty, Moulton, and Trzcinka (2017) report that 23% are held for less than 90 days.

4 Following Puckett and Yan (2011), we define the start of a round-trip trade on a stock as the date of the first trade of the stock by the fund in that quarter. Chakrabarty, Moulton, and Trzcinka (2017) trace the initiation of a round-trip trade to the start of the data set. Chakrabarty, Moulton, and Trzcinka (2017) provide detailed comparisons of the two approaches in their online appendix.

level performance, we focus on the performance of an institution's individual stock trades and directly connect a trade's performance to its timing and stock characteristics to shed light on the specific ways funds generate performance.

1. Data and Methodology

1.1 Data and summary statistics

We utilize institutional trade data from ANcerno Ltd., a transaction cost analysis provider that serves the institutional money management industry.[5] Our sample spans an 11-year sample period from January 1, 1999, to December 31, 2009. For each trade execution, the ANcerno database reports 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. The unique institution and fund identity codes provided by ANcerno in the cross-section and time series are not available from data providers such as TAQ or Plexus. However, since the identity codes are masked, we do not know the names of the funds or the institutions. Previous studies that use the Thomson Reuters holdings data to infer fund trading activity from changes in fund quarterly holding snapshots are unable to capture round-trip trades within the calendar quarter or to precisely measure performance because they cannot determine specific entry and exit dates or transaction prices (see Puckett and Yan 2011).

Since a typical order from a buy-side institution is large in size, the trading desk of the buy-side institution may break up a large order into several trades or among several brokers to reduce market impact. In the ANcerno data set, the allocation to each broker is defined as a "ticket," and each ticket may result in several executions. Like Anand et al. (2012), we evaluate trades at the ticket level, rather than focusing separately on the trades that compose the ticket.

The ANcerno database covers an extensive set of intuitional investors, including 843 institutions and 5,277 different funds within those institutions. Institutions in the ANcerno database are responsible for approximately 115 million trades involving more than $42.6 trillion and 1,417 billion shares.[6] We restrict our sample to common stocks and delete funds which cannot be reliably tracked to their institutions. We also drop fund-quarters that have a number of trades or a number of stocks traded at 1% extreme values at both ends.[7]

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[5] Previous studies that use ANcerno data include Goldstein et al. (2009), Chemmanur et al. (2009), Goldstein et al. (2011), Puckett and Yan (2011), Busse, Green, and Jegadeesh (2012), Chakrabarty, Moulton, and Trzcinka (2017), Busse et al. (2016), and Jame (2017).

[6] According to Puckett and Yan (2011), ANcerno institutions account for an estimated 10% of all institutional trading volume. See Puckett and Yan (2011) and Anand et al. (2012) for additional details for this data set.

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

Panel A of Table 1 presents summary statistics for the ANcerno trading data. 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 places 310 trades on 74 unique stocks each quarter in 1999, while it trades 763 times on 106 stocks per quarter in 2009.

Our trading measure captures the extent to which funds regularly trade, for example, trading each day rather than each week. Trading opportunities likely vary across time and across stocks. For instance, stock- and market-level liquidity and idiosyncratic news can differentially affect stock prices and the impact associated with a stock trade. A fund that actively seeks to add value via trading by capitalizing on time-varying trading opportunities would be expected to trade more regularly than a more passive investor. As an example, a relatively passive investor might mainly trade to periodically rebalance his portfolio or address cash flow imbalances, and he might accomplish these tasks in a limited subset of all trading days. By contrast, funds that closely monitor the market in search of advantageous times to execute their trades likely trade more regularly.

We compute the extent to which a fund trades regularly as follows. We first take 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. Thus, a fund's trading regularity measure each day takes a value of 0 or $\geqslant 1$, where 0 signifies no trade, 1 signifies trading one or more stocks one time each, and > 1 signifies trading at least one stock more than once. For example, our measure takes on a value of 2 for a daily round-trip transaction of one stock (buying and selling the same stock on the same day). To obtain a fund's quarterly trading regularity measure, we take the average of its daily trading regularity measure across the quarter.

Our measure of trading regularity differs from trading activity measures that positively correlate with portfolio turnover, which measure the extent to which a fund modifies its entire portfolio.[8] ANcerno data masks the identity of the firm and does not include aggregate portfolio holdings, so we are unable to match the trades to 13-F filings or other sources of fund holdings data or to determine from the data trading activity relative to fund total assets. By capturing the extent to which a fund trades regularly, our measure captures an important dimension of trading activity while not directly capturing the extent to which funds turn over their base of assets. For example, a fund that trades regularly

[8] Our trading regularity measure is not directly affected by a trade's absolute size or its size relative to fund total assets. For example, our measure does not differentiate between a 100-share trade size and a 10,000-share trade size or between a trade that comprises a small fraction of the fund's total assets and a trade that comprises a large fraction of the fund's total assets. By contrast, measures based on turnover examine trading activity relative to portfolio size.

Table 1
Descriptive statistics

A. Trade statistics by year

Year	Funds	Institutions	Stocks Total	Stocks Average	Trades Total ($x10^6$)	Trades Average	Volume Shares ($x10^9$)	Volume Dollars ($x10^{12}$)	Freq.
1999	1,871	354	6,126	74.08	3.19	310.4	42.0	1.88	0.68
2000	1,762	343	6,142	87.55	4.44	403.9	61.2	2.76	0.71
2001	1,817	358	5,324	82.53	5.42	407.4	80.2	2.43	0.73
2002	1,835	357	4,968	82.34	5.86	421.9	99.5	2.40	0.74
2003	1,592	310	4,779	77.78	5.90	408.3	82.6	2.05	0.72
2004	1,748	333	4,786	84.22	7.18	482.8	109.1	3.10	0.76
2005	1,445	302	4,786	83.32	6.30	465.9	66.3	2.00	0.80
2006	1,420	305	4,692	89.91	7.38	544.6	74.1	2.33	0.86
2007	1,352	293	4,743	93.29	8.52	575.8	75.8	2.69	0.88
2008	1,153	262	4,314	102.06	9.40	681.8	81.6	2.30	0.90
2009	1,284	306	3,968	106.35	11.01	762.6	132.9	3.39	0.88

B. Trading regularity

B1. Trading regularity distribution

Regularity	Mean	Median	Min	Max
1 (low)	0.12	0.11	0.02	0.21
2	0.36	0.36	0.22	0.52
3	0.69	0.69	0.52	0.86
4	1.00	1.00	0.86	1.12
5 (high)	1.66	1.36	1.12	11.93
All	0.78	0.72	0.02	11.93

B2. Distribution of days associated with trading regularity levels

	Number of trades per stock						
Regularity	0	[0,1]	[1,2]	[2,3]	[3,4]	[4,5]	> 5
1 (low)	56.43	5.89	0.51	0.04	0.01	0.00	0.00
2	42.00	18.32	2.33	0.18	0.04	0.01	0.01
3	23.66	32.76	5.93	0.41	0.09	0.02	0.02
4	7.05	39.78	15.40	0.51	0.10	0.02	0.02
5 (high)	5.04	14.75	31.67	7.20	2.17	0.91	1.14
All	26.83	22.31	11.17	1.67	0.48	0.19	0.24

C. Trade statistics conditional on executed trade

C1. Trading regularity

	Statistics per day conditional on executed trade			
Regularity	Trades	Stocks	Trades per stock	Stocks per quarter
1 (low)	25.67	23.25	1.08	68.30
2	7.69	6.62	1.13	58.13
3	5.93	5.16	1.15	64.13
4	8.64	7.74	1.15	97.44
5 (high)	23.88	14.04	1.85	139.98
All	14.35	11.35	1.28	85.58

C2. Trade size and volume

	Statistics per day conditional on executed trade					
	Trade size ($x10^3$)		Daily volume ($x10^3$)		Quarterly volume ($x10^3$)	
Regularity	Shares	Dollars	Shares	Dollars	Shares	Dollars
1 (low)	16.35	491	217	7,116	913	30,066
2	14.03	424	85	2,559	1,593	47,957
3	10.04	296	49	1,497	1,785	54,790
4	7.45	208	76	2,107	4,424	122,230
5 (high)	8.85	256	297	8,592	18,184	524,709
All	11.34	335	145	4,372	5,377	155,886

(continued)

Table 1
(continued)

D. Trade performance

	Mean	P25	Median	P75	SD
D1. Raw returns					
Buy EW	1.10	−2.43	1.46	4.94	8.23
Sell EW	0.74	−2.68	1.06	4.45	7.94
Buy-sell EW	0.36	−2.61	0.35	3.41	7.73
Buy PW	0.80	−2.65	1.20	4.64	8.15
Sell PW	0.62	−2.70	0.98	4.24	7.92
Buy-sell PW	0.18	−2.75	0.20	3.20	7.71
D2. DGTW-adjusted performance					
Buy EW	0.35	−1.66	0.18	2.23	5.04
Sell EW	0.03	−1.99	−0.13	1.79	5.15
Buy-sell EW	0.32	−2.30	0.30	2.99	6.80
Buy PW	0.19	−1.82	0.05	2.09	5.00
Sell PW	0.02	−1.92	−0.12	1.78	5.26
Buy-sell PW	0.17	−2.42	0.17	2.84	6.84

E. Trade holding period

	Mean	P25	Median	P75	SD
Entry to quarter end	45	21	45	67	27
Entry to exit	371	106	243	490	399

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. The total number of trades placed by all funds and the average number of trades placed by each fund in each quarter is also presented. We also report total trading volume in shares and dollars. 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. Panel B reports statistics related to the distribution of trading regularity (panel B1) and the distribution of days associated with various ranges of trading regularity (panel B2) for quintiles of funds sorted by trading regularity. [X,Y] refers to a trading regularity greater than X and less than or equal to Y. Panel C reports daily and aggregated quarterly trading statistics by fund trading regularity quintile conditional on the fund having executed a trade on that day. Panel C1 reports the daily and aggregated quarterly number of trades and number of stocks traded by funds when they trade, and panel C2 reports the size of the trades (shares and dollar volume) as well daily and quarterly aggregated trade volume. Panel D (E) reports the sample mean, 25th percentile, median, 75th percentile, and the standard deviation of fund performance (holding period). In panel D, we measure the performance of all trades placed by a fund. For each trade, we calculate the raw cumulative stock return from the execution price until the end of the quarter. We adjust the raw cumulative return by the DGTW benchmark return over the same period. For each fund in each quarter, we then compute equally weighted (EW) or principally 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. We report the performance of buy trades, sell trades, and their difference measured in raw returns (panel D1) and DGTW-adjusted returns (panel D2). In panel E, we calculate holding period from trade to quarter end, consistent with our approach for measuring performance, and from trade entry to exit, similar to Chakrabarty, Moulton, and Trzcinka (2017). All returns are expressed as a percentage.

need not show high portfolio turnover or hold a portfolio largely comprising short-term positions, as a fund can regularly trade different stocks.[9]

Table 1, panel B, reports statistics associated with the distribution of fund trading regularity for quintiles of funds sorted by trading regularity. The panel provides insight into the trading patterns associated with varying levels of trading regularity. In panel B1, the statistics indicate that the dispersion of trading regularity across sample funds is large, with the highest quintile of funds showing a mean (median) trading regularity of 1.66 (1.36) and the lowest quintile of funds showing a mean (median) trading regularity of 0.12 (0.11). Table 1, panel B2, details how trading intensity varies across days for each trading regularity quintile. The top trading regularity quintile shows a trading regularity statistic between 1 and 2 during half of the trading days in a quarter (31.7 out of 63 days), whereas the two lowest quintiles are completely inactive (i.e., 0 trades) during large portions of the quarter (for 42.0 and 56.4 days out of 63 days for quintiles 2 and 1, respectively). Thus, our trading regularity measure helps differentiate between funds that trade each day versus funds that are much less likely to trade on a given day. Panel B2 also indicates few instances of highly active trading, with the top trading regularity quintile reaching a trading regularity statistic greater than five on only 1.14 trading days per quarter on average.

Panel C of Table 1 reports daily and aggregated quarterly trading statistics by fund trading regularity quintile conditional on the fund having executed a trade on that day. Panel C1 reports the daily and aggregated quarterly number of trades and number of stocks traded by funds when they trade, and panel C2 reports the size of the trades (shares and dollar volume) as well daily and quarterly aggregated trade volume. The panels show that, conditional on executing a trade, a U-shaped pattern exists between trading regularity and daily trading activity. For instance, on days that they do trade, the lowest trading regularity quintile funds trade heavily: they execute a mean of 25.7 trades comprising an aggregate dollar volume of $7.1 million and 23.3 stocks. The activity of the low trading regularity funds is comparable to the 23.9 trades and aggregate $8.6 million dollar volume executed by the highest trading regularity quintile on their trading days and far greater than the trading activity of funds in the middle trading regularity quintiles. However, since the lowest trading regularity funds are inactive most days (as indicated in panel B2), they trade far fewer stocks (68.3 vs. 140.0) and far less aggregate dollar volume ($30.1 million vs. $524.7 million) across the quarter than the top trading regularity quintile of

[9] Conceptually, the mean holding period for a fund that regularly trades need not be unusually short. For example, suppose two funds with identical turnover and identical mean holding period both buy ten stocks during May. Fund A buys all of them on May 30, and fund B, which trades more regularly than fund A, buys the stocks on several different days during the month, waiting for what it considers to be the best buying opportunities (e.g., based on information that arises sporadically). In some sense, our measure captures heterogeneity in transaction dates driven by more regular funds' focus on trading when opportunities are best. By contrast, funds that trade less regularly are less focused on timing their trades and consequently may concentrate their trading activity across fewer days.

funds. The data highlights how some funds can trade actively during certain periods of time, but because they do not continue to trade across time, they are not classified as regular traders via our measure.

