Winter 12-2021

Essays in Mutual Funds

Aadhaar Verma

WASHINGTON UNIVERSITY IN ST. LOUIS

Olin Business School

Dissertation Examination Committee:

Zachary Kaplan (chair)

Todd A. Gormley

Mahendra Gupta

Essays in Mutual Funds

by

Aadhaar Verma

A dissertation presented to
the Olin Business School
in partial fulfillment of the
requirements for the degree of
Doctor of Business Administration

December 2021

Saint Louis, Missouri

Acknowledgments

I want to thank my advisor, Zachary Kaplan, and dissertation committee members, Todd Gormley and Mahendra Gupta for their support, guidance, and advice.

I also want to thank several current faculty members at Washington University in St. Louis including Taylor Begley, Richard Frankel, Radhakrishnan Gopalan, Chad Ham, and Anjan Thakor.

I have benefited greatly from the encouragement and advice from my colleagues including Swaminathan Balasubramaniam, Chihoon Cho, Yakshup Chopra, Yadav Gopalan, Avantika Pal, Patricio Sullivan, and Yifang Xie.

Finally, this dissertation would not have been possible without the support of my parents throughout my time at Washington University.

Aadhaar Verma

Washington University in Saint Louis

December 2021

Abstract of the Dissertation

Essays in Mutual Funds

by

Aadhaar Verma

Doctor of Business Administration

Washington University in St. Louis, 2022

Prof. Zachary Kaplan, Chair

This dissertation examines mutual fund portfolio formation, the economic forces that determine how fund managers construct their portfolios, and the market effects of fund portfolio disclosures. In the first chapter of my dissertation, I study how funds modify their portfolios around disclosure dates in order to cater to their investors' non-financial preferences. Using social norms and investor boycotts surrounding tobacco and firearm sectors as a proxy for non-financial preferences, I find that these stocks experience significant negative returns on portfolio disclosure dates and significant positive returns on the day after the portfolio disclosure. I also find that funds accelerate their trading activity in these stocks after the portfolio disclosure. These results suggest that investors' non-financial preferences can result in temporary fluctuations in asset prices around mutual fund portfolio disclosure dates. In the second chapter, co-authored with Todd Gormley and Zachary Kaplan, I examine how fund trades and stock prices vary around the quarterly fund reporting cycle. Mutual funds accelerate trades that complete the building of existing positions by disclosure dates but delay trades that initiate new positions until after the portfolio disclosure. Consistent with disclosure-based motives unrelated to new information about intrinsic values driving these quarterly trade dynamics, both stock price informativeness and commissions paid by funds drop at quarter-end.

Chapter 1

(Mis)-priced preferences: The effect of investor preferences on asset prices

1.1 Introduction

Most academic papers model sophisticated investing in capital markets as a rational process. However, like most social phenomena, investing is subject to fads, speculation, social and cultural mores (Shiller, 1984).[1] Generally speaking, if investors prefer to hold stock A, rather than stock B, they will accept lower returns for doing so. Moreover, if the demand for stock A stems from an attribute independent of its fundamental value, this could result in A's stock price deviating from its intrinsic value (Black, 1986; pg. 537).

In this paper, I empirically document how investor preferences affect asset prices by showing how security returns vary around mutual fund portfolio disclosure days in systematic and predictable ways. While mutual fund returns are observable on a daily level, their portfolios are disclosed to the general market only once each quarter. This results in funds placing more weight on those securities they think their investors would wish (or not wish) to see reported in their portfolios. We argue that this shift in and out of specific stocks around quarter-ends generates a predictable return pattern allowing us to identify when and how preferences affect asset prices.

[1] Consider the recent rise of 'meme stocks' in which stocks are hyped using internet slang and jokes on social networking websites such as Reddit and Discord, resulting in wild price swings for stocks like GameStop, AMC, Blackberry, among others.

This approach has two underlying assumptions: (i) funds concentrate their trades to cater to investor preferences around disclosure dates, and (ii) liquidity providers do not supply the required amount of liquidity to cancel out the price changes caused by the funds' trading behavior around quarter ends.

To analyze how investors' preferences affect asset prices, we examine security returns around quarter-ends (when most funds disclose their portfolios) in two 'sin' industries – tobacco and firearms. These industries have been subject to numerous investor boycotts (see Appendix A). If fund managers cater to their investors' preferences by avoiding reporting holdings in these sectors, we should find depressed prices around reporting days for stocks in these sectors. This is precisely what we find. We show that these sectors exhibit significant negative returns on quarter-end dates and significant positive returns on quarter-beginning dates. Relative to other industries, we find that tobacco (firearm) firms exhibit 45 (39) basis points lower returns on the day just before the portfolio disclosure relative to their non-sin counterparts. After the disclosure event (i.e., the first day of the quarter), tobacco (firearm) stocks experience 40 (27) basis point higher returns than their non-sin counterparts. These returns are robust to controlling for firm characteristics and asset pricing anomalies, which suggests that the flip in returns around quarter-ends arises from fund reporting requirements which in turn, we argue, are driven by investor preferences.

Given that our sample runs from 1986 to 2019, it is likely that investors' preferences towards these sectors have changed over time. To examine this, we divide our sample into each decade and re-run our analysis. We find that tobacco stocks' negative (positive) returns around quarter-end (beginning) dates become significant only from the 1990s. This was when federal and local US states started public litigation against tobacco companies for misleading the public about the health risks associated with tobacco consumption. We also observe that investors' preference not to hold firearm stocks was limited to the 2000s after the rise in mass shooting incidents which led to appeals from advocacy groups to institutional investors to divest their positions from firearm stocks. These results are consistent with the possibility that investors' preferences towards particular sectors vary with time.

Next, we examine whether the return patterns documented in sin stocks extend to the set of firms implicated in the prescription opioid epidemic that affected large parts of the US in the 2010s.[2] Analogous to how advocacy groups placed pressure on institutional investors to divest from their tobacco and firearm holdings, the opioid epidemic led to calls for institutional investors to engage with opioid manufacturers and distributors to address the risks associated with reputational harm and potential legal costs arising from opioid misuse (see Appendix A, Panel C). We identify nine publicly listed firms charged with profiting from the opioid crisis and examine whether investors' preferences effects these firms' asset prices around quarter-end dates when most mutual funds and institutional investors disclose their portfolio holdings. We find that implicated firms experience a significant negative (positive) 24 (30) basis point return on quarter-end (start) dates. This pattern of returns is felt most acutely in pharmaceutical distribution firms and retail pharmacies whose returns fall (increase) by 21 (34) and 37 (24) basis points on quarter-end (start) dates, respectively.

To ascertain whether investors' nonpecuniary preferences affect asset prices more broadly in the cross-section, we turn to stock return performance of highly rated ESG (environmental, social and, governance) around portfolio disclosure dates. While the traditional view, stemming from Friedman (1970) argues that the only responsibility of firms is to increase its shareholder

[2] For a comprehensive timeline of the opioid epidemic in the United States, see the following CDC page: https://www.cdc.gov/opioids/basics/epidemic.html

value, recent studies (e.g. Bollen, 2007; Riedl and Smeets, 2017) show that at least some investors derive utility from holding firms that score high on sustainability and social responsibility metrics. If such investors comprise a sizeable market segment, then funds would have an incentive to report larger positions in highly rated ESG stocks to become more desirable in the eyes of such investors. Showing higher portfolio positions in highly rated ESG stocks would help attract higher investment flows from existing and potential investors and maximize assets under management (Hartzmark and Sussman, 2019). Furthermore, Chen et al., 2020 show that an increase in firm's institutional holding improves their CSR performance. This leads us to hypothesize that highly rated ESG firms with high mutual fund presence will experience positive returns around quarter-end dates.

We provide evidence supporting this hypothesis. Highly rated ESG stocks with low mutual fund presence experience significant *negative* returns of 35 basis points on quarter-ends. This negative association between highly rated ESG stocks is consistent with previous findings (e.g., Krüger, 2015, Giuli and Kostovetsky, 2014, Manchiraju and Rajgopal, 2017), which document a negative relationship between 'corporate goodness' and shareholder value. On the other hand, we show that stocks with high mutual fund presence experience a significant *positive* return of 113 basis points on the last trading day of the quarter. Splitting the ESG score into its constituent components, we find that stocks with high environmental and social scores and high mutual fund presence experience a positive return of 34 and 85 basis points on the last day of the quarter. Highly rated governance stocks (with or without mutual fund presence) do not experience significant returns around quarter-ends.

Finally, we use fund-level trades from Abel-Noser (formerly Ancerno) from 1998-2010 to capture funds' trading dynamics around disclosure dates. Because only tobacco and firearm stocks exhibit negative stocks around quarter-end dates during this period, we limit our analysis of fund trading behavior to only these sectors. We begin our analysis by first creating a measure that captures how funds' trading patterns change in response to their current trade while also capturing funds' past trading patterns in that security. We create a trading slope measure for each fund's trade in a particular security by computing the ratio of the change in the fund's position in that security in the four weeks after that trade to the difference in the fund's position in the four weeks before that trade. A positive slope measure with a magnitude of less (greater) than 1 implies that the fund continues to trade in that security but at a slower (faster) rate than it had done so in the preceding four weeks. On the other hand, a negative slope would suggest that the fund reverses its trades by buying (selling) securities that it had sold (bought) in the prior four weeks.

We show that funds significantly alter their trading activity in sin stocks around quarter-ends by increasing their trades after they have disclosed their positions. While funds' trading activity in non-sin stocks increases by 8.9% on quarter-start dates, their trading activity in tobacco (firearm) stocks increases by 50% (126%). This increase in trading activity on the quarter-start dates suggests that funds strategically delay their trades in sin-stocks until they disclose their portfolios. When we partition funds into net buyers and net sellers in the month before the disclosure, we find that funds are more likely to delay the sin stocks' purchases until after the disclosure date. More specifically, we show that conditional on funds having bought sin stocks in the month before the disclosure, funds increase their purchases by 76% in the month after the disclosure.

This paper makes key contributions to at least three streams of literature. First, our evidence contributes to our knowledge of how investor preferences can result in dynamic mispricing. While the extant literature usually models return anomalies as either misestimation of cash flows or investors' behavioral biases, we show how their preferences for non-financial aspects of stocks can also result in mispricing and return predictability. Engelberg et al. (2018) show that anomaly returns are significantly higher on corporate news days and earnings announcement days. Patton and Verardo (2012) find that the daily betas of individual stocks increase on earnings announcement days and revert to their average levels in two to five days. Gormley et al. (2021) show that disclosure requirements induce a dynamic pattern in fund trading, leading funds to complete positions on quarter-end days and begin trading after disclosure dates. This paper extends these findings by showing how disclosure requirements affects trading in stocks investors prefer to own. We show predictable price changes and dynamic patterns in portfolio formation that allow funds to present these holdings.

Relatedly, this paper contributes to the growing literature that examines the market impact of investors' non-financial firm preferences. Coval and Moskowitz (1999) and Huberman (2001) examine how investors' preferences to hold locally domiciled firms affect asset prices. Similarly, Brunnermeir et al. (2007) and Harris et al. (2015) examine the price effects of investor screens on highly skewed returns and assured dividend yields, respectively. Viewed in this manner, our paper is closely related to Hong and Kacperczyk (2009), who show that social norms result in sin stocks yielding higher returns and, Chava (2014), who shows firms with greater environmental concerns face a higher cost of capital.

Finally, this study expands our knowledge of how mandatory portfolio disclosure affects fund trading decisions. Prior studies show that portfolio disclosure incentivizes fund managers to execute trades to either mask their actual positions to either prevent copycat trades (e.g., Wermers, 2001; Poterba et al., 2004; Gormley et al., 2021) or to deceive investors about the actual state of their investment portfolios (e.g., Musto, 1997 and 1999; Meier and Schaumburg, 2004; Agarwal et al., 2014). Our study contributes to this research by documenting how funds alter their portfolios to make them more attractive to existing and potential investors.

The remainder of the paper is organized as follows. The following section describes the data sources and presents summary statistics. Section 3 shows how investors' preferences result in temporary mispricing in sin stocks and opioid stocks around quarter-ends when most funds disclose their portfolio holdings. We also broaden our analysis to examine the effect of investors' preferences on asset prices by examining the asset returns of highly rated ESG stocks around quarter-end dates in this section. Section 4 examines how funds' alter their trading dynamics around disclosure dates. Finally, in Section 5, we conclude.

1.2 Data and Descriptive Statistics

1.2.1 Market Data

We construct our dataset by obtaining the daily prices of securities held from CRSP, limiting the sample to common shares (i.e., share code 10 or 11) that trade on the NYSE, AMEX, or NASDAQ and have a prior month-end market capitalization of 10 million USD or higher. We require all observations to have pricing factors identified in the asset pricing literature – beta, total asset growth, book-to-market ratio, market value of equity, gross-profitability (Fama and French, 2016; Novy-Marx, 2013), and post-earnings announcement drift (measured using standardized unexpected earnings). Our independent variables of interest are two indicator variables that flag key dates when most funds record their holdings for subsequent disclosures. The first indicator, *QtrEnd,* captures the last trading day of each calendar-year quarter (i.e., the last trading day of March, June, September, and December), and the second indicator, *QtrBeg,* captures the first trading day of each calendar-year quarter (i.e., the first trading day of January, April, July and

October). We also construct similar month-end (*MosEnd*) and month-beginning (*MosBeg*) indicators when some minority of funds record their holdings but do not report the results on these indicators for the sake of brevity.

1.2.2 Identifying sin and opioid stocks

To identify sin stocks, we follow the approach laid out in Hong and Kacperczyk, 2009. A firm is identified as a sin stock if it or any of its segments have a SIC code ranging from 2100-2199 (tobacco stock) or equal to 3482 or 3484 (firearm stocks). We then compute the percentage of sales that a firm derives from its tobacco or firearm segments. Panel A of Table 1 presents the number of sin stocks in our dataset starting from 1985 to 2019. The total number of distinct tobacco and firearm stocks in our sample are 41 and 19, respectively. The average percentage of sales derived from tobacco (firearms) sales is 74.92% (60.49%). We merge these sin-sale measures with our market-level data on the last year's sales.