Note that by defining a fund's trading regularity as the average number of trades it places on each stock, our measure controls, somewhat, for the tendency for funds with greater assets under management to hold more stocks, and hence trade more stocks, everything else equal. Also again note that we treat a trade ticket sent to a broker by the fund on a particular day as one trade, regardless of the number of executions it takes for the broker to fill the ticket.[10,11]

In another recent paper based on the ANcerno database of institutional trades, Chakrabarty, Moulton, and Trzcinka (2017) examine the performance of positions with relatively short holding periods. The authors find poor mean performance associated with short-duration positions. We find little correspondence between our measure of trading regularity and the estimate of holding period used by Chakrabarty, Moulton, and Trzcinka (2017), with a –0.19 cross-sectional correlation between the two measures. Chakrabarty, Moulton, and Trzcinka (2017) sample of short duration trades is not disproportionately associated with funds that regularly trade, and the median holding period associated with the subsample of our funds that regularly trade is not unusually low compared to that of funds that trade less regularly. Table 1,

10 As an alternative to ANcerno's ticket definition, Anand et al. (2012) examine the robustness of their results to "stitched" tickets, where they group together into tickets trades by the same fund manager on the same stock and the same trade side that occur on the same or consecutive trading days, even when the trades involve more than one broker. We utilize this same approach to examine the robustness of our results to the alternative ticket definition in Section 2.8.1. Examining stitched tickets helps control for the tendency of larger firms to break up their orders across multiple brokers and/or multiple days to mitigate price impact, whereas smaller firms more likely execute a trade via one broker during one trade day. For example, suppose fund A executes five buy orders in 1 day on a particular stock via five different brokers. Using ANcerno's ticket definition, we assign the fund a trading regularity measure of 5 (five trades divided by one stock). By contrast, after stitching together the five buy orders, these trades contribute 1.0 (i.e., one stitched ticket divided by one stock), rather than 5.0, to a quarterly stitched ticket regularity measure. Analyzing trading regularity via both ANcerno's ticket definition and stitched tickets provides insight regarding the robustness of the results to alternative perspectives on what constitutes regular trading. For instance, suppose fund B executes five buy orders in 1 day on five different stocks. Fund B, with a trading regularity measure of 1 (five trades divided by five stocks), would be assigned the same level of trading regularity as fund A if we base fund A's regularity on stitched tickets, but less regular than fund A if we base fund A's regularity on ANcerno tickets.

11 Since we average a fund's daily trading regularity across a quarter, the trading regularity measure is unable to differentiate between heavy trading concentrated in a few days combined with minimal trading during other days versus a moderate level of trading throughout the quarter. It is also unable to differentiate between trades involving the same stock versus different stocks across time. For example, suppose fund A trades the same stock 63 times in 1 day and then trades nothing during the quarter's 62 other trading days. Fund B trades the same stock once a day each trading day of the quarter. Finally, fund C trades a different stock each day of the quarter. In this example, each fund would be assigned a quarterly trading regularity measure of 1, despite widely different trading behavior across the three funds. However, the statistics in Table 1, panels B and C, suggest that the trades sample is not characterized by extreme trading behavior analogous to the fund A and fund B examples. For instance, Panel B2 indicates only 0.24 trading days per quarter, on average, are associated with more than five trades per stock. In addition, unreported tests show that 29 stock-days out of 1,746 per quarter, on average, are associated with five or more trades of the same stock by the same fund. Moreover, the statistics conditional on an executed trade in panel C1 indicate the mean number of trades per stock ranges from 1.08 to 1.85 across the trading regularity quintiles. Panel C1 also provides no indication of funds trading the same stock each day all quarter, as the total number of stocks a fund trades per quarter ranges from 68 to 140, on average, across the trading regularity quintiles.

panel C, indicates that funds in the top trading regularity quintile trade 14 stocks per day and 140 stocks per quarter. These statistics indicate that funds that regularly trade do not focus on a small set of stocks, such that holding periods need not be especially short. Thus, Chakrabarty, Moulton, and Trzcinka's (2017) finding that short-duration trades show poor performance need not imply that funds that regularly trade show poor performance. Nevertheless, given the commonality in the database utilized and the focus on trade performance and trade/trader characteristics, we further explore in the appendix the similarities and the differences between the types of trades emphasized in our analysis compared to those of Chakrabarty, Moulton, and Trzcinka (2017). Our results are robust after controlling for the holding period of the trade and also across subsamples of short-duration trades.

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. We use earnings announcement dates and the mean analyst forecast provided by I/B/E/S to calculate earnings surprise. We obtain market return data from Kenneth French's Web site.[12]

1.2 Fund performance

We measure fund performance similar to Puckett and Yan (2011) as follows. For each fund, we separate all trades within each quarter 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. We proxy for performance 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 weight performance two ways. 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. Via these two weighting schemes, we compute average performance for buys and sells separately. Finally, we calculate the difference between the average performance of buys and sells, which captures the intraquarter performance of the trades placed by a fund in a given quarter.

Panel D of Table 1 reports summary statistics of these fund performance measures. Sample funds show an equally weighted average intraquarterly DGTW-adjusted return of 0.35% (0.03%) for buys (sells) during our 1999–2009 sample period. Since trades execute throughout the quarter and we estimate performance from entry until the end of the quarter, the typical holding period associated with these performance measures is far less than one quarter. We utilize the same "quarterizing" procedure used by Puckett and Yan (2011) to

[12] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

gross up the performance measures to reflect a full quarter of performance.[13] Based on this approach, the 0.32% performance difference between equally weighted buys and sells in panel B equates to 1.48% over a full quarter and an annualized 5.92%. Note that our institutional trading results differ considerably from the performance associated with individual investors. For example, Odean (1999) finds that the average difference in returns between the buys and sells of individual investors is negative, that is, the securities individuals buy underperform the securities they sell.

As an alternative to Puckett and Yan (2011) methodology for measuring performance, Chakrabarty, Moulton, and Trzcinka (2017) measure performance from trade entry until trade exit, an approach necessitated by their focus on examining the performance of a trade as a function of its holding period. One shortcoming of this alternative approach is trade exits are not matched to trade entries within the ANcerno database. Given that positions can be entered or exited periodically across time, matching a position's entry to its exit depends on the matching procedure's starting point in instances where a stock enters and exits a fund portfolio multiple times during the sample period. For instance, a trade classified as a closing sell transaction based on a particular starting point could be classified as an opening short sale for a later starting point. Moreover, trades without an offsetting transaction cannot be matched or included in the analysis. Given that our analysis does not emphasize trade holding periods, we utilize Puckett and Yan (2011) approach to measure performance in our main analysis while also examining the robustness of our findings to Chakrabarty, Moulton, and Trzcinka's (2017) methodology. Panel E of Table 1 shows holding period statistics associated with our performance measurement approach (i.e., from the trade to the end of the quarter) as well as from trade entry to exit, like in Chakrabarty, Moulton, and Trzcinka (2017).[14] Also note that our trading regularity measure does not depend on the methodology used to measure performance. Lastly, the holding period statistics suggest that our sample does not include "high-frequency trading" (HFT) firms, whose trades are characterized by ultrashort intraday holding periods (see Brogaard, Hendershott, and Riordan 2014).

2. Results

2.1 Performance versus trading regularity

In this section, we first examine the relation between the extent to which funds regularly trade and performance. We sort funds into quintiles based

13 We multiply a trade's abnormal return by the number of trading days in the quarter divided by the number of trading days from trade entry until quarter end. We report the mean holding period performance, rather than the quarterized performance, in the tables.

14 Chakrabarty, Moulton, and Trzcinka (2017) report in their table 2 that 58.2% of fund trades have a holding period of less than 9 months, roughly consistent with the 243-day entry to exit median in Table 1, panel E.

Table 2
Fund performance for univariate sort by trading regularity

A. Gross performance

Regularity	EW	PW
A1. Raw returns		
1 (low)	−0.01	0.07
	(−0.03)	(0.36)
2	0.18	0.13
	(1.31)	(0.96)
3	0.24**	0.10
	(2.08)	(0.75)
4	0.72***	0.31**
	(5.15)	(2.18)
5 (high)	0.54***	0.27***
	(5.15)	(3.13)
4–low	0.73***	0.25
	(2.97)	(1.11)
High–low	0.55***	0.21
	(2.97)	(1.18)
A2. DGTW-adjusted performance		
1 (low)	−0.18	−0.15
	(−1.21)	(−0.95)
2	0.15	0.15
	(1.36)	(1.48)
3	0.22**	0.14
	(2.47)	(1.57)
4	0.75***	0.42***
	(7.25)	(4.04)
5 (high)	0.55***	0.31***
	(6.79)	(4.37)
4–low	0.93***	0.58***
	(5.26)	(3.62)
High–low	0.73***	0.46***
	(4.17)	(2.68)
B. Net of commissions		
B1. Raw returns		
1 (low)	−0.27	−0.13
	(−1.55)	(−0.75)
2	−0.11	−0.14
	(−0.78)	(−0.98)
3	−0.07	−0.16
	(−0.65)	(−1.21)
4	0.47***	0.04
	(3.21)	(0.31)
5 (high)	0.25**	0.01
	(2.44)	(0.08)
4–low	0.74***	0.18
	(2.97)	(0.81)
High–low	0.52***	0.14
	(2.83)	(0.8)

(continued)

on contemporaneous trading regularity and examine the performance of their trades during the quarter of the trade. Table 2 shows the results. In panel A, we report gross performance, and in panel B we report performance net of brokerage commissions. The table shows both equally and principally weighted results, and the panels report both raw returns (panels A1 and B1) and DGTW-adjusted performance (panels A2 and B2).

Table 2
(continued)

B2. DGTW-adjusted performance

1 (low)	−0.45***	−0.35**
	(−3.07)	(−2.32)
2	−0.14	−0.13
	(−1.29)	(−1.23)
3	−0.10	−0.11
	(−1.05)	(−1.33)
4	0.50***	0.15
	(4.53)	(1.49)
5 (high)	0.26***	0.05
	(3.28)	(0.64)
4–low	0.95***	0.50***
	(5.06)	(3.13)
High–low	0.71***	0.40**
	(4.04)	(2.38)

C. Index fund analysis

C1. Index funds

1 (low)	0.17	−0.07
	(0.92)	(−0.32)
2	−0.15	0.35
	(−0.51)	(0.88)
3	−0.70**	−0.82*
	(−2.16)	(−1.90)
4	0.11	0.29
	(0.41)	(0.78)
5 (high)	0.14***	0.09
	(2.45)	(1.20)
4–low	−0.06	0.37
	(−0.18)	(0.88)
High–low	−0.03	0.16
	(−0.18)	(0.69)

C2. Matched sample

1 (low)	−1.27**	−1.02
	(−2.00)	(−1.49)
2	−1.11	−0.81
	(−1.36)	(−1.09)
3	−0.27	−0.01
	(−0.57)	(−0.03)
4	0.66	0.49
	(1.34)	(0.84)
5 (high)	0.47***	0.25**
	(3.79)	(2.11)
4–low	1.93**	1.51*
	(2.30)	(1.63)
High–low	1.74***	1.28***
	(4.06)	(2.99)

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 equally weighted (EW) or principally 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 five quintiles at the end of each quarter based on their current quarter trading regularity. We then report gross performance measured in raw returns (panel A1) and DGTW-adjusted returns (panel A2) for these quintiles. Panel B reports average commission-adjusted raw returns (panel B1) and DGTW-adjusted returns (panel B2). Panel C includes only index mutual funds, but we base the trading regularity quintile cutoffs on the full sample. The matched sample in panel C2 consists of actively managed funds matched to index funds based on trading regularity and aggregate quarterly volume. All returns are expressed as a percentage. t-statistics are reported in parenthesesug*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The gross performance results in panel A1 suggest a positive relation between trading regularity and performance. For the equally weighted results, the highest trading regularity quintile outperforms the lowest trading regularity quintile by 0.55% (0.54% vs. –0.01%). The performance of the highest trading regularity quintile and the difference in performance between the highest and lowest quintiles are both statistically significant at the 1% level.[15] The principally weighted results are a bit weaker than the equal weighted results, but they show a similar pattern, with the highest trading regularity quintile (0.27%) outperforming the lowest regularity quintile (0.07%), though the difference is not statistically significant. Since transaction costs are positively related to trade size due to price impact, it is not surprising that the principally weighted results are weaker than the equally weighted results, as the larger transaction costs of the bigger trades carry greater weight. Also note that trades associated with the second highest trading regularity quintile show the best performance, especially for the equally weighted results (e.g., 0.72% for quintile 4 vs. 0.54% for quintile 5). Although the performance of trades in the highest and second-highest trading regularity quintiles do not statistically significantly differ, the superior performance of the second highest trading regularity quintile appears consistently throughout our analysis. This pattern strongly suggests that although there are benefits to trading regularly, it has its limits. Later, we further explore the tendency for performance to drop at the highest levels of trading regularity.[16]

For the DGTW-adjusted returns in panel A2, the results again show a positive relation between trading regularity and performance, with the pattern consistent across both weighting schemes. For the equally weighted results, the highest trading regularity quintile outperforms the lowest trading regularity quintile by 0.73% (0.55% vs. –0.18%), with the performance of the highest regularity quintile and the difference in performance between the highest and lowest quintiles both statistically significant at the 1% level. Similar to the raw return results in panel A1, the principally weighted DGTW-adjusted return results in panel A2 are a bit weaker than the equal weighted results, likely because of the price impact associated with larger trades. Nonetheless, they show a similar

15 Since we only observe fund trades, rather than a fund's entire portfolio of holdings, it is possible that funds that regularly trade perform poorly on their holdings and deliver average or below average total performance to their investors.

16 We repeat all of our analysis after excluding a list of 42 index funds identified in the ANcerno database by Agarwal, Tang, and Yang (2012). After removing these index funds from the sample, we find that all of the main conclusions hold. This finding is not surprising since the index fund sample is small relative to the overall sample. For example, the ex-index mutual fund results show that the more regular funds produce positive intraquarterly trade performance that is statistically significantly greater than zero and statistically significantly greater than the performance of the less regular funds. The top trading regularity quintile shows intraquarterly equally (principally) weighted performance of 0.56% (0.32%) compared to 0.55% (0.31%) for the more comprehensive sample, with both top quintile means statistically significantly greater than zero. Similarly, funds in the second highest trading regularity quintile shows intraquarterly equally (principally) weighted performance of 0.76% (0.43%) compared to 0.75% (0.42%) for the more comprehensive sample, with both top quintile means again statistically significantly greater than zero. We thank Yuehua Tang for providing the list of index funds.

pattern, with the highest trading regularity quintile (0.31%) outperforming the lowest trading regularity quintile (–0.15%). Similar to the equally weighted results, the highest trading regularity quintile shows performance that is statistically significantly greater than zero and statistically significantly greater than the performance of the low trading regularity quintile at the 1% level. Also once again evident in panel A2 is the tendency for the second highest trading regularity quintile to show the best performance (e.g., 0.75% for quintile 4 vs. 0.55% for quintile 5 based on equal weighting).[17]

Beyond statistical significance, the results in panel A are economically significant as well. As mentioned earlier, since funds generate the intraquarterly trade returns that we report over less than a quarter, we can approximate the annualized performance associated with the intraquarterly returns by quarterizing like in Puckett and Yan (2011) and then multiplying by four. Based on this approach, the highest regularity equally (principally) weighted quintile shows a substantial annualized DGTW-adjusted performance of approximately 10.35% (4.57%).

In results not evident in Table 2, we find similar results when excluding the volatile time period associated with the financial crisis. For example, when we exclude 2008 and 2009, the highest trading regularity quintile shows equally (principally) weighted intraquarterly DGTW performance of 0.57% (0.30%), which is very similar to the 0.55% (0.31%) results associated with the full sample. The best performance is associated with the second-highest trading regularity quintile in these results as well, with equally (principally) weighted intraquarterly DGTW-adjusted performance of 0.70% (0.37%). It thus appears that the relation between trading regularity and performance extends beyond periods associated with extraordinary market volatility.

Panel B mirrors panel A, except we report returns net of commissions. In the U.S., institutions typically pay a flat commission fee per share. The mean commission fee across the entire sample of trades is $0.032 per share, corresponding to 13.5 basis points of the dollar value of the trade. Since each transaction incurs a commission fee, the panel B quintile returns are roughly two commission fees lower than the returns in panel A. When equally weighting the returns, trades associated with the top two trading regularity quintiles continue to show positive raw return and abnormal performance that are both statistically significantly greater than zero and greater than the performance of funds in the lowest trading regularity quintile. In addition, the results again show maximum performance at the second highest trading regularity quintile, with 0.47% (0.50%) raw (DGTW-adjusted) returns for quintile 4 versus 0.25% (0.26%) for quintile 5.

[17] We will show later in a robustness test that the results based on stitched tickets are similar to the Table 2 results based on ANcerno tickets, with significantly positive DGTW equally and principally weighted intraquarter trade performance and an internal performance maximum at quintile 4. We present the stitched ticket results in Section 2.8.1.

The principally weighted raw return results are weaker, with positive but statistically insignificant return differences between the more regular trader quintiles and the less regular trader quintiles. Insofar as the principally weighted results place greater weight on the bigger trades typically made by bigger funds, these results are consistent with diseconomies of scale in short-term trading profits, a topic that we examine in greater detail in the next section. Although the trades associated with the top two trading regularity quintiles no longer show statistically significant positive principally weighted performance, the principally weighted DGTW-adjusted return difference between the top trading regularity quintile or the second highest trading regularity quintile and the lowest trading regularity quintile remains statistically significant at the 5% level. Quintile 4 holds a narrower advantage over quintile 5 in the principally weighted results, with the difference in raw (DGTW-adjusted) returns between quintile 4 and quintile 5 dropping from 0.22% (0.24%) when returns are equal weighted to 0.03% (0.10%) when returns are principal weighted.

Note that our institutional trading results differ from the performance associated with active individual investors. Barber and Odean (2000) show no relation between portfolio turnover and gross performance among individual investors, whereas we find that the funds in the highest trading regularity quintile outperform those in the lowest trading regularity quintile. Moreover, Barber and Odean (2000) find a strong inverse relation between trading activity and performance net of commissions among individuals, whereas we find a strong positive relation between trading regularity and performance. There are three reasons why our institutional trader results differ from the individual investor results of Barber and Odean (2000). First, institutional traders are professionals. Presumably, a prerequisite to land a trading job with an institutional money management firm is a successful track record as a trader. Also, a poorly performing institutional trader is likely to be replaced. Second, Barber and Odean (2000) show that a substantial fraction of the poor net performance associated with active retail traders is attributable to commissions, which average around 1.5% per trade in their sample. The institutions in our sample pay a far lower percentage commission that averages 0.135% per trade. The lower commission rate in our sample is partially due to our more recent sample period, which is characterized by lower commission rates, and also because institutions have the bargaining power to demand cheaper commissions than individual investors. Finally, it is possible that the difference in the trading measures employed (i.e., monthly portfolio turnover used by Barber and Odean (2000) vs. the ratio of the number of tickets divided by the number of stocks traded used in this paper) could account for some or all of the differences.

Index funds enter and exit positions in an attempt to closely match the returns of their benchmark index while addressing investor cash flows. Consequently, we would not expect our trading regularity measure to proxy for skill among a sample of index funds. Since ANcerno does not identify the institutions behind the trades in their database, it is difficult to comprehensively exclude index funds from our analysis. However, Agarwal, Tang, and Yang (2012) employ a sophisticated stock matching algorithm between ANcerno and the Thomson Reuters mutual fund holdings database to identify mutual funds within the ANcerno database. Included among the mutual funds identified by their algorithm is a list of 42 index funds in our sample. Interestingly, when evaluated relative to the full sample, index funds rank high based on our main trading regularity measure, with a mean 4.75 quintile ranking. The high average ranking likely stems from a combination of a very large number of holdings and the rebalancing activities in response to fund flows, both of which are driven by an emphasis on a low tracking error relative to the index fund's benchmark. Actively managed funds would be expected to have greater discretion, on average, in choosing when and how they invest. Nonetheless, the sample of index funds shows substantial variation in the extent to which the funds regularly trade. For example, the time-series average of the cross-sectional standard deviation of the trading regularity measure for the index fund sample is 2.69, with mean, min, and max of 2.26, 0.19, and 11.21, respectively. (By comparison, the time-series average of the cross-sectional standard deviation of the trading regularity measure for the full sample is 0.72, with a mean, min, and max of 0.78, 0.02, and 11.93, respectively.)

We repeat our main analysis of the univariate relation between trading regularity and DGTW-adjusted performance on the subsample of index funds. We base the trading regularity quintile cutoffs on the full fund sample so that we can examine differences in index fund performance across a range of trading regularity that roughly matches that of the full sample, since the index fund sample shows relatively high mean trading regularity. The results, which we report in Table 2, panel C1, show no correspondence between trading regularity and performance among index funds.[18] For instance, for the equally weighted results, the index funds in the lowest trading regularity quintile show insignificantly greater performance than the quintile 4 and 5 index funds. For the principally weighted results, no clear performance pattern exists across the five trading regularity quintiles.[19]

Since the index fund sample skews higher in trading regularity compared to the full sample of funds, we also examine whether a relation between trading regularity and performance exists among actively managed funds at the trading

[18] Results based on using the trading regularity quintile cutoffs calculated from the index fund sample also show no correspondence between trading regularity and performance.

[19] In untabulated tests, we also conduct regression analysis of DGTW-adjusted performance on trading regularity, including a dummy variable for index funds and a variable representing the interaction between the index fund dummy and trading regularity. We run the regressions with and without control variables. The control variables include fund characteristics (lag fund trading volume and lag fund performance) and the characteristics of stocks traded in the current quarter (book-to-market ratio, logarithmic of market capitalization, lag 12-month return, turnover, idiosyncratic volatility, Amihud's illiquidity, lag 1-day return, and herding). The results provide similar inference to our quintile analysis, including a significantly positive relation between performance and trading regularity for the full sample and an insignificant relation between performance and trading regularity for the index fund sample. The regression results are available upon request.

regularity levels associated with the index fund sample. In each quarter, for each index fund, we select the ten non-index funds from the same regularity quintile as the index fund with trading regularity nearest that of the index fund, and we then further select the one fund out of the ten whose aggregate trading volume (as a proxy for fund size) is nearest that of the index fund, thereby creating a one-to-one match. We repeat the trading regularity/DGTW-adjusted performance analysis on the matched sample. Table 2, panel C2, reports the results. Consistent with the full sample results in Table 2, panel A2, the matched sample shows a positive relation between trading regularity and performance, with the highest trading regularity quintile showing statistically significantly greater performance than the lowest trading regularity quintile.[20] The index fund analysis thus provides reassurance that the results associated with the broad sample of funds are not driven by a spurious mechanical relation in the data.

2.2 Alternative measures of trading regularity

Our definition of trading regularity combined with the statistics associated with the trading regularity quintiles in Table 1, panels B and C, indicate that the measure captures the extent to which funds trade more or less regularly. We thus expect alternative measures to provide similar inference provided they also capture the extent to which funds trade more or less regularly.

We examine two alternative measures of trading regularity. First, we simply measure the number of days a fund trades during the quarter. Second, we measure the extent to which a fund's quarterly aggregate dollar trading volume is evenly distributed across the quarter's trading days. In particular, we compute fund i's trading volume regularity during quarter t as

$$Trading\_volume\_reg_{i,t} = 1 - \sum_{d=1}^{D_t} \left(\frac{Trade_{volume\,i,d}}{\sum_{d=1}^{D_t} Trade_{volume\,i,d}} \right)^2, \qquad (1)$$

where $Trade\_volume_{i,d}$ represents the aggregate dollar value of fund i's transactions on day d, and there are D_t trading days during quarter t. The measure ranges from 0 to $1 - 1/D_t$, with a fund transacting on only 1 day during the quarter receiving a trading volume regularity measure of 0, and a fund transacting the same dollar amount each day during the quarter receiving a trading volume regularity measure of $1 - 1/D_t$. The measure is

[20] Note that, compared to the full sample, the matched sample shows a relatively large Q5–Q1 performance spread (e.g., 1.74% vs. 0.71% based on equal weighting). As we increase the number of funds included in the matched sample, for example, including the 2, 5, 10, or 25 funds with similar trading regularity and trading volume to the index fund, we find that the Q5–Q1 performance spread for the matched sample moves towards the Q5–Q1 performance spread of the full sample in Table 2, panel B2. We surmise that the high Q5–Q1 performance spread of the matched sample is due to randomness associated with the matching procedure. In particular, Q1 in Table 2, panel C, comprises a small fraction of the number of funds in Q1 of Table 2, panel B, since few index funds are classified in the lowest regularity quintile.

related (negatively) to the Herfindahl index, a commonly used measure of concentration.

We thus examine the univariate relation between DGTW-adjusted performance and (1) the number of days a fund trades during the quarter or (2) trading volume regularity (*Trading_volume_reg*), similar to the analysis associated with Table 2, panel A2, based on the main measure of trading regularity. The results, which we report in Table 3, panels A and B, show strong positive relations between the alternative measures of trading regularity and performance. Compared to the results in Table 2, panel A2, the results based on the alternative measures suggest a slightly more monotonic relation between trading regularity and performance, with a performance maximum at quintile 5 (i.e., no internal maximum at quintile 4) and a larger performance difference between quintile 5 and quintile 1, that is, 1.08% (0.88%) in Table 3, panel A (B), versus 0.73% in Table 2 for the equally weighted results and 0.66% (0.65%) in Table 3, panel A (B), versus 0.46% in Table 2 for the principally weighted results.