[Insert Table 1 – Panel A here]

We identify firms accused of exacerbating the opioid crisis by parsing through the defendants listed in the most prominent lawsuits filed by public prosecutors at the federal, state, and county levels.[3] The firms charged in these lawsuits fall under three major categories – distributors, retailers, and manufacturers. While the total number of accused firms is over 20, many of these firms are private (e.g., Purdue Pharma) or have been acquired by other firms (e.g., AbbVie acquired Allergan in 2015). As a result, the final number of firms in our opioid tests number 9: three distributors, four retailers, and two manufacturers. We list the firms below:

[3] A timeline of the major lawsuits and their decisions can be found here: https://www.opioidsettlementtracker.com/globalsettlementtracker

Distributor	Retailer	Manufacturer
Cardinal Health	Walmart	Johnson & Johnson
McKesson Corp.	CVS	Teva Pharmaceuticals
AmerisourceBergen Corp.	Walgreens	
	Rite Aid	

1.2.3 ESG stocks

We obtain ESG scores from the Kinder, Lydenberg, and Domini (KLD) database. KLD, now part of MSCI, is an information intermediary specializing in quantifying stakeholder relations of publicly listed firms. While KLD scores for US corporations have been available since 1991, their coverage remained limited to the S&P 500 until 2003. We limit our analysis from the year 2010 onwards because ESG concerns have become increasingly relevant in recent years. To quantify ESG performance, KLD relies on publicly available information gathered through press releases, 10-Ks, and other customized press searches. KLD classifies the data into one of the following seven stakeholder areas: (i) community, (ii) corporate governance, (iii) diversity, (iv) employee relations, (v) environment, (vi) human rights and, (vii) product. To ease our analysis, we group all stakeholder areas that are *not* corporate governance and environment under the 'social' category giving us three stakeholder categories. In each of the seven areas, KLD defines binary indicators, which are either strengths (positive) or concerns (negative). For example, a positive indicator might be concerned with offering its employees paid maternity/paternity leave, and a negative employee indicator could be concerned with the proportion of women in managerial positions. For each firm's stakeholder area, we take the sum of the strengths and concerns to obtain the firm's raw stakeholder score. Because the number of strengths and concerns vary across the sample period, we standardize each firm's raw score by the maximum possible score in that year.

[Insert Figure 01 here]

Because KLD rating criteria change annually, firm ratings can vary widely from one year to the next. This is evident in Figure 01, where we can see that the average firm's environment rating declined from 0.55 in 2009 to 0.20 in 2019. Therefore, using the raw standardized ratings in the regression analysis could lead to biased coefficients. To account for such changes, we compute the monthly percentile rank of each firm's stakeholder score before using them in the regressions.

1.2.4 Fund and institutional holding intensity

We use S12 and 13F/S34 datasets from Refinitiv to compute firm measures for the level of mutual fund and institutional investor presence. We define *MFOwn* (*InstOwn*) as the percentage of a firm's market capitalization held by mutual funds (institutional investors) on a given date. Specifically, we define *MFOwn* as:

$$MFOwn_{i,t} = \frac{\sum Pos_{i,j,t} * Prc_{i,t-1}}{CSHO_{i,t} * Prc_{i,t-1}}$$

where $Pos_{i,j,t}$ are fund's *j* disclosed holdings in firm *i* at time *t*. We split-adjust and value all the positions using last year's price and then sum the holding amount across all funds to create an aggregate measure of the value of fund disclosures in a given stock at a date level. We then scale the measure with the firm's market capitalization to create the fund ownership intensity measure. We create a similar measure using the S34/13F dataset to create an institutional ownership intensity measure. To mitigate the presence of outliers, we winsorize both measures at 1% and 99%. We examine the effect of mutual fund and institutional ownership on highly related ESG stock returns around disclosure dates in Section 4 of the paper.

1.2.5 Trade dynamics data

Finally, we use the Ancerno proprietary dataset from Abel Noser Solutions, a financial services firm that provides trading cost analytics advice to institutional asset owners, managers, and brokers, such as mutual funds and pension funds, to assess whether funds alter their trades in sin stocks around disclosure days. The Ancerno dataset allows us to observe trade-level data from institutions that subscribe to Abel Noser's services, covering about 12 percent of CRSP trading volume (Hu et al., 2018). The data includes the date of fund managers' transactions, the stock symbol of the trade, the number and value of shares traded, and any commissions paid. While Abel-Noser anonymizes the data at the institutional/fund manager level, they provide identification codes for fund managers, allowing researchers to track a fund's trades for a given security over time. For our analysis, we include only those transactions by Ancerno marks as 'good trades' (i.e., actually executed trades) over the period 1998-2010, reflecting the earliest and the latest years of the Ancerno data made available to researchers. Finally, since our analysis requires an estimate of a fund's position in a given security, we require funds to trade a security at least five times during the sample period.

For each trade, we take the ratio of the change in the fund's position in a security in the four weeks following that day's trade to the change in the fund's position in that security in the past four weeks of that day's trade. Specifically, we define *ShareSlope* as:

$$ShareSlope_{i,j,t} = \frac{SharePosition_{i,j,t+28} - SharePosition_{i,j,t}}{SharePosition_{i,j,t} - SharePosition_{i,j,t-28}}$$

where $SharePosition_{i,s,t}$ is the estimated position of fund *i* in security *s* at time *t*. A positive slope measure would suggest that a fund, in the subsequent four weeks, continues to buy/sell the security in the same direction as it had traded in the past four weeks. On the other hand, a negative slope indicates that the fund reverses its previous trades by purchasing (selling) securities that it had sold (bought) in the past four weeks. An illustration will help make this measure more transparent. Fund 21200735 in our sample held 42,600 shares of permno 10025 as of 10/17/2006. The same fund held 41,900 shares and 42,200 shares of 10025 as of 11/14/2006 and 09/19/2006, respectively. Thus, *ShareSlope* for permno 10025 on 10/17/2006 equals $\frac{41900-42600}{42600-42400} = \frac{-700}{400} = -1.75.$ The negative value of *ShareSlope* indicates that the fund reverses the position that it had built up in the security in the past four weeks. Additionally, the absolute value greater than 1 indicates that the fund exits its position in the security at a greater speed than it had initially entered into the security. We discuss the construction and interpretation of the *ShareSlope* measure at greater length in Appendix B of the paper.

[Insert Table 1 – Panel B here]

Panel B of Table 1 presents the summary statistics for *ShareSlope* for regular stocks and sin stocks around key dates. The average slope measure of our sample for non-sin stocks on non-quarter beginning or ending dates is 1.34, which suggests a high degree of autocorrelation. Specifically, it suggests that if a fund had purchased/sold 100 shares of a security in the past four weeks, it follows up on that trade by buying/selling 134 shares of that security in the next four weeks. We observe that while ShareSlope for non-sin stocks increases marginally to 1.39 on quarter-beginning dates, the corresponding value for sin stocks equals 1.94, suggesting that funds increase their trading activity in sin stocks until they have disclosed their holdings to the general market. We explore how funds alter their trading activity in sin stocks in greater length in Section 5 of the paper.

1.3. Investors preferences for sin stocks and opioid stocks

1.3.1 Sin stocks' returns around portfolio disclosure days

We start our analysis by examining whether sin stocks (i.e., tobacco and firearm firms) exhibit negative returns on portfolio reporting days. Our main hypothesis is that funds will wish to avoid reporting holdings of cigarette stocks because cigarettes are an addictive product that causes lung cancer and because the CEOs of these corporations misled the public about the risks associated with the consumption of tobacco products. Similarly, we hypothesize that funds will wish to avoid reporting firearm stocks in their portfolios because firearm manufacturers facilitate the general public's access to large magazine clips and semi-automatic firearms, increasing the casualty figures in mass shootings. To test whether fund manager preferences not to hold these securities around portfolio reporting days affect their asset prices, we regress the daily firm returns on quarter-end and quarter-beginning indicators, the most common date on which funds record and disclose their positions. Specifically, we estimate:

$$Ret_{i,t} = \alpha + \beta_1.QtrEnd + \beta_2.QtrBeg + \beta_3.SinSale_{i,t} + \beta_4.SinSale_{i,t} * QtrEnd + \beta_5.SinSale_{i,t} * QtrBeg + Controls + Firm\,FE + Month\,FE + \epsilon_{i,t} \quad (1)$$

where *QtrEnd* and *QtrBeg* are indicator variables that take a value of 1 if the day is the quarter's last and first trading day, respectively. $SinSale_{i,t}$ is defined as the sum of the percentage of sales generated from the tobacco and firearm sectors. The prediction that fund managers sell these holdings in response to reporting requirements predicts negative returns for these stocks on quarter-ends and positive returns on quarter-beginnings. In all specifications, we also include (i) indicators for the last trading day of the month (*MosEnd*) and the first trading day of the month (*MosBeg*) and their interactions with $SinSale_{i,t}$, (ii) month-year fixed effects, (iii) firm fixed effects, and (iv) asset pricing factors – namely asset growth, book-to-market ratio, beta, gross profitability, 12-month momentum, market value of equity, and SUE and their interactions with the change in quarter and month indicators. However, for the sake of brevity, we do not report these coefficients in the main tables.

[Insert Table 2 here]

In Table 2, Column 1, we see that regular stocks experience a positive return of 27 basis points on the last trading of the quarter. This is consistent with portfolio pumping (Carhart et al., 2002). In contrast, we see that the coefficient on *SinSale***QtrEnd* loads with a statistically negative coefficient of 0.0044 (t=-5.34). The coefficient magnitude syggests that sin stocks lose 44 basis points on the last trading day of the quarter. We also see *SinSale***QtrBeg* loads with a statistically significant positive coefficient of 37 basis points (t-stat=3.46).

In Column 2, we split the sin stock variable into its constituent tobacco and firearm components. We see statistically significant negative coefficients on quarter-end dates and significant positive coefficients on quarter-beginning dates for both tobacco and firearm components which is consistent with our hypothesis that reporting requirements trigger sales of sin stocks. We see that tobacco stocks experience a significant decline on the last trading day of the quarter of 45 basis points and then experience a significant positive return of 40 basis points on the first trading day of the quarter. For the same dates, firearm firms experience a decline and increase of 39 and 27 basis points, respectively.

1.3.2 Evolution of investor preferences over time

Given that our sample runs from 1985 to 2019, it would be worth examining how the return patterns reported in the previous section change over time. This could help shed light on whether funds' preferences to report lower sin stock holdings have changed during our sample period. E.g., while cigarette consumption today is universally seen as an unhealthy and harmful activity, there was a period in the 1960s and 70s when smoking was nothing out of the ordinary. Despite the deleterious effects of cigarette smoking having been established in the medical community in the 1960s, it was only in the late 1980s that the general public started becoming aware of the medical risks associated with tobacco consumption.[4] Public awareness of the risks associated with cigarette smoking increased considerably in the mid-1990s when more than 40 states commenced litigation against the tobacco industry. This litigation finally culminated in the 1998 "Master Settlement Agreement" that found the four largest tobacco companies – Philip Morris, R. J. Reynolds, Brown & Williamson, and Lorillard – guilty of having downplayed the risks associated with tobacco consumption. It is, therefore, possible for investors' preferences, similar to societal views on tobacco consumption, to have varied with time.

Along the same lines, firearm manufacturers were not considered controversial until the rise in mass shootings in the early 1990s. Societal views on gun ownership and firearm manufacturers' indirect responsibility in facilitating mass shootings began to change after the US Congress temporarily banned the manufacture and sale of semi-automatic firearms for civilian use for ten years in 1994. Views surrounding gun ownership became more polarized in the late 1990s after three high school shootings - Westside Middle School in Arkansas, Thurston High School in Oregon, and Columbine High School in Colorado occurred in just 12 months of each other. Such mass shootings were accompanied by prolonged periods of public pressure and boycotts of firearm stocks (see Appendix A for details). Simultaneously, an equally vociferous pro-gun lobby emerged that challenged such boycotts. Given how the firearm sector has become the center of political and

[4] The chronology of how risks associated with tobacco consumption were disseminated to the public at large has been chronicled by PBS show "Inside the Tobacco Deal". The chronology can be found here: https://www.pbs.org/wgbh/pages/frontline/shows/settlement/timelines/fullindex.html

social controversy since the late 1990s, it would be worth examining how investors' preferences towards firearm stocks have evolved.

[Insert Table 3 around here]

To examine the evolution of investor preferences towards sin stocks, we divide the sample from 1985 to 2019 into each decade and re-run the regression model specified in equation 1. Table 3 presents the results for each decade. In Column 1, we see that tobacco stocks did not experience any significant negative return on the last trading day of the quarter in the 1980s. This finding is not surprising since, as mentioned previously, neither the tobacco nor the firearm sectors were considered 'sinful' during the 1980s. However, by the 1990s, societal norms surrounding tobacco consumption had begun to change. Column 2 reflects the change in investor preferences, where we see tobacco stocks experiencing a decline of 104 basis points on the last trading day of the quarter and an increase of 65 basis points on the first trading day of the quarter. We continue to observe similar patterns in tobacco stocks' returns in the 2000s and 2010s, albeit with a smaller magnitude. The decline on quarter-end dates reduces to 32 basis points in the 2000s and further drops to 22 basis points in the 2010s.

We also see a similar evolution in investor preferences in firearm stocks. We see that firearm stocks do not experience any significant negative returns on the last trading day of the quarter in the 1980s or 1990s, which suggests that ownership of these stocks was not considered controversial in these decades. However, in the 2000s, firearm stocks experienced a 69 basis point decline on the last trading day of the quarter. This decline became insignificant in the 2010s, presumably because, by then, investors realized that no legal or regulatory action would be forthcoming from the government, as had been against the tobacco companies in the 1990s.