We also expect alternative measures that do not capture the extent to which funds trade more or less regularly to show less correlation with performance compared to the main trading regularity measure. As one example, quarterly aggregate trading volume quantifies a fund's total quarterly trading without considering the extent to which the fund trades regularly. Since aggregate trading volume likely more closely correlates with fund size than with a tendency to regularly trade, it is not surprising that we find no significant univariate relation between aggregate trading volume and DGTW-adjusted performance, as indicated in the results shown in Table 3, panel C. Note that we control for volume (as a proxy for fund size) in later analysis.[21]

2.3 Performance versus transaction costs

To more precisely determine the optimal level of trading within our sample, we repeat the analysis of Table 2 except by grouping funds into trading regularity deciles rather than quintiles. Figure 1 plots the equally and principally weighted DGTW-adjusted performance of each trading regularity decile. Consistent with the quintile results in Table 2, the figure shows an overall increase in performance as a function of trading regularity. Performance reaches a maximum at decile 8 and then falls thereafter. Although deciles 9 and 10 show positive DGTW-adjusted performance, their lower performance relative

[21] The number of stocks traded conditional on a trade occurring is another possible alternative measure of trading activity. However, this alternative measure would not capture the extent to which a fund trades more or less regularly because it would not reflect days with zero trades. Consequently, funds that do not trade regularly could rank highly via this alternative. Recall that Table 1, panel C, indicates that funds that do not trade regularly based on our trading regularity measure trade heavily on the days they do trade, while being inactive on 56 of 63 trading days per quarter. We confirm in our sample no relation between performance and trading intensity conditional on a trade having executed.

Table 3
Fund performance for univariate sort by trading regularity via alternative trading regularity measures

A. Number of days funds trade per quarter

Trading days	EW	PW
1 (low)	−0.28*	−0.18
	(−1.71)	(−1.11)
2	0.17	0.13
	(1.37)	(1.10)
3	0.21**	0.13*
	(2.55)	(1.68)
4	0.51***	0.27**
	(4.43)	(2.58)
5 (high)	0.80***	0.48***
	(10.88)	(7.44)
4–low	0.79***	0.45**
	(3.87)	(2.39)
High–low	1.08***	0.66***
	(5.93)	(4.00)

B. Trading volume regularity

Volume regularity	EW	PW
1 (low)	−0.08	−0.11
	(−0.59)	(−0.86)
2	0.12	0.11
	(1.03)	(0.99)
3	0.21*	0.13
	(1.70)	(1.26)
4	0.40***	0.17*
	(4.94)	(1.90)
5 (high)	0.80***	0.53***
	(11.81)	(8.21)
4–low	0.48***	0.29**
	(3.21)	(1.99)
High–low	0.88***	0.65***
	(6.21)	(4.65)

C. Aggregate quarterly dollar volume

Dollar volume	EW	PW
1 (low)	0.41**	0.31*
	(2.56)	(1.96)
2	0.34***	0.29**
	(3.32)	(2.61)
3	0.39***	0.21**
	(4.88)	(2.50)
4	0.24***	0.12*
	(3.80)	(1.90)
5 (high)	0.20***	0.01
	(4.25)	(0.23)
4–low	−0.17	−0.19
	(−1.13)	(−1.26)
High–low	−0.21	−0.30*
	(−1.22)	(−1.84)

This table presents average fund performance in quintiles sorted by fund contemporaneous number of days funds trade per quarter (panel A), trading volume regularity (panel B), or aggregate dollar volume (panel C) during the quarter. 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 count the number of days in which one or more trades were executed (panel A), the extent to which a fund's aggregate quarterly dollar trading volume is evenly spread across the quarter's trading days, that is, trading volume regularity (panel B), or aggregate dollar volume (panel C). 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 equally weighted (EW) or principally weighted (PW) DGTW-adjusted returns separately for buys and sells. Lastly, we take the difference in DGTW-adjusted returns between buys and sells. We divide all funds into five quintiles at the end of each quarter based on the number of days they trade during the quarter (panel A), trading volume regularity (panel B), or aggregate dollar volume (panel C) during the current quarter. We then report gross performance measured in DGTW-adjusted returns for these quintiles. All returns are expressed as a percentage. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

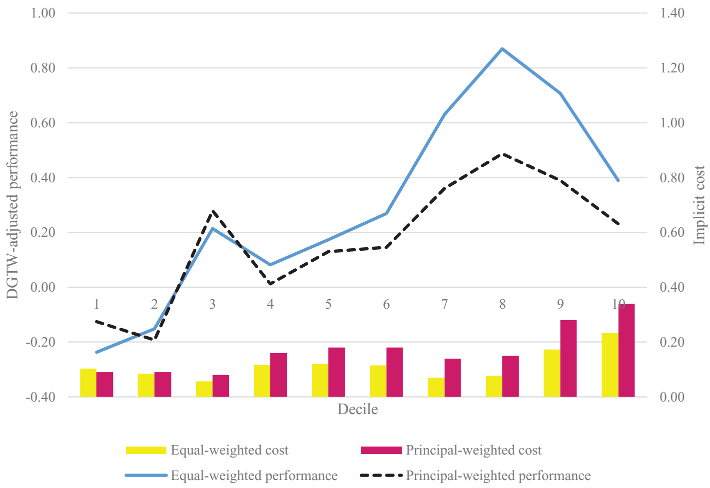

Figure 1
Performance by trading regularity decile
This figure plots the average DGTW-adjusted fund performance and implicit trading costs for deciles sorted by contemporaneous trading regularity. The sample period is from January 1, 1999 to December 31, 2009. The sample includes only common stocks. For 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. DGTW-adjusted 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 equally weighted (EW) or principally weighted (PW) DGTW-adjusted returns separately for buys and sells. Lastly, we take the difference in DGTW-adjusted returns between buys and sells. We calculate the average implicit trading cost for each fund as follows. For each buy trade, we calculate the implicit trading cost as the market price of the stock when the trade is placed with the broker less the execution price. For each sell trade, we calculate the implicit trading cost as the market price of the stock when the trade is placed with the broker less the execution price. Implicit trading costs are then scaled by price at placement and expressed as a percentage. We divide all funds into ten deciles at the end of each quarter based on their current quarter trading regularity. We then plot the gross performance and implicit trading costs for these deciles. All returns and costs are expressed as a percentage.

to decile 8 suggests that the funds in the highest trading regularity quintile in our sample trade too much.

One potential reason the funds in deciles 9 and 10 underperform the funds in decile 8 is because the funds from deciles 9 and 10 generate excessive transaction costs that undermine the performance of their trades. Novy-Marx and Velikov's (2016), for instance, find that transaction costs can dramatically impact the profitability of high-turnover anomaly strategies. To examine this possibility, we estimate implicit transaction costs for each trade and compute the mean implicit transaction cost for each trading regularity decile. We estimate the implicit transaction cost for a buy trade as the difference between the execution price and the price at order placement divided by the price at order placement (i.e., an execution shortfall like in Anand et al. 2012). For sell trades, we take the difference between the price at order placement and the execution price divided by the price at order placement. Figure 1 shows mean implicit transaction cost estimates for each trading regularity decile.

We find that estimated implicit transaction costs increase very slightly over the first eight trading regularity deciles, where they average approximately 0.09% (0.13%) based on equal (principal) weighting. However, estimated costs are noticeably higher for deciles 9 and 10, averaging an equally (principally) weighted 0.17% (0.28%) for decile 9 and 0.23% (0.34%) for decile 10.[22] The difference in transaction costs between decile 8 and decile 9 or 10 accounts for roughly half of the difference in DGTW-adjusted performance between these deciles, consistent with transaction costs being an important reason the trades of funds in the highest trading regularity quintile underperform those of funds that trade slightly less regularly. However, it is unclear exactly why the trades of funds in the highest trading regularity quintile experience unusually high transaction costs. For instance, we detect no material differences in the characteristics of the stocks traded by deciles 8–10. One possibility is that the trading activity of the funds in the highest trading regularity quintile prevents them from adequately monitoring their trades, leading to greater incidence of poor execution and high transaction costs.[23] Another possibility is that index funds in the sample (or closet index funds) disproportionately affect results associated with the highest levels of trading regularity. As shown earlier, index funds trade relatively regularly. However, they also typically emphasize low tracking error relative to their benchmark. Doing so could result in regular trading to rebalance their portfolio or address investor cash flows without information.

2.4 Performance versus size

Chan et al. (2004), among others, show that diseconomies of scale exist in the mutual fund industry. Other things equal, as a fund gets larger, trade execution gets increasingly more costly. To mitigate greater transaction costs, Busse et al. (2016) show that funds move into more liquid stocks as they increase in size, which lowers their gross returns as they earn less of the return premium associated with illiquid stocks. Beyond missing out on the return premium from holding less liquid stocks, larger funds might also forgo trading opportunities when they are expected to generate large trading costs. In this section, we examine the relation between trading regularity, performance, and the size of the fund. If diseconomies of scale in the money management industry is attributable, in part, to larger funds performing worse than smaller funds when

22 In additional untabulated analysis, we find no implicit trading cost peak among funds in the highest trading regularity quintile via either of the alternative measures of trading regularity that we examine in Table 3 (i.e., the number of days a fund trades during the quarter and trading volume regularity). For instance, when sorting on the number of days a fund trades during the quarter, quintile 5 shows mean equally (principally) weighted implicit trading costs of 0.12% (0.12%) versus 0.12% (0.19%) on average across quintiles 1–4.

23 Although it is unclear exactly why implicit trading costs do not peak in the highest trading regularity quintile for the alternative measures of trading regularity (number of days funds trade per quarter and trading volume regularity), one possibility is that both alternative measures focus more on the number of days funds trade rather than daily trading intensity, such that a lack of adequate trade monitoring is not as severe in quintile 5 for the alternative measures compared to the main trading regularity measure.

they regularly trade, we would expect to see a negative relation between fund size and the performance of the trades of funds that regularly trade. In Tables 1 and 2, lower returns when weighting by the size of the trade compared to equal weighting are consistent with this possibility.

Since ANcerno does not identify institutions in its database, we follow Puckett and Yan (2011) and proxy for fund size with a fund's aggregate quarterly dollar trade volume. That is, we sum up each fund's dollar trade volume across all the trades they make in a quarter. The rationale for this proxy is that larger funds need to trade more, in aggregate, than smaller funds since they have more capital to invest. Table 4, panel A, reports the average ticket size of funds double sorted into 5×5 portfolios each quarter, first by fund aggregate quarterly dollar trading volume and then by trading regularity.[24] As expected, we see a positive relation between trading volume and average ticket size, consistent with larger funds (as proxied for by greater aggregate dollar trading volume) executing larger-size trades.

In Table 4, panel B, we report the implicit transaction costs associated with the trade ticket sizes in panel A, again based on execution shortfall estimates. Panel B shows that implicit transaction costs increase with trading volume, which coincides with the increase in ticket size that we see in panel A. Thus, implicit transaction costs are larger for the bigger trades made by the larger funds, consistent with expectations. We thus expect the trades of larger funds to perform worse than the trades of smaller funds, as transaction costs detract more from their performance. Notice, however, that within the trading volume quintiles, transaction costs increase as trading regularity increases despite a decrease in ticket size. This effect is especially prominent at increasing levels of aggregate volume. The higher transaction costs for the smaller trades of the funds in the highest trading regularity quintile are consistent with funds that regularly trade trading more aggressively compared to less regular funds. For example, the funds in trading regularity quintile 5 generate mean implicit transaction costs of 0.38% on an average ticket size of \$465 thousand, which is greater than the 0.31% implicit transaction costs on an average ticket size of \$539 thousand associated with the trades of funds that trade less regularly in quintile 4.

Hu (2009) shows that implicit transaction cost estimates are sensitive to the benchmark and that estimates based on pre-trade benchmarks, such as implementation shortfall, can materially differ from estimates based on during-the-trade benchmarks. As an alternative to execution shortfall estimates, we estimate implicit transaction costs based on using the volume weighted average price (VWAP) on the day of the trade as a benchmark price similar to

[24] The time-series average of the cross-sectional correlation between trading regularity and trade volume is 0.19, consistent with the idea that the more one trades, the larger the trade volume and the larger the trading regularity. Double sorting on trading regularity and volume can help disentangle any relation between performance and trading regularity that is attributable to volume.

Table 4
Double sort by trading volume and regularity

	Trading volume				
Regularity	1	2	3	4	5
A. Average ticket size in $1,000					
1 (low)	223.3	443.8	595.7	828.0	1649.7
2	148.8	186.8	289.3	483.5	952.2
3	86.6	101.4	147.6	264.2	553.5
4	51.1	52.8	70.6	130.0	539.4
5 (high)	20.1	26.4	48.0	96.0	464.7
4–low	−172.2***	−390.9***	−525.1***	−698.0***	−1110.2***
High–low	−203.2***	−417.3***	−547.8***	−732.0***	−1185.0***
B. Implicit trading costs					
1 (low)	0.01	0.08***	0.13***	0.20***	0.20***
2	0.06*	0.08***	0.17***	0.28***	0.27***
3	0.02	0.11***	0.18***	0.23***	0.25***
4	0.03	0.08***	0.13***	0.20***	0.31***
5 (high)	0.02	0.15***	0.26***	0.35***	0.38***
4–low	0.02	0.00	0.00	0.00	0.12***
High–low	0.01	0.07***	0.14***	0.15***	0.18***
C. Gross performance					
C1. Equally weighted					
1 (low)	−0.54	−0.34*	−0.27*	−0.25*	−0.26*
2	0.30	0.10	0.04	0.01	0.08
3	0.48	0.21	0.37**	0.14	0.33***
4	0.74***	0.70***	0.90***	0.83***	0.55***
5 (high)	0.71***	1.04***	0.75***	0.41***	0.34***
4–low	1.28***	1.04***	1.17***	1.08***	0.81***
High–low	1.25***	1.38***	1.02***	0.66***	0.60***
C2. Principally weighted					
1 (low)	−0.42	−0.17	−0.18	−0.12	−0.37
2	0.27	0.11	0.05	−0.01	−0.01
3	0.43	0.20	0.18	0.09	0.09*
4	0.43**	0.43*	0.47***	0.45***	0.22***
5 (high)	0.57**	0.84***	0.40***	0.23**	0.11***
4–low	0.85**	0.60**	0.65***	0.57***	0.59***
High–low	0.99**	1.01***	0.58***	0.34	0.48***
D. Performance net of commissions					
D1. Equally weighted					
1 (low)	−0.76**	−0.57***	−0.53***	−0.47***	−0.46***
2	−0.10	−0.18	−0.22	−0.24*	−0.17
3	−0.14	0.01	0.09	−0.24	0.07
4	0.48*	0.36*	0.60***	0.54***	0.29***
5 (high)	0.63*	0.69***	0.44***	0.11	0.03
4–low	1.24***	0.93***	1.13***	1.01***	0.75***
High–low	1.38***	1.26***	0.97***	0.58**	0.49***

(Continued)

Puckett and Yan (2011), taking the difference between the execution price and the VWAP divided by the execution price for buys and the difference between the VWAP and the execution price divided by the execution price for sells. We report these implicit cost estimates in Table IA.1 in the Internet Appendix. VWAP costs are consistently lower than execution shortfall and even negative

Table 4
(Continued)

D2. Principally weighted

1 (low)	−0.42	−0.39*	−0.42***	−0.31**	−0.54**
2	−0.07	−0.14	−0.20	−0.24**	−0.22**
3	−0.01	−0.06	−0.08	−0.16	−0.14
4	0.15	0.12	0.19	0.19	−0.02
5 (high)	0.26	0.54***	0.13	−0.04	−0.13*
4–low	0.57	0.51**	0.61***	0.50**	0.52***
High–low	0.68*	0.93***	0.54***	0.27***	0.40**

This table presents average fund characteristics and performance in quintiles sorted by contemporaneous trading volume and 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. At the end of each quarter, we divide all funds into $5 \times 5 = 25$ portfolios based on their current quarter trading dollar volume and trading regularity. In panel A, we report the average trade size (in $1,000) in each of these 25 portfolios. In panel B, we calculate the average implicit trading cost for each fund as follows. For each buy trade, we calculate the implicit cost as the execution price less the market price of the stock when the trade is placed with the broker. For each sell trade, we calculate the implicit trading cost as the market price of the stock when the trade is placed with the broker less the execution price. Implicit trading costs are then scaled by price at placement and expressed as a percentage. Panel C presents the average fund gross performance in quintiles sorted by contemporaneous volume and trading regularity. 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 equally weighted or principally weighted DGTW-adjusted returns separately for buys and sells. Lastly, we take the difference in DGTW-adjusted returns between buys and sells. Panel D reports the average fund commission-adjusted performance for these 25 portfolios. All returns are expressed as a percentage. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

among some of the funds that trade less regularly, consistent with funds trading in the direction of the stock price on the day of the trade (e.g., buying as prices are increasing).[25] Although cost estimates based on VWAP show a positive relation between implicit costs and trading regularity, the pattern is not as clear as that shown in Table 4, panel B.

To examine the relation between trading regularity, performance, and fund size, we again double sort funds based on trade volume and trading regularity quintiles and compute the average DGTW-adjusted intraquarterly trade performance for each cell. Results associated with this double sort indicate whether the positive relation between trading regularity and performance depends on the size of the fund. Table 4, panel C, reports results that are gross of brokerage commissions (but net of implicit transaction costs). Panel C1 reports equally weighted results, and panel C2 reports results weighted by the size of the trade (i.e., the principally weighted results). The results in panel C1 show a positive relation between trading regularity and performance for each trade volume quintile, with a statistically significant difference in performance between funds in the highest or second highest trading regularity quintile and funds in the lowest trading regularity quintile. Similar to Table 2, the equally weighted results in panel C1 are a bit stronger than the principally weighted results in panel C2, likely because large trades generate larger percentage

[25] Frazzini et al. (2015) also find much lower VWAP costs compared to costs based on a pre-trade benchmark price in their sample of trades from one large institutional money manager.

transaction costs that reduce net performance. Consistent with the univariate results, performance peaks overall among funds in the second-highest trading regularity quintile within four (three) of five trading volume quintiles in the equally (principally) weighted results, with the effect more prominent as trading volume increases. This pattern is consistent with the implicit transaction cost pattern in panel B. Funds in the highest trading regularity quintile appear to generate relatively high transaction costs, possibly via aggressive trading, that reduces their performance compared to funds that trade slightly less regularly.

Panel D mirrors panel C, except we adjust the returns for commissions. The higher aggregate volume funds in quintiles 4 and 5 no longer show statistically significantly positive performance associated with the trades of funds in the highest trading regularity quintile for either the equally weighted results in panel D1 or the principally weighted results in panel D2. Thus, larger funds in the highest trading regularity quintile do not earn positive risk-adjusted returns net of commissions in the short run. Similar to the results in panel C, funds in the highest trading regularity quintile show slightly worse performance than funds in the second highest trading regularity quintile as trading volume increases, consistent with the implicit transaction cost pattern in panel B.

The negative relation between fund size and trade performance indicates that an important driver for the negative relation between fund size and overall performance, that is, for diseconomies of scale in the fund industry, is attributable to the inability of larger funds to exploit trading opportunities to the same extent that small funds do. Thus, it is not only that larger funds hold more liquid stocks that leads to their underperformance relative to small funds (Busse et al. 2016) but also because they earn lower returns than small funds when they regularly trade.

2.5 Lag regularity

The results in Tables 2–4 show that funds that regularly trade outperform funds that trade less regularly, on average, and are consistent with the idea that trading regularly proxies for an ability to generate abnormal performance via trading, for example, by exploiting short-lived opportunities. Ceteris paribus, a fund with this type of ability would trade more regularly to capitalize on available opportunities. By contrast, a fund without the ability to generate performance via its trading activities would likely trade less regularly, insofar as trading generates transaction costs that accumulate over time. To the extent that trading regularly proxies for a genuine ability to generate abnormal returns, trading regularity should persist across time, as certain funds persistently try to leverage their ability, and we would thus expect trading regularity to predict future performance. That is, we would expect funds in the highest trading regularity quintile during quarter t to not only outperform funds that trade less regularly during quarter t, but also during quarter $t+1$.

To examine whether relative trading regularity persists, Table 5, panel A, reports transition matrices that examine the extent to which funds remain in

Table 5
Lag regularity

A. Trading regularity transition matrices

	To quintile				
From quintile	1	2	3	4	5
A1. From one quarter to the next					
1 (low)	74.1%	20.7%	3.0%	1.2%	0.9%
2	18.9%	55.4%	21.3%	2.9%	1.5%
3	3.0%	21.4%	55.6%	16.9%	3.0%
4	1.1%	2.5%	18.0%	64.6%	13.8%
5 (high)	0.8%	1.4%	3.3%	14.8%	79.7%
A2. From one quarter to four quarters later					
1 (low)	70.2%	22.3%	4.5%	1.7%	1.3%
2	19.6%	49.8%	23.6%	4.5%	2.5%
3	4.5%	22.2%	48.9%	19.1%	5.4%
4	1.8%	4.2%	20.4%	58.3%	15.3%
5 (high)	1.4%	2.2%	5.4%	18.4%	72.6%

B. Performance for sorting by lag regularity and lag trading volume

	Lag trading volume				
Lag regularity	1	2	3	4	5
B1. Equally weighted					
1 (low)	−0.19	−0.42**	−0.16	0.01	−0.52***
2	0.27	0.16	0.10	−0.32**	−0.18
3	0.59**	0.10	0.48**	0.23	0.46***
4	0.38	0.47**	0.79***	0.78***	0.53***
5 (high)	0.91***	0.91***	0.73***	0.66***	0.36***
4–low	0.57*	0.89***	0.95***	0.77***	1.05***
High–low	1.10***	1.33***	0.89***	0.64***	0.89***
B2. Principally weighted					
1 (low)	−0.33	−0.08	−0.07	−0.12	−0.42**
2	0.45	0.12	0.01	−0.24	−0.10
3	0.46**	0.02	0.31*	0.15	0.22*
4	0.06	0.23	0.47***	0.47***	0.20**
5 (high)	0.68***	0.68***	0.42***	0.37**	0.09
4–low	0.39	0.31	0.54**	0.59**	0.62***
High–low	1.01***	0.75***	0.50*	0.49**	0.51***

Panel A reports transition matrices that examine the extent to which funds remain in the same trading regularity quintile from one quarter to the next (panel A1) or four quarters later (panel A2). Panel B presents average fund performance in quintiles sorted by one-quarter lag trading volume and one-quarter lag 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. At the end of each quarter, we divide all funds into $5 \times 5 = 25$ portfolios based on their lag quarter trading dollar volume and lag quarter trading regularity. Panel B1 (panel B2) presents the equally weighted (principally weighted) fund DGTW-adjusted performance for each of the 25 portfolios. 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 the equally weighted or principally weighted DGTW-adjusted returns separately for buys and sells. Lastly, we take the difference in DGTW-adjusted returns between buys and sells. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

the same trading regularity quintile from one quarter to the next (panel A1) or four quarters later (panel A2). The panels show a very high degree of consistency in trading regularity across time, especially among funds in the highest trading regularity quintile and funds in the lowest trading regularity quintile. For instance, 79.7% (74.1%) of the funds in the highest (lowest) trading regularity quintile remain in the same quintile from one quarter to the next, and 72.6% (70.2%) remain in the same quintile four quarters later. Thus, funds that regularly trade do not do so intermittently, as a response, perhaps, to sporadic trading opportunities. Our evidence suggests that funds that regularly trade are consistently on the lookout for new prospects and continue to regularly trade across time.

To examine the lead-lag relation between trading regularity and performance, Table 5, panel B, reports the trade performance of funds sorted into quintiles based on lagged (i.e., prior quarter) trading regularity and lagged trading volume, similar to Table 4, panel C, except that we base the sort on information from the previous quarter. To the extent that trading regularity proxies for genuine ability to generate abnormal performance, we would expect trading regularity to predict future performance. The results in Table 5, panel B, are consistent with this expectation and similar to the contemporaneous results in Table 4, panel C, with the two highest lag trading regularity quintiles outperforming the low lag trading regularity quintiles by a statistically and economically significant amount that ranges from 0.57% to 1.33% (0.31% to 1.01%) across the trading volume quintiles based on equally (principally) weighting the results, with 16 of the 20 differences statistically significant at the 1% or 5% level. The results are thus consistent with the notion that skilled funds regularly trade and generate abnormal performance from their trades. In this analysis, we see less evidence of a reduction in performance at the highest level of trading regularity among funds that trade smaller volumes, such that it appears that funds that trade smaller volumes have yet to exhaust their trading capacity. For increasing levels of trading volume, however, performance peaks within the second highest quintile of trading regularity, consistent with the results in Tables 2 and 4.

2.6 Persistence

In the mutual fund literature, a fund's ability to outperform consistently is interpreted as evidence of skill. The alternative—outperformance one period that does not persist in the future—is more consistent with the fund manager outperforming due to luck. The results in Tables 2–5 provide evidence that the performance of funds that regularly trade persists in the short run, insofar as they generate positive abnormal returns during both the current and subsequent quarters. To examine whether the trades of funds that regularly trade show longer-term performance persistence, we double sort funds into quintiles each quarter (i.e., quarter Q+0, the sort quarter), based first on trading regularity and then on trade performance.[26] Funds remain in the same trading regularity and performance quintiles over the next four quarters (i.e., quarters Q+1 to Q+4)

[26] We control for our fund size proxy in this analysis as follows. During the Q+0 sort quarter, we initially sort funds into trading volume quintiles, and then within each trading volume quintile, we sort into trading regularity

that they were assigned to in quarter Q+0, so once assigned, funds do not change quintiles. We gauge the extent to which the performance of funds that regularly trade persists by examining the following performance statistics over quarters Q+1 to Q+4: (a) the performance of funds in the two highest trading regularity quintiles (i.e., quintile 4 or 5) that also have quintile 5 performance during the sort quarter, (b) the difference in performance between funds in the top and bottom performance quintiles in the two highest trading regularity quintiles from the sort quarter, and (c) the difference in performance between funds in the top performance quintile in the two highest trading regularity quintiles and funds in the top performance quintile in the two lowest trading regularity quintiles from the sort quarter.[27] The alternative statistics in (a)–(c) provide different benchmarks against which to gauge persistence.

Table 6 reports the persistence results, with the equally weighted results in panel A and the principally weighted results in panel B. The panels show the statistics defined above in addition to the quarter Q+0 through quarter Q+4 performance of each performance quintile from the sort quarter within the two highest and two lowest trading regularity quintiles of funds. Broadly, we see noticeably higher quarter Q+1 to Q+4 performance among the two highest trading regularity quintile funds compared to the two lowest trading regularity quintile funds, consistent with our earlier results that indicate a positive relation between trading regularity and performance.

The results also indicate statistically significant positive performance across all four post-sort quarters for the top-performing quintile of funds (5; High) among the two highest trading regularity quintiles (4,5; High). Although the performance of these funds drops from 7.71% (7.04%) during the sort quarter to 0.98% (0.96%) during the fourth quarter after the sort quarter based on equal weighting (principal weighting), the post-sort abnormal returns are economically meaningful considering that these performance statistics represent holding periods that are less than a full calendar quarter. By contrast, with the exception of Q+4 in panel B, the post-sort performance of the top-performing quintile of funds (5; High) among the two lowest trading regularity quintiles (1,2; Low) is neither statistically nor economically significant, despite showing comparable to greater sort-quarter performance than the top performing funds from the two highest trading regularity quintiles.