1.3.3 Prescription based opioid firms' returns around portfolio disclosure days

Our previous tests suggest that investors' preferences not to own tobacco and firearm stocks induce funds to sell these stocks on portfolio reporting days. This section examines whether another set of firms – those implicated in the manufacture, distribution, and sale of prescription-based opioid painkillers – exhibit similar return patterns around disclosure dates. Like tobacco and firearm firms, firms involved in the manufacture, distribution, and sale of prescription-based opioid medications took the blame for causing the opioid epidemic that engulfed large parts of the US in the early 2010s.

While the original intention of prescription-based opioid medications, such as OxyContin, was to treat chronic pain in hospitalized and recovering cancer patients, the pharmaceutical industry, led by Purdue Pharma, began promoting such medication for general pain relief in the early 2000s within the medical community by organizing 'pain management' conferences and conducting sophisticated advertising campaigns (Van Zee, 2009). By 2009, according to the Centers for Disease Control (CDC), prescription opioid overdose deaths had exceeded motor vehicle deaths and deaths from illegal street drugs, such as heroin, cocaine, and amphetamines. However, it was only in 2013 that the general US public became aware of the severity of opioid misuse when the Drug Enforcement Agency (DEA) imposed civil penalties of $80 million on Walgreens, a major pharmaceutical retailer, for illegally diverting prescription opioids and failing to maintain adequate controls over controlled substances. Other pharmaceutical distributors and retailers such as McKesson, Cardinal Health, and CVS were also accused of similar wrongdoings, and since then, more than 3400 lawsuits have been filed at the county and state level against pharmaceutical manufacturers, distributors, and pharmacies for failing to highlight the risks associated with opioid use.

Given the scale of the opioid abuse, several institutional investors called such firms to take corrective action (see Appendix A). We identify the nine publicly listed firms charged with profiting from the opioid crisis and examine whether investors' preferences effects these firms' asset prices around quarter-end dates when most mutual funds and institutional investors disclose their portfolio holdings. Our sample period starts from 2013 because that was when the DEA charged Walgreens for failing to prevent the abuse of opioid painkillers, thereby revealing the extent of opioid misuse to the public. Specifically, we run the following regression specification:

$$\begin{aligned} Ret_{i,t} = \alpha + \beta_1.QtrEnd + \beta_2.QtrBeg + \beta_3.Opioid_i + \beta_4.Opioid_i * QtrEnd \\ + \beta_5.Opioid_i * QtrBeg + Controls + \ Firm\ FE + Month\ FE + \epsilon_{i,t} \end{aligned} \quad (2)$$

where $Opioid_i$ is an indicator variable that takes a value of 1 if it has an active opioid-related lawsuit at the county or state level.

[Insert Table 4 around here]

Table 4 presents the results of our analysis. In Column 1, we see that the coefficient on $Opioid_i * QtrEnd$ loads with a statistically negative coefficient of 0.003 (t=-2.81). This coefficient suggests that opioid-related stocks lose three basis points on the last trading day of the quarter. We also see $Opioid_i * QtrBeg$ loads positively with a coefficient of 0.027 (t=2.25). In Column 2, we limit our attention to the three pharmaceutical wholesalers and distributors charged with failing to maintain adequate controls for prescription-based opioid medications. We see that these firms experienced a significant negative return of 2 basis points on the last trading day of the quarter and a positive return of 3.6 basis points on quarter-start dates. Column 3 limits our attention to the retail pharmacies charged with illegally supplying opioid medications without valid medical prescriptions. These firms include Walmart, CVS, Rite Aid, and Walgreens. We see that these firms experience statistically significant negative returns of 4.8 basis points on the last trading day of the quarter. While these firms experience positive returns on the quarter-start dates, the coefficient is not statistically different from zero.

In Column 4, we limit our attention to the pharmaceutical firms that manufacture opioid painkillers. We do not see any significant negative (positive) returns on quarter-end (start) dates. There could be two reasons behind these insignificant results. First, while the number of firms involved in the manufacture of prescription-based opioid medications, the number of firms that qualified the sample selection criteria are just two – Johnson & Johnson and Teva Pharmaceuticals – resulting in a small sample size problem. An alternate reason for the non-result could be that these firms were involved in the manufacture of other drugs, and the opioid segment of their firms comprised only a small size of their overall operations, which shielded them from the blame heaped on other pharmaceutical firms like Purdue Pharma which made the majority of its revenue from the sale of opioid medication. Finally, in Column 5, we focus on the four firms - McKesson, Cardinal Health, AmerisourceBergen, and Johnson & Johnson - that settled with US state attorneys to pay $26 billion in July 2021. We see that these firms experienced a significant negative (positive) return of 2.1 (2.9) basis points on the last (first) trading day of the quarter.

1.3.4 Investors' preferences for highly rated ESG stocks around quarter-end dates

Our previous set of results suggest that the asset price of controversial stocks subject to investor boycotts experience significant mispricing during funds' disclosure dates. One potential explanation for the quarter-end shifts in returns could be that investors, for some personal reasons, prefer not to hold these sectors, and funds cater to these preferences by selling firms in these sectors before they disclose their portfolios. In this section we examine the converse, i.e., whether funds' preference for holding stocks that contribute positive to society leads these first to enjoy positive returns on quarter-end days. We ascertain this by examining the return of highly rated ESG (environmental, social and governance) stocks around quarter-ends.

However, it is worth pausing to consider what preferences investors would have for highly rated ESG stocks. A long literature stemming from Friedman (1970) argues that the responsibility of any firm is to increase its shareholder value. Pursuing any other desirable 'social end' is shortsighted, subversive, and 'harms the foundation of a free society.' Indeed, Manchiraju and Rajgopal (2017) find that the introduction of corporate social responsibility mandates in India adversely affected stock prices and subsequent firm value. Similarly, Krüger (2014) finds that investors respond negatively to positive CSR news when it is more likely to result from agency problems. However, recent studies (e.g., Hartzmark and Sussman, 2019) find that at least some investors derive utility from holding high sustainability stocks and that this demand is driven by institutional investors (Chen et al., 2020). Thus, we posit that only highly rated ESG stocks with a high mutual fund or institutional investor presence will experience more mispricing around quarter-end dates. We run the following regression specification to test the hypothesis:

$$\begin{aligned} Ret_{i,t} = \alpha + \beta_1.QtrEnd + \beta_2.QtrBeg + \beta_3.Rank(ESG)_i + \beta_4.FundOwn_{i,t} + \\ \beta_5.Rank(ESG)_i * QtrEnd + \beta_6.Rank(ESG)_i * QtrBeg + \beta_7.FundOwn_{i,t} * QtrEnd \\ \beta_8.Fundown_{i,t} * QtrBeg + \beta_9.Rank(ESG)_i * FundOwn_{i,t} + \\ \beta_{10}.FundOwn_{i,t} * Rank(ESG) * QtrEnd + \beta_{11}.FundOwn_{i,t} * Rank(ESG) * QtrBeg + \\ Controls + \ Firm\ FE + Month\ FE + \epsilon_{i,t} \qquad (3) \end{aligned}$$

We start our sample from 2010 because CSR and ESG concerns became financially prominent only from that period onwards.[5] Table 5 presents the results from the analysis. In Column 1, we run a simple regression without controls for mutual fund, *MFOwn*, or institutional

[5] Our results remain qualitatively similar if we start our sample in 2009 or 2011.

investor ownership, *InstOwn*. We see that highly ranked ESG stocks do not experience statistically significant negative or positive returns around quarter-end or quarter-beginning dates.

In the next column, we introduce the mutual fund ownership measure, *MFOwn*, and fully interact it with the quarter-end and quarter-start dates. We observe that while highly rated ESG stocks with high mutual fund ownership experience significant positive returns (11.7 basis points; t-stat=3.47), highly rated ESG stocks with low fund ownership experience significant negative returns. In Column 3, we introduce the institutional ownership measure, *InstOwn*, and re-run the analysis. We continue to observe significant positive returns in highly rated ESG stocks with a high mutual fund presence. We also see that highly rated ESG stocks with high institutional investor presence experience significant positive returns on quarter-end dates. These findings confirm our hypothesis that funds and institutional investors, to cater to investor preferences, increase their holdings of highly-rated ESG stocks around disclosure dates.

[Insert Table 5 around here]

In Columns 4-6, we split the firm's ESG rating into its constituent environment, social, and governance components and repeat the analysis carried out in the first three columns. Echoing the results from Column 1, we see that none of the ESG components load significantly on either quarter-ends or quarter-start dates. In Column 5, we observe that firms with high environment (social) ratings and high mutual fund presence experience significant positive returns of 3.6 (8.6) basis points on quarter-end dates. However, firms widely held by mutual funds with high governance scores do not experience significant returns on quarter-end dates. Finally, in Column 6, when we control institutional ownership at the firm level, we continue to observe significant positive returns in firms with high environment scores and social scores with high mutual fund ownership on quarter-end dates. We also see that firms with high institutional ownership experience with high environment and governance scores experience significant positive returns on quarter-end dates.

1.4. Funds trading behavior in sin stocks around disclosure dates

So far, we have shown that sin (highly rated ESG) stocks experience significant negative (positive) returns on the last trading day of the quarter and significant positive returns on the first day of the quarter. While we attribute these return patterns as funds catering to investors' preferences before disclosing their holdings to their investors, we now focus on the trading patterns that give rise to this phenomenon. To ascertain whether fund trading activity drives the observed shift in returns for sin stocks around quarter-ends, we turn to the Ancerno dataset to examine how fund managers alter their trading activity in sin stocks around these dates. If, as we hypothesize, fund managers cater to the clientele's preferences to not invest in sin stocks, we should expect them to reduce their trading activity in sin stocks before the disclosure and ramp up their trades after the portfolio disclosure has taken place.

To test for this hypothesis, we construct a measure, *ShareSlope*, which captures how a fund alters its future trades in a security in response to its previous trades in that security. For each fund transaction, we take the ratio of the change in the fund's position in that security in the four weeks after the transaction to the change in its position in that security in the four weeks before that transaction.[6] We regress the *ShareSlope* measure on the indicators for the first and last trading day of the quarter, percentage sales derived from the sale of sin segments, and their interactions. Specifically, we run the following regression specification:

[6] See Appendix B for a more detailed discussion on the construction and interpretation of the *ShareSlope* measure.

$$ShareSlope_{i,j,t} = \alpha + \beta_1.QtrEnd + \beta_2.QtrBeg + \beta_3.SinSale_{i,t} + \beta_4.SinSale_{i,t} * QtrEnd + \beta_5.SinSale_{i,t} * QtrBeg + \ Firm * Month\ FE + Fund\ FE + \epsilon_{i,t} \quad (4)$$

An increase in the trading activity just after the portfolio disclosure, i.e., on the interaction of *SinSale* and *QtrBeg*, would be consistent with our hypothesis that funds withhold from trading in sin stocks until after the disclosure has taken place. Table 6 presents the results from the analysis. The regression intercept is 1.34, which suggests that fund managers' trades, on average, are positively autocorrelated. We see that the coefficient on *QtrEnd* (*QtrBeg*) is significantly negative (positive) at -0.23 (0.12). These coefficients suggest that relative to non-quarter end dates, funds reduce (increase) their trading activity in non-sin stocks by 17% (9%) on quarter-end (beginning) dates. This is consistent with earlier research (e.g., Gormley et al., 2021), which shows that funds avoid building new positions or exit existing positions just before the disclosure to prevent disclosing key information to the market. When considering sin stocks, while we do not observe any significant decline in trading activity compared to their non-sin counterparts, we see a significant increase in trading activity at the start of the quarter. The *ShareSlope* for sin stocks increases by 64% on the first trading day of the quarter, consistent with our hypothesis that funds delay their regular trades in sin stocks in the month leading up to the disclosure. Funds resume their trading activity in sin stocks only after their portfolio disclosure, resulting in a spike in the trading slope.

[Insert Table 6 here]

When we split the *SinSale* into its firearm and tobacco components (Table 6, Column 2), we observe that the spike in trading slope is more pronounced in firearm stocks than in tobacco stocks. Whereas the *ShareSlope* measure for firearm stocks increases by 135% on the first trading day of the quarter, the increase for tobacco stocks is 59%. Interestingly, funds start altering their trading patterns in firearm stocks on the last trading day of the quarter itself. While this may seem to run counter to our hypothesis, it should be noted that because the *ShareSlope* measure uses the trades 28 days into the future as the numerator, the trades captured when measuring *ShareSlope* on *QtrEnd* take place after the disclosure takes place.

While the results shown in Table 6 show that funds significantly increase their trading activity in sin stocks after portfolio disclosures, they do not make clear the direction in which funds trade in sin stocks on quarter-start dates. To examine this, we create an indicator, $NetBuy_{i,s,t}$, which equals one when the change in the fund *i*'s position in the security *s* in the 28 days before date *t* is positive. Similarly, we create a $NetSell_{i,s,t}$ indicator that equals one if the change in fund i's position in security s in the 28 days before date t's trade is negative.[7] We then fully interact these indicators with the dependent variables in Equation 2 (i.e., *SinSale*, *QtrBeg*, and *QtrEnd*) and re-estimate the regression model. This decomposition of a fund's past trades allows us to estimate the direction in which funds increase their trading activity at the turn-of-the-quarter.

[Insert Table 7 here]

Table 7 presents the results from this analysis. We see that while funds do not increase their purchasing activity of non-sin stocks on quarter-start dates, they significantly increase their buying activity of sin stocks on quarter-start dates. Specifically, while the *ShareSlope* for regular buy trades on non-quarter start/end dates equals 0.91 (1.79-0.88), this increases to 1.60 (1.79-0.88+0.69) for sin stock purchases on the first trading day of the quarter. In contrast, non-sin stocks do not experience any significant increase in buying activity on quarter-start dates.