To more formally examine whether the top performing funds within the highest trading regularity quintile produce greater post-sort quarter performance than the top performing funds within the lowest trading regularity quintile, we examine whether the post-sort differences in performance between the sort-quarter top performers across the two groups (i.e., the top performers

quintiles. This approach ensures variation in trading volume (which proxies for fund size) within each trading regularity quintile.

27 In this analysis, we group together trading regularity quintiles 1 and 2 and trading regularity quintiles 4 and 5 to ensure well-populated quintiles after the secondary performance sort.

Table 6
Persistence

Regularity	Performance	Quarter Q+0	Q+1	Q+2	Q+3	Q+4
A. Equally weighted						
	1 (low)	−6.41***	0.34**	0.38**	0.44**	0.32*
	2	−1.34***	0.55***	0.38***	0.60***	0.34***
4,5 (high)	3	0.72***	0.56***	0.61***	0.56***	0.59***
	4	2.80***	0.84***	1.07***	0.79***	0.83***
	5 (high)	7.71***	1.00***	0.87***	1.09***	0.98***
	Mean	0.70***	0.66***	0.66***	0.70***	0.62***
	High–low	14.12***	0.66**	0.49**	0.65***	0.66***
	1 (low)	−8.90***	−0.20	−0.18	−0.15	−0.04
	2	−2.18***	−0.27***	−0.20	−0.45**	−0.28**
1,2 (low)	3	−0.11*	−0.27**	−0.15	−0.04	−0.26
	4	1.95***	−0.05	−0.21	0.03	0.00
	5 (high)	8.70***	0.23	0.14	0.10	0.38
	Mean	−0.10	−0.12	−0.12	−0.10	−0.05
	High–low	17.61***	0.42	0.32	0.24	0.42*
	HighHigh-LowHigh	−0.99***	0.78***	0.73***	0.99***	0.60**
B. Principally weighted						
	1 (low)	−6.28***	−0.23	−0.04	0.22	0.02
	2	−1.55***	0.10	0.23*	0.27**	0.21*
4,5 (high)	3	0.41***	0.50***	0.40***	0.46***	0.28**
	4	2.43***	0.55***	0.75***	0.31**	0.46***
	5 (high)	7.04***	0.93***	0.63***	0.82***	0.96***
	Mean	0.41***	0.37***	0.39***	0.42***	0.39***
	High–low	13.32***	1.16***	0.67**	0.59***	0.94***
	1 (low)	−8.98***	−0.36*	−0.14	−0.10	0.05
	2	−2.36***	−0.27**	−0.10	−0.20	−0.18
1,2 (low)	3	−0.11**	−0.13	−0.16	−0.27**	−0.29*
	4	2.12***	0.12	−0.05	0.18	0.00
	5 (high)	8.92***	0.34	0.14	0.26	0.49***
	Mean	−0.08	−0.07	−0.07	−0.03	0.00
	High–low	17.90***	0.70	0.28	0.36	0.44*
	HighHigh-LowHigh	−1.88***	0.59**	0.48**	0.55***	0.46**

The table presents the DGTW-adjusted future performance of portfolios of high or low trading regularity funds sorted by past performance. 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. At the end of each quarter Q+0, we divide all of the funds in trading regularity quintiles 4 or 5 into 5 portfolios based on their current quarter performance (measured by equally weighted or principally weighted DGTW-adjusted performance) and calculate the average DGTW-adjusted performance of each portfolio during the next four quarters. We repeat the procedure for all of the funds in trading regularity quintiles 1 or 2. Fund DGTW-adjusted performance is defined like in Table 4. All returns are expressed as a percentage. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

within trading regularity quintile 5, HighHigh, minus the top performers within trading regularity quintile 1, LowHigh) are statistically significant. We find that the differences (HighHigh–LowHigh) are all positive and statistically significant, ranging from 0.60% to 0.99% (0.46% to 0.59%) based on equal (principal) weighting. These results reinforce our interpretation that trading regularity proxies for the ability to generate abnormal performance. The results in Table 6 suggest that trading regularity can be used in conjunction with past performance to help forecast future performance, and they provide insight into what contributes to evidence of performance persistence.

Lastly, within the two highest trading regularity quintiles (4,5; High), the performance difference between funds in the top performance quintile and the bottom performance quintile (High–Low) is also significantly positive during all four post-sort quarters. These differences range from 0.49% to 0.66% (0.59% to 1.16%) for the equally weighted (principally weighted) results. But, with the exception of Q+4, there is no statistical significance for the lowest trading regularity quintiles. Thus, based on both absolute and relative comparisons, our evidence suggests that among funds that regularly trade, top performing funds continue to show strong performance over the following four quarters.

2.7 Why do funds that trade regularly outperform?

Having documented that funds that regularly trade earn statistically and economically significant abnormal returns from their trades, we next explore the source of the abnormal returns. Although it would be impossible to determine precisely how funds that regularly trade leverage a limitless set of trading opportunities, we consider two possibilities. First, funds that regularly trade might behave as contrarians, buying (selling) stocks with relatively poor (strong) recent returns. Abnormal performance associated with this possibility would be consistent with earning returns related to short-term reversals (e.g., Jegadeesh 1990 or Lehmann 1990). Second, funds that regularly trade might exploit informational advantages.

2.7.1 Contrarian trading. We determine whether funds that regularly trade behave more as contrarians, for example, buying stocks with poor recent returns, than as short-term momentum traders, for example, buying stocks with relatively strong past returns, based on two alternative approaches. In our first approach, we classify funds as contrarian when they buy (sell) stocks with relatively poor prior-day returns.[28] For each fund, each quarter, we compute the mean lag 1-day return across all stocks traded by the fund (multiplying by –1 for sells) to determine whether a fund behaves as a contrarian trader or a short-term momentum trader. In particular, we classify a fund that buys (sells) stocks with negative (positive) lag 1-day returns as contrarian, whereas a short-term momentum trader does the opposite. In our second approach, we classify funds as contrarian (short-term momentum) based on the extent to which they herd with other funds, which we proxy for by the extent to which they trade in the opposite (same) direction as other funds within the ANcerno database. Specifically, 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 of

[28] Results are similar if we classify funds based on the lag 5-day return of the stocks they trade or on the average of the lag 1-day and lag 5-day returns of the stocks they trade.

all funds in the ANcerno data set on the same day. The two approaches appear to capture different aspects of contrarian behavior, as the time-series average of the cross-sectional correlation between the lag 1-day return variable and the herding variable is 0.03.

Using these measures, each quarter t, we double sort funds into terciles based on their quarter t contrarian/short-term momentum measure and, independently, into quintiles based on their quarter t trading regularity.[29] Lastly, we compute the quarter t DGTW-adjusted performance difference between the quintile 5 trading regularity funds and the quintile 1 trading regularity funds for each contrarian / short-term momentum tercile.[30] Table 7 reports the results. Panel A (B) classifies funds as contrarian or short-term momentum based on their trading regularity relative to the lag 1-day return of the stocks they trade (the trades of other funds, i.e., going with or against the herd). The first column in panels A and B shows the performance associated with contrarian trades, the third column in panels A and B shows the performance associated with short-term momentum trades, and the last column reports the difference in performance between funds that trade as contrarians and funds that trade on short-term momentum (i.e., Column 1 minus Column 3).

In panel A, performance is significantly greater among the top trading regularity quintile funds when they trade as contrarians, that is, buying (selling) stocks with poor (strong) lag 1-day returns. For the equally weighted results, the quintile 5 trading regularity performance drops from 0.89% for tercile 1 (i.e., buying (selling) stocks with low (high) prior-day returns) to 0.71% for tercile 2 to 0.17% for tercile 3. Similarly, for the principally weighted results, the quintile 5 trading regularity performance drops from 0.60% for tercile 1 to 0.41% for tercile 2 to 0.00% for tercile 3. Thus, funds that regularly trade appear to generate consistently better performance by buying (selling) stocks with poor (strong) prior-day performance. The superior performance associated with contrarian trading extends to funds that trade less regularly as well. Contrarian traders generate greater performance than short-term momentum traders across all trading regularity quintiles, with the difference statistically significant in all of the quintiles.

In panel B, the tendency for the higher trading regularity funds to generate greater performance via contrarian behavior is only statistically significant among the quintile 4 trading regularity funds, which show a pattern in performance across the herding terciles similar to the pattern across the lag 1-day return terciles in panel A. For instance, for the equally weighted results, the quintile 4 trading regularity performance drops from 0.92% for tercile 1 (i.e.,

29 We group by contrarian terciles rather than quintiles because the herd contrarian measure consists of a high fraction of observations where funds that trade regularly trade with the herd, rendering more granular groupings unnecessary.

30 Note that DGTW controls for 12-month (lag 1 month) momentum, but not for the 1-day returns that we use to measure short-term momentum.

Table 7
Contrarian behavior and fund performance

A. Lag 1-day return

Regularity	Lag 1-day return 1	2	3	1–3
A1. Equally weighted				
1 (low)	0.19	−0.33*	−0.43*	0.62*
2	0.86***	0.05	−0.46**	1.32***
3	0.57**	0.10	−0.05	0.62*
4	1.01***	0.74***	0.50***	0.52*
5 (high)	0.89***	0.71***	0.17	0.72**
4–low	0.82***	1.07***	0.93***	
High–low	0.70***	1.04***	0.60*	
A2. Principally weighted				
1 (low)	0.18	−0.23	−0.43	0.61*
2	0.86***	0.04	−0.44**	1.29***
3	0.43*	0.17	−0.23	0.66*
4	0.73***	0.39***	0.12	0.60***
5 (high)	0.60***	0.41***	0.00	0.60*
4–low	0.54**	0.62***	0.55*	
High–low	0.42*	0.64***	0.43	

B. Herding

Regularity	Herding 1	2	3	1–3
B1. Equally weighted				
1 (low)	−0.41**	−0.08	−0.10	−0.31
2	0.18	−0.36	0.10	0.08
3	0.35***	0.19	0.10	0.25
4	0.92***	0.66***	0.60***	0.32**
5 (high)	0.59***	0.49***	0.54***	0.06
4–low	1.33***	0.74**	0.70***	
High–low	1.00***	0.56*	0.63**	
B2. Principally weighted				
1 (low)	−0.24	−0.29	−0.13	−0.10
2	0.02	−0.38	0.18	−0.16
3	0.17	0.40**	0.11	0.06
4	0.58***	0.43**	0.25*	0.33**
5 (high)	0.32***	0.23*	0.32***	0.00
4–low	0.82***	0.72*	0.38*	
High–low	0.56***	0.52	0.46**	

This table presents fund performance in groups sorted by a measure of fund contrarian behavior and trading regularity. The sample period is from January 1, 1999 to December 31, 2009. The sample includes only common stocks. We measure fund contrarian behavior using the lag 1-day return of stocks they trade (Panel A) or the percentage of their herding trades in each quarter (panel B). The lag 1-day return is the mean of the past 1-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 of all funds in the ANcerno data set on the same day. 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. At the end of each quarter, we double sort funds into terciles based on their current quarter contrarian behavior measure and independently into quintiles based on trading regularity. We report the equally weighted or principally weighted fund DGTW-adjusted performance for each of the 15 groups. Fund DGTW-adjusted performance is defined like in Table 4. All returns are expressed as a percentage. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

low herding) to 0.66% and 0.60% for terciles 2 and 3, respectively. Similarly, for the principally weighted results, the quintile 4 trading regularity performance drops from 0.58% for tercile 1 to 0.43% and 0.25% for terciles 2 and 3, respectively. The performance differences between the quintile 4 contrarian traders and short-term momentum traders are statistically significant at the 5% level for both the equally weighted and the principally weighted results. Performance is a bit worse, overall, for the quintile 5 trading regularity funds, and performance does not significantly drop across the herding terciles.

Also note that, in addition to evidence that the higher trading regularity funds show better performance for contrarian trades (especially in panel A), the DGTW-adjusted performance differences between the trading regularity funds of quintiles 4 and 5 and the trading regularity funds of quintile 1 are largely significantly positive irrespective of whether the fund trades like a contrarian (i.e., across all three contrarian columns). Lastly, we again see evidence of quintile 4 outperforming quintile 5, on average, across the alternative columns in Table 7. Consistent with the trading cost analysis in Figure 1, the superior performance for quintile 4 is possibly partly attributable to relatively high transaction costs in the highest trading regularity quintile.

Overall, our evidence in Table 7 suggests that superior performance from contrarian trading only partially explains why funds that regularly trade outperform. Later, we explore how funds that regularly trade perform when trading prior to earnings announcements.

2.7.2 Multivariate analysis. The results in Table 7 suggest stronger performance associated with the contrarian trades of funds that regularly trade, but they also indicate some evidence of positive abnormal returns when funds that trade regularly trade with the herd. To formally examine whether the positive relation between trading regularity and abnormal performance extends beyond the tendency for funds that regularly trade to trade based on the recent price movements of the traded stocks, we examine the relation between abnormal performance and trading regularity with the following cross-sectional regression:

$$r_{i,t} = a + b\,regular_{i,t-1} + c\,return1_{i,t} + d\,herd_{i,t} + \lambda Z_{i,t-1}, \tag{2}$$

where $r_{i,t}$ represents fund i's equally or principally weighted DGTW-adjusted performance (as defined previously) across all of its trades (both buys and sells) during quarter t, $regular_{i,t-1}$ represents fund i's trading regularity (as defined previously) during quarter $t-1$, $return1_{i,t}$ is the mean lag 1-day return for stocks traded by fund i during quarter t, $herd_{i,t}$, represents the percentage of fund i's trades during quarter t that are in the same direction as the net imbalance across all trades in the ANcerno data set on the same day, and $Z_{i,t-1}$ captures lag fund-level variables and characteristics of the stocks traded by fund i. The characteristics include book-to-market ratio, market capitalization, turnover, idiosyncratic volatility, lag 12-month return, and Amihud illiquidity

Table 8
Regression of future performance on lag trading regularity and stock characteristics

	DGTW-adjusted performance	
	EW	PW
Intercept	0.060***	0.058**
	(3.35)	(2.64)
Lag regularity	0.005***	0.003***
	(5.47)	(4.22)
Lag fund aggregate volume	−0.001***	−0.001***
	(−3.86)	(−3.82)
Lag performance	0.024*	0.045***
	(1.80)	(3.24)
Book-to-market ratio	0.002	0.002
	(0.68)	(1.24)
Market capitalization	−0.002**	−0.001**
	(−2.30)	(−1.99)
Turnover	−0.881	−0.749
	(−0.46)	(−0.37)
Idiosyncratic volatility	−0.029	−0.032
	(−0.68)	(−0.77)
Lag 12-month return	−0.003	−0.002
	(−1.36)	(−0.84)
Lag 1-day return	−0.290***	−0.300**
	(−2.73)	(−2.39)
Illiquidity ratio	−0.008	−0.014
	(−0.77)	(−1.21)
Herd	0.001	0.003
	(0.16)	(0.51)
R-squared	0.052	0.058

This table presents estimation results from regressing fund performance on lag trading regularity. The sample period is from January 1, 1999 to December 31, 2009. The sample includes only common stocks. Each quarter, we define fund quarterly equally (principally) weighted DGTW-adjusted performance like in Table 4. 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 1-day return is the mean of the past 1-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 data set on the same day. Each quarter, a linear regression model is estimated by regressing quarterly fund equally weighted (EW) or principally weighted (PW) DGTW-adjusted performance on funds' lag quarter trading regularity. 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 1-day return, and herding). Lag fund aggregate volume represents the fund's aggregate trading volume across all stocks during the previous quarter. The time-series averages of coefficients and the associated t-statistics (in parentheses) for both regressions are reported. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

ratio. We calculate lag 12-month return, turnover, idiosyncratic volatility, and Amihud illiquidity using 12 months of data ending at the end of the previous quarter. Fund-level variables include aggregate trading volume, which we again use as a proxy for fund size, and performance, both from the previous quarter. We run the cross-sectional regression in (2) each quarter with each fund that traded during the quarter comprising one cross-sectional observation. Table 8 reports the time-series average of the quarterly coefficient estimates like in Fama-MacBeth (1973).

The coefficient on lag 1-day return in Table 8 is negative and statistically significant. The interpretation is that funds, in general, generate positive performance by buying (selling) stocks with low (high) prior-day returns, consistent with a positive relation between contrarian behavior and trade performance. The negative coefficient also implies that the greater the contrarian signal (i.e., the lower the past 1-day return), the better the performance. Moreover, it also suggests poor performance when funds behave like short-term momentum investors. Even after controlling for the relation between performance and past stock returns, however, the results indicate that a fund's abnormal performance remains positively related to its trading regularity. For the specification based on equally (principally) weighting the abnormal returns, the coefficient on lag trading regularity has a t-statistic of 5.47 (4.22) and is positive in 34 (32) of the 43 individual quarterly regressions. In economic terms, a one standard deviation increase in trading regularity increases equally (principally) weighted intraquarterly returns by 0.34% (0.24%) or approximately 5.49% (3.62%) annually (i.e., based on annualizing the quarterized performance). Thus, funds that regularly trade appear to generate abnormal performance via a variety of strategies, extending beyond the contrarian trades that are often associated with profitable short-term trading strategies.

The results also show a negative relation between a fund's lag aggregate volume and performance, consistent with our Table 4 results that suggest diseconomies of scale in the performance associated with trading regularly. The coefficients associated with the stock characteristics show no correspondence between abnormal returns and the liquidity of the stocks a fund trades: the proxies for liquidity, including turnover and Amihud's illiquidity ratio, do not statistically significantly differ from zero. Lastly, the coefficient on lag performance is positive in both specifications and attains marginal (strong) statistical significance when performance is equally (principally) weighted, consistent with the Table 6 results that indicate that trading performance persists.

We conduct two sets of robustness tests for the Equation (2) analysis. First, we use fund raw return, rather than DGTW-adjusted performance, as the dependent variable. Second, as an alternative to the quarterly Fama-MacBeth cross-section regressions, we analyze Equation (2) via a panel regression, controlling for time fixed effects with standard errors clustered by fund. We report the results associated with these alternative specifications in Table IA.2 in the Internet Appendix. Most of the major relations apparent in the Table 8 results are statistically significant via the alternative specifications using both equally and principally weighted returns, including negative relations between performance and lag 1-day return, lag trade volume, and market capitalization, and positive relations between performance and trading regularity and lag performance. The main differences in Table IA.2 compared to Table 8 include (1) a weaker relation between performance and lag 1-day return exists in the Fama-MacBeth cross-sectional specification using raw returns and (2) the panel regression results are consistent with a stronger negative relation between performance and the liquidity of the stocks a fund trades, with a significant negative relation between performance and the Amihud illiquidity ratio.

2.7.3 Earnings announcements. Next, we examine whether funds that regularly trade produce positive performance by making informed trades, for example, by buying (selling) stocks that are subject to positive (negative) future price movements. To explore this possibility, we examine the trading activity prior to company news of funds that regularly trade. Although stocks respond to an endless variety of news, we focus on the performance of funds during the period of time surrounding earnings announcements. The advantage of studying earnings announcements is earnings dates are easy to obtain (via Compustat, e.g.). By contrast, many news events that affect stock prices are difficult to identify because they are not systematically collected by financial data providers.

Each quarter t, we first classify funds based on their prior quarter's (i.e., $t-1$) overall trading regularity and separate them into four trading regularity groups: (1) the highest trading regularity quintile of funds, (2) the second highest trading regularity quintile of funds, (3) the lowest trading regularity quintile of funds, and (4) other funds (i.e., quintiles 2 and 3). For each trading regularity group, for each stock, we sum up the net trading volume in the stock across all funds in that trading regularity group during the ten business days prior to the stock's earnings announcement. We then sort the stocks into quintiles based on aggregate 10-day net trading volume, such that the quintile ranking proxies for the trading regularity group's interest level in trading the stock during the ten business days prior to its earnings announcement. As an example, if quintile 5 trading regularity funds heavily sell a particular stock during the ten business days prior to its earnings announcement, then that stock would show a relatively low earnings trading volume quintile rank among funds in category (1). Note that a particular stock's earnings announcement trade quintile ranks across the (1)–(4) trading regularity groups are not mutually exclusive. That is, an earnings stock could have a high earnings trading volume quintile rank across all four trading regularity groups, as the earnings trading volume quintile ranks are based on each trading regularity group's interest level in the stock relative to other earnings stocks during that quarter, not relative to the interest level of other trading regularity groups. Thus, each earnings announcement stock has four earnings trading volume quintile rankings, one for each trading regularity group.

We then cross-sectionally regress the 2-day cumulative abnormal market-adjusted returns of stocks that reported earnings during quarter t on the four earnings trading volume quintile ranks and control variables,

$$\begin{aligned} CAR[0,1]_{i,t} = a + \sum_{j=1,2,4,5} b_j ES_{i,j,t} + cCAR[-100,-1]_{i,t} + d_1 T5rank_{i,t} \\ + d_2 T4rank_{i,t} + d_3 T1rank_{i,t} + d_4 T2,3rank_{i,t} + \varepsilon_t, \end{aligned} \tag{3}$$

where $CAR[M,N]_{i,t}$ represents stock i's cumulative, market-adjusted return from day M through day N, where M and N are measured relative to the earnings announcement date (day 0), $ES_{i,j,t}$ is a dummy variable equal to 1 if stock i had an earnings surprise ranked within quintile j among all earnings surprises during the quarter,[31] $T5rank_{i,t}$, $T4rank_{i,t}$, $T1rank_{i,t}$, and $T2,3rank_{i,t}$ represent the earnings trading volume quintile rank (taking an integer value in the range of 1 to 5) in stock i of the quintile 5, quintile 4, quintile 1, and quintile 2–3 funds, respectively, during the 10 days prior to stock i's earnings announcement (i.e., capturing the relative 10-day trading volume in stock i of the quintile 5, quintile 4, quintile 1, and quintiles 2–3 funds, respectively, compared to their trading volume in other earnings announcement stocks during the quarter, as defined above).[32] We run the cross-sectional regression in (3) each quarter and compute the time-series average of the quarterly coefficient estimates like in Fama-MacBeth (1973).

The first column in Table 9 presents the results associated with regression (3). The coefficient on the earnings trading volume quintile rank of the quintile of funds in the highest trading regularity quintile ($T5$*rank*) is positive and statistically significantly greater than zero at the 1% level, while the corresponding coefficient associated with the second-highest trading regularity quintile of funds ($T4$*rank*) is positive but insignificant. These results imply that, on average, only the funds in the highest trading regularity quintile correctly anticipate abnormal returns during earnings announcements. In particular, the quintile of funds in the highest trading regularity quintile buy (sell) stocks that show positive (negative) returns during earnings announcement periods. Economically, the 0.070 coefficient on $T5$*rank* implies that if funds in the highest trading regularity quintile increased net trading from the bottom to the top quintile (i.e., a change of 4 in the $T5$*rank* variable), then that would coincide with an increase in the 2-day announcement return of approximately 28 basis points.

The finding that the highest trading regularity quintile is associated with higher 2-day stock returns than the second-highest trading regularity quintile (seemingly in contrast to many of our earlier results) could be attributable to the analysis here focusing on 2-day post-announcement gross stock returns, rather than net trade performance. In regression (3), we measure the relation between trading regularity and information proxied by the stock's 2-day post-announcement return, rather than each trade's performance net of implicit transaction costs. Quintile 4 funds also might not emphasize trading around

31 We use earnings announcement dates and the mean analyst forecast provided by I/B/E/S to calculate earnings surprise. We define earnings surprise as the difference between actual earnings and the earnings forecast divided by the price at the prior quarter end. We sort stocks into quintiles based on earnings surprise.

32 $T5$*rank*, $T4$*rank*, $T1$*rank*, and $T2,3$*rank* show low correlation with one another. The time-series mean of the cross-sectional correlation of pairs of these four variables averages 0.09 (across six pairs). The low correlations indicate heterogeneity in the trading activity of the different trading regularity groups prior to a particular stock's earnings announcement.

Table 9
Stock returns predictability: Earnings announcement return

	(1)	(2)
Intercept	0.004***	0.004***
	(3.62)	(5.88)
ES1	−0.031***	−0.031***
	(−18.30)	(−16.66)
ES2	−0.020***	−0.021***
	(−15.87)	(−15.44)
ES4	0.016***	0.016***
	(13.53)	(13.51)
ES5	0.027***	0.027***
	(15.99)	(15.48)
CAR[-10,-1]	−0.075***	−0.071***
	(−17.94)	(−14.67)
T5rank (/100)	0.070***	
	(4.60)	
T4rank (/100)	0.023	
	(1.26)	
T1rank (/100)	−0.027	
	(−1.31)	
T2,3rank (/100)	−0.046***	
	(−2.78)	
T5buy (/100)		0.220**
		(2.02)
T5sell (/100)		−0.089
		(−0.89)
T4buy (/100)		0.083
		(0.98)
T4sell (/100)		−0.037
		(−0.35)
T1buy (/100)		0.030
		(0.28)
T1sell (/100)		0.60
		(0.63)
T2,3buy (/100)		−0.087
		(−0.70)
T2,3sell (/100)		0.085
		(0.71)

This table presents a regression analysis relating abnormal returns on the event of earnings announcements (EA) to pre-event trading by funds in the ANcerno data set. We cross-sectionally regress the 2-day cumulative abnormal market-adjusted return of the stock that reported earnings on four net trading volume ranks (i.e., of funds in the highest trading regularity quintile, the second-highest trading regularity quintile, the lowest trading regularity quintile, and others) and control variables. $CAR[M,N]_{i,t}$ represents stock i's cumulative, market-adjusted return from day M through day N, where M and N are measured relative to the earnings announcement date (day 0). $ES_{i,j,t}$ is a dummy variable equal to 1 if stock i had an earnings surprise ranked within quintile j among all earnings surprises during the quarter. T5rank, T4rank, T1rank, and T2,3rank represents the earnings announcement trade quintile rank in stock i of funds in the highest trading regularity quintile, the second-highest trading regularity quintile, the lowest trading regularity quintile, and others (quintiles 2-3) respectively during the ten days prior to stock i's earnings announcement. In the second column, T5buy (T5sell) is a dummy variable that equals 1 when stock i is bought (sold) on net only by funds in the highest trading regularity quintile during the 10-day window prior to the earnings announcement, and zero otherwise. T4buy, T4sell, T1buy, T1sell, T2,3buy, and T2,3sell are defined similarly for funds in the second-highest trading regularity quintile, the lowest trading regularity quintile, and others (quintiles 2–3). The time-series averages of coefficients and the associated t-statistics (in parentheses) for both regressions are reported. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

earnings announcements.[33] Also note that we find a statistically significant (insignificant) negative relation between the quintile 2 and 3 (quintile 1) funds and abnormal returns around earnings announcements. Together, these results suggest that one of the ways that funds that regularly trade are able to generate positive performance is by trading on information that others in the market are not aware of.