[7] Note that since we drop all observations in which trades in which funds don't trade even once in the four weeks proceeding to a trade, *NetBuy* and *NetSell* are mirror opposites of each other.

When we decompose *SinSale* into *TobaccoSale* and *FirearmSale*, we see that the increase in buying activity on quarter-start dates is limited only to tobacco stocks (Table 7, Column 2). While the coefficient on firearm purchases (*QtrBeg*×*NetBuy*×*FirearmsSale*) is positive, it is not statistically significant from zero. However, the coefficient on firearm purchases on quarter-end dates (*QtrEnd*×*NetBuy*×*FirearmsSale*) is significantly positive. As explained previously, while this may appear to run counter to our hypothesis, this is to be expected given how we construct the *ShareSlope* measure. Since all future trades enter into the measure's numerator, a positive coefficient on *QtrEnd* suggests that funds significantly buy more firearm stocks in the 28 days after their portfolios are disclosed to the general market.

1.5 Conclusion

We find that stocks involved in the sale or manufacture of tobacco, firearms, and opioids experience significant negative returns on quarter-end dates when most funds and institutional investors disclose their portfolio holdings. In addition, we find that highly rated ESG stocks with high mutual fund and institutional investor presence experience significant positive returns on quarter-ends. We regard this as evidence that funds alter their portfolios to appeal to socially conscientious investors to cater to investor preferences. To corroborate these findings, we show, using mutual fund trades, that funds accelerate their trading activity in tobacco and firearm stocks after their portfolio disclosures.

This study makes three significant contributions to the literature. First, we add to the literature on how investors' preferences, through the mutual fund channel, affect asset prices on disclosure dates. Second, our findings further our understanding of the effect of non-financial preferences in capital markets. Finally, our findings contribute to the literature that documents the effects of mandatory portfolio disclosure on the holdings funds' actually report.

Appendix 1.A – Examples of Investor Boycotts and Institutional Pressure on Sin Stocks and Opioid Stocks

	Date and Source	Details
Panel A – Tobacco Stocks		
1	24th May 1990 – New York Times	Harvard and City University of New York eliminate stocks of tobacco companies from their investment portfolios. President Derek Bok of Harvard University, in a letter dated 18th May disclosed that Harvard had decided on the divestment in September 1989 and completed the stock sale in March 1990.
2	16th June 2000 – University of Michigan	The University of Michigan Board of Regents voted at its June 15-16 meeting to divest the University of its holdings in tobacco manufacturing companies. Robert Kasdin, U-M executive vice president and chief financial officer, will instruct the University's investment managers to sell all relevant stocks within the next 10 months. In divesting itself of the tobacco-related investments, the U-M joins several other institutions—Wayne State, Harvard and Northwestern universities—and public pension funds in California, Florida, Maryland, Texas and New York.
3	23rd May, 2016 – Bloomberg	Axa SA, France's largest insurer, said it will stop investing in tobacco and divest all of its $2 billion dollars of assets in the industry. Axa did not disclose its tobacco investments. According to data compiled by Bloomberg, its holdings include stakes in Philip Morris International Inc., British American Tobacco Plc and Altria Group Inc. "This decision has a cost for us, but the case for divestment is clear: the human cost of tobacco is tragic; its economic cost is huge," Deputy Chief Executive Officer Thomas Buberl, said in the statement. "It makes no sense for us to continue our investments within the tobacco industry."
Panel B – Firearm Stocks		
4	18th December 2012 – Wall Street Journal	Within hours of Friday's shooting at Sandy Hook Elementary School in Connecticut, executives at Cerberus Capital Management LP made the call that Cerberus would put Freedom Group up for sale. Freedom Group is one of the nation's biggest makers of guns and ammunition including the Bushmaster rifle that was used in the shooting at the school.
5	12th April 2013 - CalSTRS	In December 2012, following the Sandy Hook Elementary School tragedy in Connecticut, CalSTRS board member and California State Treasurer, Bill Lockyer, issued a call for the fund to divest from companies which manufacture

		firearms and high-capacity magazines that are illegal for sale to, or possession by, the general public in the state of California. As of December 31, 2012, the total market value of CalSTRS holdings in Sturm Ruger and Smith & Wesson was approximately $3 million, which represented 0.3 basis points of the Global Equity portfolio.
6	15th July, 2016 – Pensions & Investments	New York City Employees' Retirement System's board voted to become the first of the city's five retirement systems to divest its holdings of some gun retailers, said Scott M. Stringer, the fiduciary for the five city pension funds, in an e-mail.
7	22nd August, 2018 – Pensions & Investments	Yale University's board of trustees has adopted a policy prohibiting its $27.2 billion endowment from investing in retail outlets that market and sell assault weapons. The university announced in a statement on Tuesday that the policy was adopted by the board following a recommendation by the board's Committee on Investor Responsibility.
8	22nd February, 2018 - CNBC	New Jersey state lawmakers on Thursday moved to restrict the state's public pensions from investing in the stocks of gun manufacturers. State pensions that own stocks of gun makers, and to a lesser extent, gun retailers, came under criticism after the Feb. 14 shooting, in which 17 people died. After the mass shooting at a concert in Las Vegas last year, California Treasurer John Chiang urged the state's teacher and public employee pensions to sell their holdings of companies that sell assault weapons, ammunition and gun accessories.
	Panel C – Opioid Stocks	
9	30th October 2017 – Pensions & Investments	A coalition of 30 investors representing more than $1.3 trillion in assets is calling on 10 opioid distributors and manufacturers to examine how they are responding to business risks related to opioids. "The opioid crisis has already taken many lives and is a blight on the pharmaceutical industry," said Denise L. Nappier, Connecticut treasurer, principal fiduciary of the Hartford-based $34 billion Connecticut Retirement Plans & Trust Funds, and a member of Investors for Opioid Accountability, in a news release Monday.
10	13th May 2018 – Financial Times	Shareholders of AmerisourceBergen delivered a strong message to the US's third-largest drug distributor in March. Nearly two-thirds of independent voters supported a resolution calling for information on how the board is addressing business risks related to the opioid epidemic. "There are four key areas we currently focus on in healthcare, and of those, the use of opiates is the main one

		right now," says Andy Mason, responsible investment analyst at fund manager Aberdeen Standard Investments.
11	[19th June 2018 – Kentucky.gov]	Attorney General Andy Beshear is urging […] Kentucky Retirement Systems (KRS) and the Kentucky Teachers' Retirement System (KTRS) […] to stop investing funds in the six opioid manufactures and distributors that his office is currently suing over their role in fueling the state's opioid epidemic. Similar letters will be sent to other state agencies and quasi-state agencies that have invested in opioid companies. Beshear wrote based on a March 31, 2018, monthly report of pension investment holdings, it appears that KRS investments in the six companies total nearly $38 million. The Kentucky Teachers' Retirement Systems March 31, 2018, monthly report of pension investment holdings shows the system owns more than 1 million shares between the six companies.
12	[29th April 2019 – Chief Investment Officer]	The California State Teachers' Retirement System (CalSTRS) is taking a role in engaging corporate boards and management of opioid manufacturers, distributors, and pharmacy retail chains it owns in its $115.5 billion global equity portfolio, shows a new pension system report. The CalSTRS report said at the end of 2018, the pension plan, as part of The Opioid Accountability Coalition, has collaborated with other institutional investors on engagements with 17 opioid distributors, manufacturers, and retail pharmacy chains, and achieved reforms with 13 of those companies. Since 2017, the coalition has filed 33 resolutions and reached a settlement with 28 of those companies, the report said.

Appendix 1.B – Explaining *ShareSlope*

In our Ancerno trade tests, we compute the share slope of a trade based on the fund's date *t* trade in security *s* with the change in the position of that fund in that security over the next four weeks and past four weeks of that trade. The *ShareSlope* measure captures how a fund alters its future trades in a security in response to its previous trading activity. Specifically, it is the ratio of the change in a fund's position in a security 28 days after each trade to the change in the fund's position in the 28 days before that trade. It should be kept in mind that the *ShareSlope* measure cannot differentiate from a fund building its position in a security from a fund divesting its position from that security. The following two scenarios should make this clearer.

Scenario A – Positive Accumulation

Date	Position	*ShareSlope*
t-28	150	
t	120	$\frac{100-120}{120-150} = +0.66$
t+28	100	

Scenario B – Positive Divestment

Date	Position	*ShareSlope*
t-28	100	
t	130	$\frac{150-130}{130-100} = +0.66$
t+28	150	

In Scenario A, the fund's position in security *s* at date *t-28* was 150. The fund then reduces its position to 120 by date *t* and 100 by date *t+28*. Then, as of date *t*, *ShareSlope* equals 0.66, indicating that the fund is *exiting* from this security but at a slower rate than it had done so in the past. In Scenario B, the fund starts at an initial position of 100 shares in security *s* at date *t-28*. It then increases its position to 130 by date *t* and 150 by date *t+28*. In this scenario, the *ShareSlope* measure again equals 0.66, but the fund is now *entering* the security. In general, the positive slope measure indicates that the fund has traded in two consecutive buys or two consecutive sells in the security.

Analogously, a negative *ShareSlope* measure suggests that the fund's future trading direction is in the opposite direction to its prior four weeks' trading activity. However, the negative sign cannot differentiate between funds that are reversing their previous sales from funds that are reversing their previous buys. Again, consider these two scenarios:

Scenario C – Negative Accumulation

Date	Position	*ShareSlope*
t-28	130	
t	100	$\frac{120-100}{100-130}=-0.66$
t+28	120	

Scenario D – Negative Divestment

Date	Position	*ShareSlope*
t-28	70	
t	100	$\frac{40-100}{100-70}=-2$
t+28	40	

In Scenario C, the fund's position at date *t-28* stands at 130 shares which reduces to 100 shares by date *t* and then increases to 120 shares by date *t+28*. The *ShareSlope* measure at date *t* equals -0.66, which suggests that the fund's coming four weeks will reverse the previous sale transactions, but not completely. Finally, Scenario D presents the last possible pattern – the fund starts at 70 shares, increases its position to 100 shares, and then reduces the position to 40 shares. In this case, the *ShareSlope* measure equals -2, which suggests that the fund's coming four weeks of trade do not only reverse the past 28 day's purchases but cancel them out.

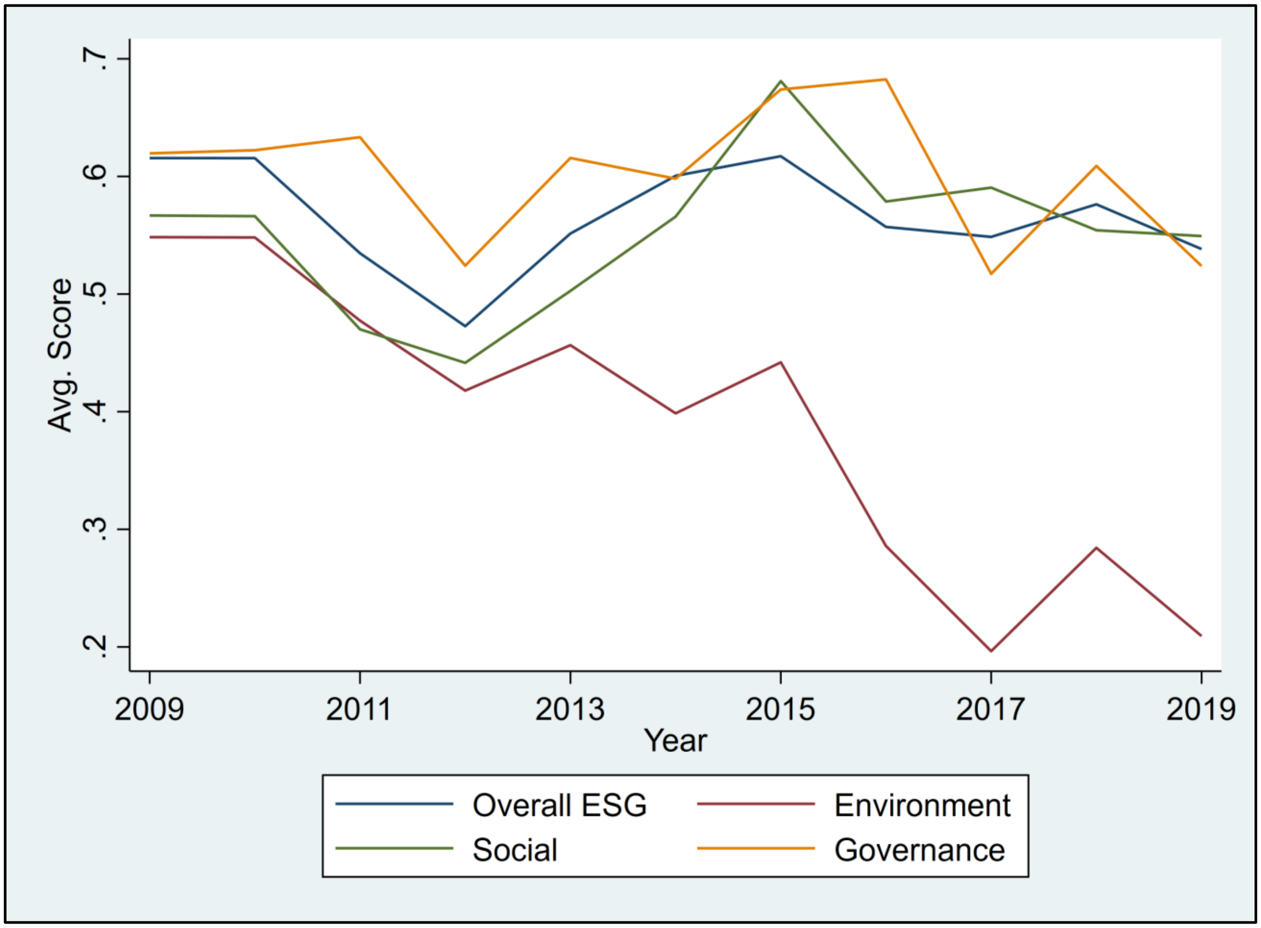
Since the *ShareSlope* measure cannot differentiate between Scenarios A and B (C and D), we define two indicators *NetBuy* and *NetSell*, that take a value of 1 if the fund's change in the position in the past 28 trading days is positive and negative respectively. Interacting these indicators with the *ShareSlope* variable allows us to differentiate between these two scenarios. We use these indicators in Tables 6 and7 of our paper. Finally, since small values in the denominator could result in extremely large values of *ShareSlope*, we winsorize the measure at the 1% and 99% levels.

Appendix 1.C – Variable definitions

Variable Name	**Variable Description**
Change-of-quarter-end and beginning indicators	
QtrEnd$_t$	An indicator variable takes the value of one if date *t* is the last trading day of a quarter (i.e., the last trading day of March, June, September, and December).
QtrBeg$_t$	An indicator variable takes the value of one if date t is the first trading day of a quarter (i.e., the first trading day of January, April, July, and October).
RegularDay$_t$	An indicator variable takes the value of one if date t is not the first or last trading day of a quarter
Stock-level variables	
Ret(t)	Return on trade date *t*.
Sin stock variables	
TobaccoSale	Percentage of sales that a firm derives from the sale of cigarettes, tobacco, and products associated with tobacco use
FirearmSale	Percentage of sales that a firm derives from the sale of civilian firearms and products associated with civilian firearms
SinSale	Sum of *TobaccoSale* and *FirearmSale*
Opioid variables	
OpioidFirm	Indicator variable that takes a value of 1 if the firm has been sued in an opioid epidemic related lawsuit; 0 otherwise
OpioidDistributor	Indicator variable that takes a value of 1 if the firm is a pharmaceutical distributor and has been sued in an opioid epidemic related lawsuit; 0 otherwise
OpioidPharmacy	Indicator variable that takes a value of 1 if the firm is a pharmaceutical retailed and has been sued in an opioid epidemic related lawsuit; 0 otherwise
OpioidManufacturer	Indicator variable that takes a value of 1 if the firm is a pharmaceutical manufacturer and has been sued in an opioid epidemic related lawsuit; 0 otherwise
OpioidLawsuit	Indicator variable that takes a value of 1 if the firm is Johnson & Johnson, AmerisourceBergen, McKesson, or Cardinal Health; 0 otherwise
ESG Variables	
Rank(ESG)	The monthly percentile rank of the firm's standardized ESG rating
Rank(Env)	The monthly percentile rank of the firm's standardized Environmental rating
Rank(Soc)	The monthly percentile rank of the firm's standardized Social rating
Rank(Gov)	The monthly percentile rank of the firm's standardized Governance rating

Fund Ownership Variables	
MFOwn	Percentage of the firm's market capitalization held by mutual funds
InstOwn	Percentage of the firm's market capitalization held by institutional investors
Fund trade level variables	
$ShareSlope_{i,s,t}$	Ratio of the change in position of a fund *i* in security *s*in 28 days after date *t* to the change in position 28 days before date *t*
$NetBuy_{i,s,t}$	An indicator variable that takes the value of one if the change in position of fund *i* in security *s* in the past 28 days before date *t* is positive.
$NetSell_{i,s,t}$	An indicator variable that takes the value of one if the change in position of fund *i* in security *s* in the past 28 days before date *t* is negative.
Control variables	
agr	Annual percentage change in total assets
bm	Book value of equity divided by fiscal-year-end market capitalization
beta	Estimated market beta from weekly returns and equal-weighted market returns for three years ending month t-1 with at least 52 weeks of returns
sue	Unexpected quarterly earnings divided by fiscal-quarter-end market cap. Unexpected earnings equal I/B/E/S actual earnings minus median forecasted earnings if available, else equals seasonally differenced quarterly earnings before extraordinary items from Compustat quarterly file.
gma	Revenues minus cost of goods sold divided by lagged total assets
mve	Natural log of market capitation at the end of month t-1
mom12m	11-month cumulative returns ending one month before month-end.

Figure 1.1 – Average ESG ratings by Year



This figure plots the average standardized ESG score from 2009 to 2019. To arrive at the average yearly ratings, we first calculate the difference of a firm's yearly strength score from the yearly weakness score in each rating category to obtain an overall rating score. We then standardize the score, setting the lowest possible score equal to 0 and the highest possible score equal to 1. We then take the average of the yearly standardized score in each category to arrive at the average rating for that given year.

Table 1.1: Panel A – Distribution of Sin Stocks by Year

	Number of firms			*Percentage of Sales*		
Year	***(1) Tobacco***	***(2) Firearms***	***(3) Sin***	***(4) Tobacco***	***(5) Firearms***	***(6) Sin***
1985	10	3	13	44%	36%	42%
1986	9	3	12	46%	38%	44%
1987	9	3	12	58%	41%	55%
1988	10	3	13	50%	51%	50%
1989	10	2	12	50%	47%	49%
1990	9	4	13	46%	42%	47%
1991	9	4	13	48%	45%	47%
1992	10	4	14	51%	53%	52%
1993	10	3	13	54%	57%	54%
1994	11	3	14	52%	49%	51%
1995	11	4	15	58%	41%	54%
1996	10	4	14	70%	34%	62%
1997	13	5	18	78%	35%	67%
1998	10	5	15	74%	35%	63%
1999	10	5	15	86%	47%	78%
2000	8	3	11	85%	46%	77%
2001	7	3	10	85%	70%	80%
2002	7	4	11	85%	73%	82%
2003	8	4	12	85%	74%	82%
2004	9	4	13	87%	80%	85%
2005	9	4	13	83%	80%	82%
2006	8	4	12	91%	79%	88%
2007	8	4	12	92%	75%	86%
2008	8	4	12	100%	81%	94%
2009	8	4	12	100%	81%	94%
2010	7	3	10	99%	80%	93%
2011	8	3	11	84%	82%	83%
2012	7	4	11	91%	82%	88%
2013	7	4	11	89%	82%	87%
2014	7	4	11	85%	79%	83%
2015	7	5	12	90%	75%	84%
2016	6	5	11	90%	70%	83%
2017	7	5	12	84%	57%	72%
2018	6	6	12	79%	59%	70%
2019	6	6	12	79%	61%	71%

This table tabulates the summary stats of sin stocks. In columns 1-3, we report the year-by-year number of sin stocks listed on the NYSE, AMEX, or NASDAQ. In columns 4-6, we report the annual percentage sales derived by these firms from their sin segments.

Table 1.1: Panel B – *ShareSlope* around key portfolio disclosure dates

	Tobacco	*Firearms*	*Sin*	*Non-sin*
QtrEnd	0.953	1.964	1.078	1.223
QtrBeg	1.974	1.673	1.937	1.396
RegularDay	1.239	1.480	1.271	1.342

The table tabulates the average *ShareSlope* measure around quarter-end dates (i.e., last trading days of March, June, September, and December), quarter-start dates (i.e., first trading days of January, April, July, and October) when most funds record their portfolio positions for future disclosure and non-quarter-end dates (i.e., all other trading days) for tobacco, firearm, and all other stocks.

Table 1.2 – Sin stocks' returns around quarter-ends and beginnings

	(1)	(2)
	Ret(t)	*Ret(t)*
QtrEnd	0.0027***	0.0027***
	(3.34)	(3.34)
QtrBeg	0.0008	0.0008
	(0.90)	(0.90)
*QtrEnd*SinSale*	-0.0044***	
	(-5.34)	
*QtrBeg*SinSale*	0.0037***	
	(-3.46)	
*QtrEnd*TobaccoSale*		-0.0045***
		(-5.37)
*QtrBeg*TobaccoSale*		0.0040***
		(3.26)
*QtrEnd*FirearmSale*		-0.0039*
		(-1.82)
*QtrBeg*FirearmSale*		0.0027*
		(1.68)
Firm FE	Yes	Yes
Month-year FE	Yes	Yes
Asset pricing controls	Yes	Yes
Clustered S.E	Firm & Month-Year	Firm & Month-Year
Observations	30059791	30059791
Adjusted R-squared	0.007	0.007

This table reports regressions of daily returns on indicators for dates around the change in quarters *QtrBeg*, and *QtrEnd*, percentage sale derived from tobacco, *TobaccoSale*, percentage sale derived from the sale of firearms, *FirearmSale*, and their interactions. We also include indicators for changes in months, *MosBeg* and *MosEnd*, lower-order controls (i.e., *SinSale*, *TobaccoSale*, and *FirearmSale*), and other asset pricing controls (see below), their interactions with *QtrBeg*, *QtrEnd*, *MosBeg*, and *MosEnd*. However, for brevity, we do not report the coefficients on these additional controls. Our sample consists of all firms from 1990-2019 having (i) a listing on NYSE, AMEX, or NASDAQ, (ii) exchange code 10 or 11, and (iii) a market capitalization of greater than 10 million USD. Full variable definitions are provided in Appendix C. Standard errors are two-way clustered by security and month-year. t-statistics are reported in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Asset pricing controls: Beta, book-to-market ratio, market value of equity, gross profitability, 12-month momentum, standardized unexpected earnings and asset growth.

Table 1.3 – Evolutions of sin stocks' returns over time

	(1)	(2)	(3)	(4)
	Ret(t)	*Ret(t)*	*Ret(t)*	*Ret(t)*
QtrEnd	0.0048***	0.0031*	0.0014	0.0025**
	(5.30)	(1.80)	(1.06)	(2.07)
QtrBeg	0.0023	-0.0006	0.0009	0.0010
	(1.28)	(-0.45)	(0.59)	(0.45)
*QtrEnd*TobaccoSale*	-0.0001	-0.0104***	-0.0032*	-0.0022**
	(-0.04)	(-4.65)	(-1.69)	(-2.30)
*QtrBeg*TobaccoSale*	0.0020	0.0065**	0.0044*	0.0014
	(0.97)	(1.98)	(1.80)	(1.05)
*QtrEnd*FirearmSale*	-0.0036	0.0028	-0.0069***	-0.0022
	(-0.52)	(0.87)	(-2.95)	(-0.71)
*QtrBeg*FirearmSale*	-0.0082	0.0014	0.0021	0.0048
	(-1.20)	(0.39)	(0.78)	(1.13)
Sample duration	1985-90	1991-00	2000-10	2011-19
Firm FE	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes
Asset pricing controls	Yes	Yes	Yes	Yes
Clustered S.E	Firm & Month-Year	Firm & Month-Year	Firm & Month-Year	Firm & Month-Year
Observations	4519556	10609716	8560905	6369554
Adjusted R-squared	0.011	0.006	0.008	0.009

This table reports regressions of daily returns on indicators for dates around the change in quarters *QtrBeg* and *QtrEnd*, percentage sale derived from the sale of tobacco, *TobaccoSale*, percentage sale derived from the sale of firearms, *FirearmSale*, and their interactions. We also include indicators for changes in months, MosBeg and MosEnd, lower-order controls (i.e., *SinSale*, *TobaccoSale*, and *FirearmSale*), and other asset pricing controls (see below), their interactions with *QtrBeg*, *QtrEnd*, *MosBeg*, and *MosEnd*. However, for brevity, we do not report the coefficients on these additional controls. Our sample consists of all firms from 1990-2019 having (i) a listing on NYSE, AMEX, or NASDAQ, (ii) exchange code 10 or 11, and (iii) a market capitalization of greater than 10 million USD. Full variable definitions are provided in Appendix C. Standard errors are two-way clustered by security and month-year. t-statistics are reported in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Asset pricing controls: Beta, book-to-market ratio, market value of equity, gross profitability, 12-month momentum, standardized unexpected earnings and asset growth.

Table 1.4 – Opioid stocks' returns around quarter-ends and beginnings

	(1)	(2)	(4)	(3)	(5)
	Ret(t)	*Ret(t)*	*Ret(t)*	*Ret(t)*	*Ret(t)*
QtrEnd	0.0017	0.0017	0.0017	0.0017	0.0017
	(1.22)	(1.22)	(1.22)	(1.21)	(1.22)
QtrBeg	0.0003	0.0003	0.0003	0.0003	0.0003
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
*QtrEnd*OpioidFirm*	-0.0030***				
	(-2.81)				
*QtrBeg*OpioidFirm*	0.0027**				
	(2.25)				
*QtrEnd*OpioidDistributor*		-0.0020**			
		(-1.99)			
*QtrBeg*OpioidDistributor*		0.0036**			
		(2.09)			
*QtrEnd*OpioidPharmacy*			-0.0048**		
			(-2.30)		
*QtrBeg*OpioidPharmacy*			0.0019		
			(1.26)		
*QtrEnd*OpioidManufacturer*				-0.0009	
				(-0.58)	
*QtrBeg*OpioidManufacturer*				0.0031	
				(1.52)	
*QtrEnd*OpioidLawsuit*					-0.0021**
					(-2.54)
*QtrBeg*OpioidLawsuit*					0.0029**
					(2.05)
Firm FE	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes
Asset pricing controls	Yes	Yes	Yes	Yes	Yes
Clustered S.E.	Firm & Month-Year	Firm & Month-Year	Firm & Month-Year	Firm & Month-Year	Firm & Month-Year
Observations	5189303	5189303	5189303	5189303	5189303
Adjusted R-squared	0.009	0.009	0.009	0.009	0.009

This table reports regressions of daily returns on indicators for dates around the change in quarters, *QtrBeg* and *QtrEnd*, indicators variables that take a value of 1 if the firm was implicated in the US opioid epidemic. We also include indicators for changes in months, *MosBeg* and *MosEnd*, lower-order controls (i.e. *OpoidFirm*, *OpioidDistributor, etc.*), and other asset pricing controls (see below), their interactions with *QtrBeg*, *QtrEnd*, *MosBeg*, and *MosEnd*. However, for brevity, we do not report the coefficients on these additional controls. Our sample consists of all firms from 2013-2019 having (i) a listing on NYSE, AMEX, or NASDAQ, (ii) exchange code 10 or 11, and (iii) a market capitalization of greater than 10 million USD. Standard errors are two-way clustered by security and month-year. Full variable definitions are provided in Appendix C. t-statistics are reported in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Asset pricing controls: Beta, book-to-market ratio, market value of equity, gross profitability, 12-month momentum, standardized unexpected earnings, and asset growth.