To further explore the relation between funds that regularly trade and earnings announcement returns, we define dummy variables to capture separately effects associated with buy and sell transactions. The alternative specification is as follows:

$$
\begin{aligned}
CAR[0,1]_{i,t} = a + \sum_{j=1,2,4,5} b_j ES_{i,j,t} + cCAR[-100,-1]_{i,t} \\
+ d_1 T5buy_{i,t} + d_2 T5sell_{i,t} + d_3 T4sell_{i,t} + d_4 T4buy_{i,t_t} + d_5 T1buy_{i,t} \\
+ d_6 T1sell_{i,t} + d_7 T2,3buy_{i,t} + d_8 T2,3sell_{i,t} + \varepsilon_t, \qquad (4)
\end{aligned}
$$

where $T5buy_{i,t} = 1$ ($T5sell_{i,t} = 1$) when a buy (sell) net trade imbalance exists across all stock i trades among funds in the highest trading regularity quintile during the 10-day window prior to earnings announcement while other funds show a net trade imbalance in the opposite direction (or no net imbalance). $T4buy_{i,t} = 1, T4sell_{i,t} = 1, T1buy_{i,t} = 1, T1sell_{i,t} = 1, T2,3buy_{i,t} = 1$, and $T2,3sell_{i,t} = 1$ are defined similarly. As before, we run the cross-sectional regression in (4) each quarter and compute the time-series average of the quarterly coefficient estimates like in Fama-MacBeth (1973).

The second column in Table 9 shows the results associated with this alternative specification. Of the eight dummy variables, only the coefficient on the buy variable associated with the highest trading regularity quintile ($T5buy$) is statistically significant. Although the coefficient on $T4buy$ is positive, and the coefficients on $T5sell$ and $T4sell$ are negative, they are statistically insignificant. Consistent with the results associated with regression Equation (3), the results suggest that funds that regularly trade earn positive returns by buying (selling) stocks prior to the positive (negative) returns associated with the 2-day period during and after their earnings announcements. Also consistent with the regression (3) results, we find stronger effects associated with the funds in the highest trading regularity quintile than with funds in the second-highest trading regularity quintile, possibly because the funds in the highest trading regularity quintile are not penalized in this analysis for relatively high implicit trading costs.

33 Given that Harvey, Liu, and Zhu (2016) document 316 factors that have been shown to contribute to the cross-section of expected returns, there is no shortage of alternative possible trading strategies that funds that trade regularly might pursue.

2.8 Robustness tests

2.8.1 Stitched tickets. In our main analysis, we utilize the trade tickets provided by ANcerno. ANcerno groups trades into tickets only when they involve the same broker, and in many instances the data indicate separate tickets for trades that involve the same ticker, the same trade side, and the same broker or multiple brokers on consecutive trading days, or multiple brokers on the same trading day. However, institutions commonly break up large orders into trades executed on the same day or on different days and via different brokers. Not accounting for this tendency could positively bias the trading regularity measure. As an alternative to ANcerno's ticket definition, Anand et al. (2012) examine the robustness of their results to "stitched" tickets, where they group together into tickets trades by the same fund manager on the same stock and the same trade side that occur on the same day or on consecutive trading days, even when the trades involve more than one broker. We utilize this same approach to examine the robustness of our results to the alternative ticket definition, defining a fund's quarterly trading regularity as the ratio of the number of stitched tickets executed during the quarter to the number of unique stocks traded during the quarter.

Based on the stitched ticket measure of trading regularity, we find that all of the main conclusions hold. For example, Table 10 reports stitched ticket univariate trading regularity / performance results that mirror the results based on ANcerno tickets reported in Table 2, panel A2. Note that the Table 10 results utilize quintile trading regularity cutoffs based on the new stitched-ticket measures of trading regularity. Similar to Table 2, panel A2, for both equally weighted and principally weighted results, we find the top two trading regularity quintiles show intraquarter trade performance that is statistically significantly positive, at 0.52% (0.29%) for quintile 5 when the results are equally (principally) weighted compared to 0.55% (0.31%) for the results based on ANcerno tickets. Also, trade performance largely increases across the stitched-ticket trading regularity quintiles, reaching a maximum at quintile 4, similar to the pattern associated with the ANcerno trade tickets in Table 2. Untabulated stitched-ticket results associated with the analyses in Tables 4, 5, 6, 7, 8, and 9 reveal no important differences relative to the reported results based on ANcerno tickets.

2.8.2 Analysis based on the methodology of Chakravarty, Moulton, and Trzcinka (2017). In our main analysis, we utilize the methodology of Puckett and Yan (2011) to track trades and measure performance. A reasonable alternative to Puckett and Yan (2011) methodology is to track trades from entry to exit, like in Chakravarty, Moulton, and Trzcinka (2017). Since both holding period and performance are sensitive to this methodological choice, we examine the robustness of our main findings to using Chakravarty, Moulton, and Trzcinka's (2017) methodology. We continue to find a positive relation between trading regularity and performance. For example, Table IA.3 in the

Table 10
Robustness analysis: Stitched tickets

Regularity	EW	PW
1 (low)	−0.27**	−0.21*
	(−2.13)	(−1.67)
2	0.17*	0.15*
	(1.90)	(1.69)
3	0.52***	0.35***
	(6.23)	(3.37)
4	0.58***	0.30***
	(6.74)	(2.99)
5 (high)	0.52***	0.29***
	(5.60)	(3.44)
4–low	0.85***	0.51***
	(6.34)	(4.03)
High–low	0.79***	0.50***
	(5.45)	(3.72)

This table presents average fund performance in quintiles sorted by contemporaneous trading regularity based on stitched tickets, where we group together into tickets trades by the same fund manager on the same stock and the same trade side that occur on the same or consecutive trading days, even when the trades involve more than one broker. 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 a fund's quarterly trading regularity as the ratio of the number of stitched tickets executed during the quarter to the number of unique stocks traded during the quarter. 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 equally weighted (EW) or principally weighted (PW) DGTW-adjusted returns separately for buys and sells. Lastly, we take the difference in DGTW-adjusted returns between buys and sells. We divide all funds into five quintiles at the end of each quarter based on their current quarter trading regularity. We then report DGTW-adjusted performance for these quintiles. All returns are expressed as a percentage. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Internet Appendix repeats the Table 2 analysis that examines the univariate relation between trading regularity and performance. The results continue to show a positive relation, with funds that regularly trade outperforming funds that trade less regularly and funds that regularly trade generating statistically significant positive performance based on raw returns and on DGTW-adjusted performance.

2.8.3 Subsamples of long-lived sample funds. The size of the sample declines from 1,871 funds in 1999 to 1,284 funds in 2009. To examine whether changes in the sample constituents affect the results, we analyze two subsamples of funds that remain in the sample for extended periods of time, including the subsample of 107 funds that remain in the sample over the entire sample period and the subsample of 1,316 funds that exist in the sample at least 5 years. We examine fund performance associated with double sorts based on trading volume and trading regularity, similar to our full-sample analysis in Table 4, panel C. We report these results in Table IA.4 in the Internet Appendix. Because of the small number of funds that exist over the entire sample period, we sort into terciles, rather than quintiles, in the 107-fund subsample double sort analysis.

Results based on subsamples of funds that exist in the sample for extended periods of time are consistent with our evidence of a positive relation between trading regularity and performance. This relation is evident among the 107-fund results in Table IA.4, panels A and B, and in the 1,316-fund results in Table IA.4, panel C. In all of the panels, the higher trading regularity quintiles generate greater performance than the lower trading regularity quintiles, with statistically significant positive performance across most of the trading volume terciles and quintiles in panels B and C, respectively. However, the prior evidence that the quintile 4 trading regularity funds produce the best performance is not as clear among the results associated with the 107-fund sample in panel A.

3. Conclusion

We find that institutions that regularly trade generate greater performance, on average, than institutions that trade less regularly, with their investments earning returns that more than offsets the transaction costs associated with their trades. We find that funds that regularly trade do so persistently, and their persistence pays off, as we find a strong relation between the past performance of funds in the highest trading regularity quintile and their future performance. We find that funds that regularly trade perform particularly well when trading as contrarians, buying (selling) after stock prices decrease (increase). Moreover, trading activity prior to company earnings announcements suggests that funds that regularly trade earn abnormal returns in part by trading on short-lived information.

However, not all institutions are able to exploit opportunities associated with trading regularly. Larger funds perform worse than smaller funds, as their relatively high transaction costs dampen their performance. Furthermore, we find a noticeable decrease in performance at the highest level of trading regularity that is partly attributable to transaction costs. These results suggest that although institutional investors benefit from regularly trading, the benefits are limited.

At face value, the finding that institutions that regularly trade generate abnormal returns should give pause to those who mechanistically favor low expense index funds. The index fund argument is largely based on the idea that markets are efficient, and that funds that are not careful about their costs are doomed to long-run underperformance. While it is difficult to argue with the idea that expenses should be minimized, our evidence suggests that strategies that require trading regularly can sometimes dominate more passive approaches, insofar as the trades of funds that regularly trade persistently generate positive abnormal returns.

Appendix. Comparison to Chakrabarty, Moulton, and Trzcinka (2017)

Chakrabarty, Moulton, and Trzcinka (2017) use the ANcerno institutional trade database to examine the performance of positions held for relatively short holding periods and find evidence of poor performance among trades held for less than 90 days. We examine the extent to which our subsample of funds that regularly trade emphasize short-duration trades. Given Chakrabarty, Moulton, and Trzcinka (2017) results, if trading regularity proxies somewhat for relatively short holding periods, then we would expect funds that regularly trade to show relatively poor performance.

Table A1
Holding period analysis

A. Median holding period by trading regularity quintile

	Holding period				
Regularity	1	2	3	4	5
1 (low)	67	167	285	471	955
2	69	183	326	554	1,041
3	54	151	279	483	887
4	50	126	223	373	701
5 (high)	43	119	219	378	753

B. Double sort by holding period and trading regularity

	Holding period					
Regularity	1	2	3	4	5	Long-short
B1. Returns						
1 (low)	−0.95**	−1.37	−0.76	1.97	6.97***	7.92***
2	−0.16	−0.25	1.58	3.78*	7.95***	8.12***
3	−1.04	0.38	2.81*	3.91**	5.27**	6.30**
4	0.02	1.05	1.92	5.73***	7.68***	7.66***
5 (high)	−0.05	0.62	2.13	5.32***	6.95***	6.99***
High-low	0.90**	1.99***	2.89***	3.35***	−0.02	
B2. DGTW-adjusted performance						
1 (low)	−1.02***	−2.32***	−2.60***	−0.68	0.43	1.45**
2	−0.60**	−1.17***	−1.17**	−0.29	−0.44	0.17
3	−1.22***	−0.92**	−0.45	−0.76**	−1.72***	−0.50
4	−0.67*	−0.59	−0.39	0.96*	1.04*	1.71**
5 (high)	−0.19	−0.29	0.28	1.52***	1.95***	2.14***
High-low	0.83***	2.03***	2.88***	2.20***	1.53**	

Panel A presents the median holding period within each cell in a 5×5 matrix based on double sorting first on trading regularity and then on holding period. In panel B, we independently double sort funds into 5×5 portfolios each quarter by mean holding period and trading regularity. Principally weighted returns (DGTW-adjusted performance) are reported for each portfolio in panel B1 (B2). All returns are expressed as a percentage. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

We use Chakrabarty, Moulton, and Trzcinka's (2017) methodology to determine trade holding periods for our sample of trades.[34] In particular, we match trades from entry to exit regardless of whether the trade is held across quarters, finding a match for 88.4% of trades. We then compute the median holding period within each cell in a 5×5 matrix based on double sorting first on trading regularity and then on holding period. Table A1 shows these median holding periods. Although the holding periods associated with trading regularity quintiles 4 and 5 are shorter than the holding periods associated with funds that trade less regularly, the median holding periods for funds that regularly trade are not abnormally low. Across all trades among trading regularity quintiles 4 and 5, the median holding period is 220 calendar days, greatly exceeding the 90-day cutoff emphasized by Chakrabarty, Moulton, and Trzcinka (2017) to define short-duration trades. Furthermore, only 22% of the trades of the trading regularity funds of quintiles 4 and 5 are held for less than 90 days. Consequently, Chakrabarty, Moulton, and Trzcinka's (2017) finding that

[34] In our holding period analysis, we restrict our sample to funds that exist for at least 5 years during the sample period to be consistent with Chakrabarty, Moulton, and Trzcinka (2017).

short-duration trades underperform need not imply that funds that regularly trade underperform, as the vast majority of their trades are not of short duration.

We also examine the extent to which our evidence of a positive relation between trading regularity and performance holds regardless of holding period. Using Chakrabarty, Moulton, and Trzcinka (2017) holding period methodology, we double sort funds into 5×5 portfolios each quarter independently by mean holding period and by trading regularity. The principally weighted results, reported in Table A1, panel B, indicate that the positive relation between trading regularity and performance generally holds regardless of mean holding period for both returns (panel B1) and DGTW-adjusted performance (panel B2). Note, however, that short-duration trades generate relatively poor performance, a finding consistent with Chakrabarty, Moulton, and Trzcinka's (2017) main findings.

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