Table 1.5 – ESG stock returns around quarter-ends

	(1) *Ret(t)*	(2) *Ret(t)*	(3) *Ret(t)*	(4) *Ret(t)*	(5) *Ret(t)*	(6) *Ret(t)*
QtrEnd	0.0019	0.0010	0.0015	0.0020	0.0015	0.0027
	(1.13)	(0.56)	(0.80)	(1.13)	(0.72)	(1.21)
QtrBeg	0.0019	0.0014	0.0008	0.0021	0.0013	0.0007
	(0.72)	(0.48)	(0.27)	(0.75)	(0.43)	(0.22)
*QtrEnd*Rank(ESG)*	-0.0007	-0.0040***	-0.0050***			
	(-1.40)	(-3.47)	(-3.31)			
*QtrBeg*Rank(ESG)*	-0.0010	-0.0009	-0.0008			
	(-1.19)	(-0.87)	(-0.58)			
*QtrEnd*Rank(ESG)*MFOwn*		0.0117***	0.0112***			
		(3.47)	(3.36)			
*QtrBeg*Rank(ESG)*MFOwn*		0.0059	0.0055			
		(0.43)	(0.40)			
*QtrEnd*Rank(ESG)*InstOwn*			0.0031*			
			(1.80)			
*QtrBeg*Rank(ESG)*InstOwn*			-0.0004			
			(-0.19)			
*QtrEnd*Rank(Env)*				-0.0001	-0.0010	-0.0021**
				(-0.22)	(-1.49)	(-2.13)
*QtrBeg*Rank(Env)*				-0.0002	-0.0001	0.0000
				(-0.26)	(-0.14)	(0.03)
*QtrEnd*Rank(Env)*MFOwn*					0.0036**	0.0031*
					(2.02)	(1.76)
*QtrBeg*Rank(Env)*MFOwn*					0.0033	0.0028
					(0.39)	(0.33)
*QtrEnd*Rank(Env)*InstOwn*						0.0031**
						(2.18)
*QtrBeg*Rank(Env)*InstOwn*						-0.0005
						(-0.24)
*QtrEnd*Rank(Soc)*				-0.0004	-0.0029***	-0.0031**
				(-0.82)	(-2.94)	(-2.57)
*QtrBeg*Rank(Soc)*				-0.0010	-0.0010	-0.0013
				(-1.58)	(-1.20)	(-1.10)
*QtrEnd*Rank(Soc)*MFOwn*					0.0086***	0.0083***
					(3.06)	(2.96)
*QtrBeg*Rank(Soc)*MFOwn*					0.0032	0.0032
					(0.29)	(0.29)
*QtrEnd*Rank(Soc)*InstOwn*						0.0009
						(0.59)
*QtrBeg*Rank(Soc)*InstOwn*						0.0008
						(0.47)
*QtrEnd*Rank(Gov)*				-0.0004	-0.0010	-0.0022**
				(-1.29)	(-1.25)	(-2.15)
*QtrBeg*Rank(Gov)*				-0.0002	0.0003	0.0006
				(-0.58)	(0.78)	(0.73)
*QtrEnd*Rank(Gov)*MFOwn*					0.0024	0.0019
					(0.82)	(0.65)
*QtrBeg*Rank(Gov)*MFOwn*					-0.0171**	-0.0173**
					(-2.08)	(-2.11)
*QtrEnd*Rank(Gov)*InstOwn*						0.0036**
						(2.29)
*QtrBeg*Rank(Gov)*InstOwn*						-0.0008
						(-0.46)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Asset Pricing Controls	Yes	Yes	Yes	Yes	Yes	Yes
Clustered S.E.	Firm & Month-Year	Firm & Month-Year	Firm & Month-Year	Firm & Month-Year	Firm & Month-Year	Firm & Month-Year
Observations	4716928	4716928	4716928	4716928	4716928	4716928
Adjusted R-squared	0.009	0.009	0.009	0.009	0.009	0.009

This table reports regressions of daily returns on indicators for dates around the change in quarters, *QtrBeg* and *QtrEnd*, monthly percentile rank of the firm's ESG score, *Rank(ESG)*, the percentage of a firm's market capitalization owned by mutual funds, *FundOwn*, and their interactions. In Columns 4-6, we split firm's ESG rank into its constituent environment rank, *Rank(Env)*, social rank, *Rank(Soc)*, and governance ranks, *Rank(Gov)*. We also include changes in months, *MosBeg* and *MosEnd*, and other asset pricing controls (see below), but we do not report the coefficients on these additional controls for brevity. Our Sample consists of all firms from 2010-2019 having (i) a listing on NYSE, AMEX or NASDAQ, (ii) exchange code 10 or 11, and (iii) a market capitalization of greater than 10 million USD. Standard errors are two-way clustered by security and month-year. t-statistics are reported in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Asset pricing controls: Beta, book-to-market ratio, market value of equity, gross profitability, 12-month momentum, standardized unexpected earnings, and asset growth.

Table 1.6 – Funds trading activity around quarter-ends and beginnings

	(1) *ShareSlope*	(2) *ShareSlope*
QtrEnd	-0.2323***	-0.2324***
	(-3.25)	(-3.25)
QtrBeg	0.1209***	0.1209***
	(3.00)	(3.00)
*QtrEnd*SinSale*	-0.1857	
	(-0.76)	
*QtrBeg*Sinsale*	0.7408**	
	(2.48)	
*QtrEnd*TobaccoSale*		-0.3221
		(-1.14)
*QtrBeg*TobaccoSale*		0.6713**
		(2.05)
*QtrEnd*FirearmSale*		1.5864**
		(2.11)
*QtrBeg*FirearmSale*		1.6914*
		(1.83)
Intercept	1.3416***	1.3416***
	(1037.02)	(1037.04)
Fund FE	Yes	Yes
Security-by-month FE	Yes	Yes
Two-way clustered SE	Firm & Month-Year	Firm & Month-Year
Observations	39882373	39882373
Adjusted R-squared	0.014	0.014

This table reports regressions of *ShareSlope* on the interactions between indicators for dates around the change in quarters, *QtrEnd* and *QtrBeg*, percentage sale derived from the sale of tobacco, *TobaccoSale*, percentage sale derived from the sale of firearms, *FirearmSale*, and their interactions. We estimate this regression using all transactions marked by Ancerno as 'good trades' over the period 1998 – 2010 after excluding trades from client managers that do not execute at least one trade in both the prior and subsequent month. Full variable definitions are provided in Appendix C. Standard errors are two-way clustered by security and month-year. t-statistics are reported in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 1.7 – Funds trading direction around quarter-ends

	(1) *ShareSlope*	(2) *ShareSlope*
NetBuy	-0.8842***	-0.8841***
	(-32.68)	(-32.68)
*QtrEnd*NetBuy*	-0.2008**	-0.2009**
	(-2.22)	(-2.22)
*QtrEnd*NetSell*	-0.2457***	-0.2457***
	(-3.19)	(-3.19)
*QtrBeg*NetBuy*	0.0604	0.0604
	(1.47)	(1.47)
*QtrBeg*NetSell*	0.1531**	0.1531**
	(2.45)	(2.45)
*QtrEnd*NetBuy*SinSale*	0.2816	
	(1.19)	
*QtrEnd*NetSell*SinSale*	-0.6454	
	(-1.27)	
*QtrBeg*NetBuy*SinSale*	0.6985***	
	(2.80)	
*QtrBeg*NetSell*SinSale*	0.7818	
	(1.10)	
*QtrEnd*NetBuy*TobaccoSale*		0.0195
		(0.07)
*QtrEnd*NetSell*TobaccoSale*		-0.6457
		(-1.22)
*QtrBeg*NetBuy*TobaccoSale*		0.6221**
		(2.38)
*QtrBeg*NetSell*TobaccoSale*		0.7190
		(0.95)
*QtrEnd*NetBuy*FirearmSale*		3.1482***
		(2.70)
*QtrEnd*NetSell*FirearmSale*		-0.6422
		(-0.77)
*QtrBeg*NetBuy*FirearmSale*		1.5431
		(1.11)
*QtrBeg*NetSell*FirearmSale*		1.8500
		(1.52)
Intercept	1.7961***	1.7961***
	(126.69)	(126.73)
Fund FE	Yes	Yes
Security-by-month FE	Yes	Yes
Two-way clustered SE	Firm & Month-Year	Firm & Month-Year
Observations	39882373	39882373
Adjusted R-squared	0.015	0.015

This table reports regressions of *ShareSlope* on the interactions between indicators for dates around the change in quarters, *QtrEnd* and *QtrBeg*, percentage sale derived from the sale of tobacco, *TobaccoSale*, percentage sale derived from the sale of firearms, *FirearmSale*, and indicators for whether the net trades in the prior one month of trade were buys, *NetBuy* or sells, *NetSell*, and their interactions. We estimate this regression using all transactions marked by Ancerno as 'good trades' over the period 1998 – 2010 after excluding trades from client managers that do not execute at least one trade in both the prior and subsequent month. Full variable definitions are provided in Appendix C. Standard errors are two-way clustered by security and month-year. t-statistics are reported in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Chapter 2

More informative disclosures, less informative prices? Portfolio and price formation around quarter-ends

2.1 Introduction

Because portfolio disclosures convey information incremental to fund returns, they play a vital role in allocating capital. Asset managers scrutinize the specific stocks mutual funds hold when making allocation decisions, and fund flows respond to media coverage and assessments of reported positions (e.g., Solomon et al., 2014; Hartzmark and Sussman, 2019). Disclosures can also be combined with information about fund benchmarks and realized returns to predict future fund performance, providing further justification for scrutinizing disclosed positions (e.g., Kacperczyk et al., 2008; Sensoy, 2009; Cremers and Petajisto, 2009; Cremers and Pareek, 2016). This scrutiny is likely to affect fund managers' trading decisions, and in turn, price formation. Consistent with this possibility, practitioners argue that disclosures affect funds' allocation choices in the days before they record holdings (e.g., Durden, 2018), and the timing of these disclosures, which primarily occur on a quarterly basis, coincides with what Jim Cramer of CNBC referred to as the "quarter-end phenomenon," a perception that prices are less informative around quarter-ends. In this paper, we analyze whether portfolio formation and, ultimately, price discovery do in fact change around when most funds make disclosures.

To analyze whether portfolio formation varies with the reporting cycle, we use Abel-Noser's fund-level trading data (Ancerno) to create a novel classification of every trade based on its association with prior and future trades of the fund. Using a four-week window around each trade, we classify trades into one of four categories: initiating, building, completing, and one-off. "Initiating" trades do not resemble prior trades within the window but do predict future trades [e.g., a fund makes an initial purchase (sale) of a particular stock and continues to be a net purchaser (seller) over the next four weeks], while "completing" trades are predicted by past trades but do not resemble future trades [e.g., a purchase (sale) was preceded by earlier purchases (sales) of the same stock but no additional net purchases (sales) over the next four weeks]. Trades that "build" a position are both preceded and followed by similar trades, while "one-off" trades are neither preceded nor followed by similar trades. We then analyze whether the distribution of trade types shift around the most common dates that funds record positions for disclosure. In particular, because funds record positions for voluntary and mandatory disclosures on month-end days, with most of these occurring on quarter-ends, we focus on trading dynamics around these dates.

Using our trade classification system, we show that funds construct positions on a quarter-by-quarter basis, consistent with disclosures affecting portfolio formation. First, relative to other days, funds are 13.6% less likely to initiate new positions on the last day of a quarter (i.e., the day when most position recordings occur) but 7.4% more likely to initiate new positions the first day of the quarter. The opposite pattern occurs for trades that complete positions. The cyclical pattern around quarter-ends also extends to one-off and building trades. Specifically, we find more one-off trades around quarter-ends, both before and after the quarter-end, while finding the opposite for building trades. For example, a trade is 40.1% (14.2%) more likely to be a one-off trade on quarter-end (quarter-start) days. We observe similar, but attenuated, dynamics around other month-end days when fewer funds report positions.

We next analyze the potential disclosure-related motives for these trade dynamics. One possibility is that funds are timing their trades to exert price pressure and inflate net asset values before recording positions (e.g., Carhart et al., 2002; Hu et al., 2013). A second possibility is that fund managers are putting less weight on maximizing expected returns when making pre-disclosure trades and putting more weight on the specific positions they wish investors to see (e.g., Haugen and Lakonishok, 1988; Musto, 1997, 1999). For example, funds might rebalance or accelerate the completion of trading campaigns to make their reported holdings more reflective of their planned allocation. Funds might also conceal positions by temporarily trading out of them or by delaying intended positions they need more time to build or do not want to disclose.

Portfolio-pumping trades do not appear to drive these quarterly dynamics. Although buy trades increase relative to sell trades on quarter-end days (e.g., Hu et al. 2013), this dynamic is not concentrated in certain trade types, as would be predicted by portfolio pumping. Instead, the quarter-end dynamics we document are driven by both buy and sell trades for each trade type. We also find no evidence that the quarter-end increases in completing and one-off purchases are concentrated among a fund's larger holdings, where the mark-to-market motive would be greatest.

The quarterly trade dynamics instead appear to reflect an attempt by funds to manage the information they disclose to potential investors. On the one hand, funds appear to execute trades designed to make their quarterly disclosures more informative of planned future holdings. In particular, funds accelerate the completion of existing positions and execute more one-off trades that rebalance positions back to desired levels. At the same time, funds also appear to decrease the informativeness of their disclosures by not initiating new positions until the start of the next quarter. This delay appears driven by a desire to create more time to get the trades done before disclosing them. Consistent with this motive, the delay in initiating trades is larger among illiquid and small-cap stocks, for which funds might want to build a position slowly to avoid exerting price pressure, and trading campaigns begun on the first day of the quarter are larger in size and spread across more trades. Funds likely less able to manage illiquidity, smaller funds and funds that trade less frequently, are also more likely to delay trading campaigns until the next quarter.

On net, the observed quarterly trade dynamics appear to increase the overall informativeness of disclosures. Specifically, we find that quarter-end portfolios do a better job of predicting funds' future positions than portfolios on other days. Thus, while the delay in initiating new positions would tend to decrease the informativeness of disclosures, the increased informativeness caused by accelerating planned positions appears to more than offset this impact.

We next examine whether the quarterly trade dynamics we document are associated with changes in price formation. Because funds earn the bulk of their excess returns when initiating and building long-term positions (e.g., Di Mascio et al., 2017; Chakrabarty et al., 2017), the quarter-end decline in such trades could reduce price discovery. More generally, if quarterly disclosures cause fund managers to execute trades for reasons unrelated to new information or intrinsic values, the resulting trades could reduce price informativeness on quarter-end days.

Consistent with funds executing quarter-end trades for disclosure- rather than information-based motives, we find that price informativeness declines at quarter-ends. Specifically, returns on quarter-end days explain less of the variation in longer-term price changes than returns on other days. The magnitude of the decline is economically significant. Relative to other days, returns on the last day of the quarter are 32% less informative about 30-day returns. This decline in price informativeness is present (though smaller in magnitude) in other days leading up to the quarter-end and present for each of the four quarter-ends. There is little evidence of a change in the relative informativeness of daily returns on the first day of the quarter or around other month-ends.

Finally, we analyze commissions. Because brokers provide access to information (Green et al., 2014) and funds compensate brokerages using commissions (e.g., Goldstein et al., 2009), a quarter-end drop in commissions would also be indicative of funds trading on less new information around quarter-ends. Consistent with this possibility, we find that the commissions paid by funds decline around quarter-ends, and a drop in commissions paid within a given fund-broker pair drives this decline. There is no evidence of funds shifting to lower fee brokerages at quarter-end. The total commissions paid by a fund over the year are also smaller when a larger proportion of the trades executed with that broker occur on quarter-end dates.

This paper makes two key contributions. First, our evidence expands our knowledge of how disclosure affects fund trading decisions. The prior literature investigates whether disclosures induce funds to execute trades designed to deceive investors or conceal investment strategies, which will tend to make disclosures less informative.[8] In contrast, we document that disclosures lead funds also to adjust the timing of trading campaigns. In particular, funds delay initiating new positions until after quarter-end and accelerate the completion of existing positions before quarter-end. Moreover, while the delayed trades conceal fund managers' intentions, the trades that fund managers accelerate and execute at quarter-end tend to make subsequent disclosures more (not less) informative about positions the fund will hold going forward.

The second contribution is related to the literature on the information externalities of disclosures. Many studies implicitly assume these externalities are positive because the information has an ameliorative effect on market functioning (e.g., Leuz and Wysocki, 2016). For example, reporting requirements can discipline managers into doing research and executing trades that accelerate information into the price. If true, we would expect price changes on quarter ends to exhibit momentum as subsequent investors trade in the same direction as the informed trades induced by disclosure (Campbell et al., 1993). However, others argue that disclosures can distort prices (e.g., Haugen and Lakonishok, 1988; Musto, 1997, 1999).[9] We find evidence of the latter. Quarter-ends, when most funds record positions, are associated with less informative prices and subsequent return reversals, and these

[8] Such "window-dressing" strategies analyzed by the prior literature include: (i) concealing risk (e.g., Musto, 1997 and 1999), (ii) buying winners and selling losers (e.g., Haugen and Lakonishok, 1988; Lakonishok et al., 1991; Meier and Schaumburg, 2004; Agarwal et al., 2014), (iii) concealing fund strategy (e.g., Wermers, 2011), and (iv) reporting high dividend yield (e.g., Hartzmark and Solomon, 2013; Harris et al., 2015).

[9] Haugen and Lakonishok (1988) argue that the "January effect," where stock returns tend to surge in early January, might be driven by institutions' attempt to make their annual disclosures appear stronger by selling small stocks at year-end or by not buying such stocks until the new year begins. Similarly, Musto (1997; 1999) provides evidence that such window-dressing motives also affect year-end commercial paper prices.

price dynamics appear partly driven by how funds' adjust portfolios for quarter-end disclosures. These findings indicate that, on net, providing information about fund holdings tends to distort secondary market prices around quarter-ends.

2.2 Potential impact of disclosures on trading and prices

Investors receive information about fund portfolios through both mandatory SEC filings and voluntary disclosures to large data vendors. Institutional investors are subject to mandatory ownership disclosure requirements by the SEC – Form 13F and Forms N-CSR and N-Q (these latter two forms replaced Form N-30D in May 2004). While both disclosures are filed quarterly, Form 13-F filings are aggregated at an institution level and reported on quarter-end days of the calendar year while Forms N-CSR and N-Q are filed at the individual fund level and reported on quarter-end days of the fund's fiscal year (which frequently coincides with the calendar year). In addition, mutual funds often provide voluntary, fund-level disclosures to major data vendors, like CRSP, Morningstar, and Thomson Reuters, and for convenience reasons, these voluntary disclosures typically coincide with quarter-end days of the calendar year when institutions are already having to file their Form 13F (Schwarz and Potter, 2016).

The importance of quarter- and month-end dates for disclosures is shown in Table 1, which tabulates the frequency of reported holdings by date across two databases commonly used by investors. In the Thomson-Reuters S-12 dataset, which includes a mixture of mandatory and voluntary disclosures, the vast majority of disclosed holdings occur on quarter-end days of the calendar year (i.e., the last day of March, June, September and December). By dollar value, 80.9% of reported holdings were recorded on these dates, and almost all of the remaining holdings are recorded on other month-end days (19.1%) (Table 1, Column 1). Prior to 2008, the pattern is similar for recorded holdings reported through the CRSP Mutual Fund Database (Column 2), but the number of other month-end recordings in CRSP is slightly higher in more recent years (Column 3). In 2008, CRSP migrated to using data from Lipper instead of Morningstar, and this seems to have resulted in an increase in its proportion of SEC-mandated disclosures, which are more likely made on other month-end days (Schwarz and Potter, 2016). However, even in these later years, roughly half of all disclosures occur on quarter-ends, meaning CRSP fund holdings are still twice as likely to be recorded on a quarter-end than on other month-ends.

These disclosures (whether they be voluntary or mandated) are important as they are scrutinized by asset managers and can influence investor allocations. For example, wealth advisory firms like JP Morgan, Edward Jones, and Wells Fargo Advisors, typically employ a team of analysts to review these portfolio disclosures and make recommendations that impact the funds their organizations invest clients' money in. These fund analysts use reported holdings to assess whether the funds' holdings are consistent with its stated strategy, to assess the riskiness of the portfolio, and to question fund managers about their investment strategy and comparative advantage. Consistent with reported portfolio holdings affecting assets under management, Solomon et al. (2014) show that positions that attract media attention tend to generate flows. Relatedly, Hartzmark and Sussman (2019) show that the Morningstar ESG rankings of funds, which are a function of reported holdings, also affect fund flows.

The intense scrutiny of these disclosures might in turn affect portfolio allocation through a number of channels. Funds might engage in portfolio-pumping trades to inflate reported returns (Carhart et al., 2002; Hu et al., 2013). Funds might also engage in trades designed to manage the information being disclosed to investors (Haugen and Lakonishok, 1988). For example, numerous practitioner-focused articles argue that funds make window-dressing trades (e.g., Kansas, 2011) to conceal past or future positions of the fund. On the other hand, funds might rebalance their portfolios before revealing them to investors to achieve their preferred mix of assets (e.g., D'Allegro, 2016; Durden, 2018), thus making disclosures more informative of future positions.

It is also possible that disclosures cause firms to shift the timing of trading campaigns and the type of information they trade upon so as to avoid disclosing incomplete positions. For example, funds might delay initiating trading campaigns based on new information so as to avoid disclosing a position that is not yet fully built and that they are not yet ready to discuss with potential investors. This desire to delay could be particularly salient for new positions where the fund seeks to build a larger position or do so over a longer time period. Funds might also be more likely to complete trading campaigns that were previously started based on past information so as to use the next disclosure to market these positions and provide investors with a better sense of the weighting each stock will receive in the portfolio moving forward.

The evaluation process of major fund customers, including Edward Jones and JP Morgan, could also affect fund managers' disclosure-motivated trading incentives. These large fund customers often conduct automated 'attribution' tests on disclosed portfolios to assess the proportion of abnormal performance that is explained by individual positions and to flag performance that cannot be explained by disclosed positions. Avoiding unexplained performance, which often leads to a follow-up call with a wealth manager, provides motivation for fund managers to make reported positions informative about their funds' holdings.

How these potential shifts in portfolio formation around quarterly disclosures affect price efficiency will depend on their connection to intrinsic value. If disclosures cause fund managers to trade for reasons unrelated to intrinsic value (e.g., to engage in portfolio pumping, to manage the information being disclosed, or to avoid reporting incomplete positions), the trades could induce price movements that do not reflect intrinsic values and are less informative of the future price. Alternatively, if disclosure induces investors to adopt positions that better reflect their information about intrinsic values, the resulting price movement would be more informative of longer-term price movements as the trades push price towards its intrinsic value.

Because it is ex-ante unclear how fund managers portfolio formation strategies will react to disclosure requirements or how this potential shift might affect price efficiency, it is necessary to test for their impact. We now turn to discussing our empirical strategy.

2.3 Data and variable definitions

Our independent variables of interest are four indicator variables that flag key dates around when most funds record their holdings for subsequent disclosures. The first indicator, *Qtr_End*, captures the last trading day of each calendar-year quarter (i.e., last trading day of March, June, September, and December), and the second indicator, *Month_End*, captures the end of all other months. Collectively, these two indicators capture the dates on which nearly all funds record their holdings (see Table 1). We then construct two similar indicators to capture the first trading day after when most positions are recorded. Specifically, we define *Qtr_Beg* as the first trading day of each calendar-year quarter (i.e., first trading day of January, April, July, and October) and *Month_Beg* as an indicator for the first trading day of all other months.

To assess whether trading dynamics differ around these dates, we use the Ancerno proprietary dataset from Abel Noser Solutions, a financial services firm that provides trading cost analytics advice to institutional asset owners, managers, and brokers, such as mutual funds and pension funds. The Ancerno dataset allows us to observe trade-level data from institutions that subscribe to Abel Noser's services, which covers about 12 percent of CRSP trading volume (Hu et al., 2018). The data includes the date of fund managers' transactions, the stock symbol of the trade, the number and value of shares traded, and any commissions paid. While the dataset anonymizes the name of the trading fund manager, identification codes for managers are provided, which allows us to track each fund's trades across stocks and over time. For our analysis, we include all transactions marked by Ancerno as 'good trades' (i.e., trades that were actually executed) over the period 1998 – 2010, which reflect the earliest year of the Ancerno data and the latest year made available to us. We further require that the client manager execute at least one trade in both the prior and subsequent month, to ensure our findings are unaffected by a subscription lapse.[10]

We classify each trade by its association with the sign of both past and future trades executed by the same fund. To do this, we begin by summing across trades to create a fund-security-date measure of shares transacted. We then take the sign of these trades (*Sign*(Vol_t)) and delete the small number of cases for which sells and buys net out to zero (~0.2% of the sample). At the fund-security level, we then aggregate trades over the previous and subsequent four weeks and calculate the sign of both the past and future volume, *Sign*($Vol_{previous}$) and *Sign*($Vol_{subsequent}$).

We categorize all day *t* trades into the four categories, *Building*, *Initiating*, *Completing*, and *One-off*, based on the association between the sign of the trade on day *t* and the sign of past and future trades. Specifically, we define *Building* trades as those for which day *t* volume has the same sign as both the past and future volume of trades in that stock by that fund. Consistent with funds building positions gradually (e.g., Di Mascio et al., 2017; Chakrabary et al., 2017), this is the most common trade type (44.2% of trades). We define *Initiating* trades as day *t* trades that predict the sign of future trade volume but is not predicted by the sign of past trade volume (e.g., the fund is a net seller of the stock on day *t* and over the next four weeks but was not a net seller of the shares in the prior four weeks). This is the least common type of trade (17.6% of trades). We define *Completing* trades as those for which the sign of past trade predicts day *t* trade, but day *t* trade does not predict the sign of future trade (e.g., the fund was a net buyer in the prior four weeks and on day *t*, but not in the subsequent four weeks). Finally, we classify *One-off* trades as those for which day *t* trade is neither predicted by past volume nor predicts future volume. Our subsequent findings are robust to using either a shorter or longer trading window to classify each trade; in particular, the paper's findings are similar when using

[10] Because fund names are anonymized in Ancerno, we are not able to ascertain when each fund's fiscal year ends, which prevents us from determining when each fund records positions for its mandatory SEC disclosures. Moreover, because asset managers often demand information on a fund's holdings when they are considering a change in asset allocation, many funds provide voluntary disclosures of their holdings to large data vendors on month- and quarter-ends that do not coincide with the funds' fiscal quarter. Therefore, trades around these times can be disclosure-motivated even if the disclosure is not made to the SEC.

one-, two-, or six-week windows. A breakdown of the trades and their frequency in our data is given below:

Classification of day *t* trades	Predicted by prior trade *$Sign(Vol_t)=Sign(Vol_{previous})$*	Not predicted by prior trade *$Sign(Vol_t)\neq Sign(Vol_{previous})$*
Predicts future trade *$Sign(Vol_t)=Sign(Vol_{subsequent})$*	*Building* (44.2%)	*Initiating* (17.6%)
Does not predict future trade *$Sign(Vol_t)\neq Sign(Vol_{subsequent})$*	*Completing* (18.0%)	*One-off* (20.2%)

There are considerable differences in the average characteristics of the different trade types. Table 2, where we provide descriptive statistics for the characteristics of each trade type, illustrates these differences. For example, *One-off* trades are more likely to be sales while *Building* and *Completing* trades are more likely to be purchases. Among the four trade types, *One-off* trades tend to have the smallest volume, while *Building* trades tend to have the largest.

We also construct an additional measure of trade, the commissions paid per share (*CommissionsPerShare*). Commissions are often used to compensate brokerages for information from both the brokerage and management companies (e.g., Goldstein et al., 2009). To compute commissions per share, we sum commissions over all trades at the fund-security-date level and divide by the number of shares traded. We winsorize *CommissionsPerShare* at zero and ten cents to constrain ourselves to commissions commonly paid by funds (e.g., Goldstein et al., 2009; Anand et al., 2011). In our sample, the average commission is about two cents per share.

To assess whether pricing dynamics differ around common disclosure days or when the types of trades being executed in a stock differ, we calculate stock returns by obtaining the security prices from the Center for Research in Security Prices (CRSP) database and limiting the sample to common shares (i.e., share code 10 or 11) that trade on the NYSE, AMEX or NASDAQ with a prior month-end market capitalization larger than ten million dollars. We provide a full description of these variables, along with all other variables, in Appendix A.

2.4 Fund trading patterns around quarter- and month-ends

In this section, we first analyze whether trading dynamics are different around the days in which most funds record positions for subsequent disclosures. We then analyze the potential disclosure-related explanations for any observed shifts in trading dynamics.

2.4.1 Frequency of trade types around quarter- and month-ends

To test for whether reporting cycles are associated with shifts in trade dynamics, we begin by estimating a simple linear regression to understand how the frequency of each trade type changes around the end of the quarter, the most common date on which funds record and disclose positions. Specifically, we regress our four trade-type indicators, which are unique at the fund-security-date level, on indicators for whether the date coincides with one of the last five (i.e., $[t-4, t]$) or first five trading days (i.e., $[t+1, t+5]$) of a quarter. Specifically, we estimate

$$Trade\_Cat_{ist} = \alpha + \sum_{n=-4}^{5} \gamma_n QTR\_End_{t-n} + \varepsilon_{ist}\ , \quad (1)$$

where $Trade\_Cat_{ist}$ is one of our four trade-type classifications measured at the fund level *i*, for security *s*, on date *t*, and Qtr_End_{t-n} are indicators for days around the quarter-end. Specifically, Qtr_End_{t-3} indicates three trading days before the end of the quarter, Qtr_End_{t} indicates the last trading day of the quarter, and Qtr_End_{t+3} indicates three trading days after the quarter end. To be conservative, we cluster the standard errors at both the security and month-year levels.[11]

The coefficient estimates on our indicators equals the difference in trade-type frequency between days around the quarter-end and the intercept, α, which equals the trade-type frequency for trades not within five trading days of a quarter-end. For example, because 15.2% of trades on the last

[11] We use two-way clustering at the security and month-year levels as this yields the most conservative *t*-statistics. The *t*-statistics are higher if we instead cluster at the security and day levels or if we do not cluster at all.

day of the quarter (i.e., *t*) are *Initiating* trades and 17.6% of trades not around the quarter-end are *Initiating* trades, the regression coefficient we plot in the graph, -2.4 percentage points, represents the abnormal frequency of *Initiating* trades on that day.

We find strong evidence of a shift in the likelihood that funds initiate new positions around quarter-ends. This is seen in Panel A of Figure 1. Funds initiate positions with below average frequency on the last day of the calendar quarter (-2.4 percentage points) and above average frequency on the day after the quarter-end (1.3 percentage points). Each of these differences are statistically significant at conventional levels, as indicated by the *t*-stats reported in parenthesis next to each point estimate. Because 17.6% of trades in our sample are classified as *Initiating*, the day *t* difference indicates that funds are 2.4/17.6 = 13.6% less likely to initiate positions on quarter-ends relative to an average trading day, and 1.3/17.6 = 7.4% more likely to initiate positions on the first trading day of the quarter. While the quarter-end decrease in *Initiating* trades is concentrated at the last day of the quarter, the increase in *Initiating* trades persists for four days after the quarter-end, with an abnormal frequency of about 1.0 percentage points each day.

For *Completing* trades, we observe the inverse dynamic, as seen in Figure 1, Panel B. *Completing* trades are 1.6 percentage points more likely the day before the quarter-end and 0.9 percentage points less likely on the post-quarter-end day. Funds also complete positions with above average frequency the day prior to the calendar quarter-end, but the increase is only marginally significant (*t*-stat = 1.88). There is also suggestive evidence that funds complete positions with below average frequency on each of the four trading days following the post-quarter-end day, but none of these differences are significantly different from zero.

The trading dynamics for *One-off* trades and *Building* trades are also different around quarter ends, but unlike *Initiating* and *Completing* trades, these trade types show similar shifts both before and after the quarter-end. Specifically, funds are more likely to execute *One-off* trades at both the end and start of the quarter, with the effects being particularly pronounced on the last trading day of the quarter (Figure 1, Panel C). Trades are 8.0 and 2.8 percentage points more likely to be a *One-off* trade on the last and first trading day of quarters, respectively, which corresponds to increases of 40.1% and 14.2% relative to all other days. *Building* trades, however, exhibit the inverse pattern by declining in frequency both before and after the quarter end, with the biggest decrease of 7.2 percentage points occurring on the quarter-end day (Panel D).[12]

2.4.2 Regression analysis of trade types around quarter- and month-ends

The univariate patterns in trades around quarter ends suggest that funds construct portfolios on a quarter-by-quarter basis by completing existing positions before the quarter-end and initiating new positions afterward. In this section, we construct multivariate tests to examine whether these univariate trading patterns might instead be explained by differences in the type of securities traded, transaction characteristics, or the types of funds that choose to transact on these days. In addition to using our multivariate analysis to examine trade-type frequencies around quarter-ends, we also examine trade-type frequencies around other month-ends, another frequent reporting day.

We test whether these shifts in trading dynamics are robust to controlling for various fund, stock, and trade characteristics around quarter- and month-ends by estimating

$$Trade\_Cat_{ist} = \beta_1 Qtr\_End_t + \beta_2 Qtr\_Beg_t + \beta_3 Month\_End_t + \beta_4 Month\_Beg_t + X_{ist} + \delta_s \times MonthFE + \alpha_i + \varepsilon_{ist}, \quad (2)$$

where *Qtr_End*, *Qtr_Beg*, *Month_End*, and *Month_Beg* are indicators to flag the last and first trading days of the quarter and other months. To account for the potential confounding effect of fund

[12] Motivated by Lakonishok et al. (1991), who present evidence that year-end portfolio holdings are scrutinized more intensively, we also investigate whether trading dynamics differ between year-ends and other quarter-ends. In untabulated analysis, we find that the observed quarterly trade dynamics occur around both types of quarter-ends. However, the observed shift for *Initiating* trades is larger at year-end, consistent with funds' managing the flow of information about new trading campaigns more at year-end (Haugen and Lakonishok, 1988).

redemptions, which are more frequent around quarter-ends, we include two controls for order-imbalances at the fund-level and their interactions with our four turn-of-the-month indicators, X_{ist}.[13] To ensure our results are not driven by prices, trade sizes and signs, and the volume of trade, we include a bevy of controls for these trade characteristics.[14] We include fund fixed effects α_i to control for fixed differences in funds' trading patterns and security-by-month-year fixed effects, $\delta_s \times MonthFE$, to control for time-varying differences in security characteristics (such as liquidity). We continue to cluster our standard errors two ways, on security and month-year.

The shift in trading dynamics around quarter-ends is not driven by a shift in other trade or stock characteristics or their importance around these particular dates. This is shown in Table 3. Even with the additional controls, we still find that funds execute *Initiating* trades less frequently before quarter-ends and more frequently after them (Table 3, Column 1), and the opposite is true for *Completing* trades (Column 2). Moreover, we continue to see an increase in *One-off* trades (Column 3) and a decrease in *Building* trades (Column 4). The coefficient magnitudes are also comparable to those presented in our univariate plots. For example, *Qtr_End* loads with a coefficient of -2.5 percentage points in the estimation (Column 1), similar to the -2.4 percentage-point difference for quarter-end days reported in Figure 1. We find similar patterns, though less prominent, around other month-end days, as seen by comparing the coefficients on *Month_End* and *Month_Beg* to those found for *Qtr_End* and *Qtr_Beg*. The attenuated pattern around other month ends is consistent with fewer firms recording positions on those days (see Table 1).

[13] Specifically, we include an indicator for whether the fund has net outflows on that date and the signed log of the dollar value of fund flows for that date. We also include interactions between each of these two variables and our four turn-of-month indicators.

[14] We include the following trade-level controls: sign of trade (i.e., buy or sell), shares traded, signed log of number of shares traded, absolute value of log of number of shares traded, dollar volume of trade, signed log of dollar volume of trade, absolute value of log dollar volume, price, price squared, and price logged.

2.4.3 Interpretation

The shift in trading dynamics documented in Figure 1 and Table 3 is consistent with funds adjusting their trading strategies in response to the quarterly reporting cycle. For example, some of the dynamics, including the spike in *One-off* trades, might be driven by a desire to deceive investors. Such shifts in trade dynamics could reduce the informativeness of disclosures. On the other hand, the increase (decrease) in *Completing* trades prior to (after) the quarter's end could be driven by funds seeking to finish existing trading campaigns so that reported holdings are reflective of the positions the funds plan to hold and market in subsequent sales-related discussions. Such shifts, if present, would tend to increase the informativeness of fund disclosures. And the decrease (increase) in *Initiating* positions prior to (after) the quarter's end could be driven by funds' desire to avoid trading on new information the fund is not yet ready to discuss with investors.

We next analyze these and other possible motives for why funds might undertake different trades around quarter- and month-ends, and how these trade dynamics affect disclosure informativeness. In particular, we analyze the potential role of portfolio pumping and funds' incentives to manage the information released in their disclosures. We also analyze whether funds are delaying some trades to avoid having a disclosure interfere with the building of a new position.

2.4.3.1 Portfolio pumping?

One potential explanation for the quarter-end shifts in portfolio formation is that funds are timing their trades because of concerns regarding the quarter-end marking of their positions (e.g., Carhart et al., 2002). For example, a fund manager might execute buy trades at quarter-end because the resulting price pressure increases the quarter-end valuation of an existing position, not because a larger position is otherwise warranted. And by extension, the manager might delay selling some of a position at quarter-end – though would not avoid selling all of it – because the resulting price pressure decreases the marked valuation of the remaining position. Consistent with such motives, Hu et al. (2013) find the percentage of buy trades increases on quarter-ends, and we find a similar pattern in our data. If these increased buys and decreased sales are concentrated in different trade types, then portfolio pumping might explain the observed quarter-end trade dynamic. Specifically, for trade types that increase in frequency at quarter-end (i.e., *Completing* and *One-off*), we would expect buy trades, not sales, to drive this change. And for trade types that decrease in frequency (i.e., *Building* and *Initiating*), we would expect reduced sales, not reduced buys.[15]

To assess this possibility, we examine whether the quarter-end shift in trade types is driven by more purchases and fewer sales. We evaluate this in Table 4 by including indicators for *Buy* and *Sell* and their interactions with *Qtr_End* and *Qtr_Beg* in our estimation of Equation (2), giving us four variables of interest (*Qtr_End*Buy*, *Qtr_End*Sell*, *Qtr_Beg*Buy* and *Qtr_Beg*Sell*). This estimation allows us to examine the change in frequency for the buys and sells of each trade type at the turn-of-the-quarter. To focus on the turn-of-the-quarter, when both the recording of positions for disclosures and the shift in trade types are highest, we drop the month-end indicators. For brevity, we do not report the coefficient for the *Buy* indicator, which just captures the average difference in the *Buy* and *Sell* frequency of each trade type (see Table 1).

This decomposition of trades shows portfolio-pumping has limited ability to explain the observed dynamics. For each trade-type, we observe similar shifts in the quarter-end frequency of buys and sells; the sign of the coefficient on *Qtr_End×Buy* (*Qtr_Beg×Buy*) equals the sign of *Qtr_End×Sell* (*Qtr_Beg×Sell*) in each regression (Table 4, Columns 1-4). This similarity across trade types is not predicted by portfolio pumping. For example, while portfolio pumping predicts the quarter-end increase in *Completing* buy trades (Table 4, Column 2), which could reflect firms exerting price pressure on existing positions, it does not predict the quarter-end decreases in *Building* and *Initiating*

[15] While short-sellers can engage in portfolio-pumping via increased sales (Blocher, Engelberg, and Reed, 2012), this motive would be absent for the mutual funds, which only hold long positions, and pension funds covered by Ancerno.

buy trades (Columns 1 and 4). Likewise, while portfolio pumping predicts the quarter-end decrease in *Initiating* and *Building* sell trades (Columns 1 and 4), which could reflect funds avoiding sales on positions they will continue to hold at quarter-end, it does not predict the quarter-end increases in *Completing* and *One-off* sell trades (Columns 2-3).

Cross-sectional evidence on the positions traded differently around quarter-ends also indicate that a number of the observed dynamics are likely driven by non-pumping motives. For example, if funds are executing more quarter-end *Completing* and *One-off* buy trades to increase the valuation of existing positions, we would expect these trades to be concentrated in a fund's larger positions, particularly those with lower liquidity. Moreover, we might expect funds with better performance to have a greater incentive to pump prices (Carhart et al., 2002). To test these possibilities, we repeat the estimation of Table 4 after adding interactions for the relative size of the fund's position in the stock at the time of the trade and the relative past performance of the fund. Contrary to what portfolio pumping might predict, we find no evidence that the quarter-end increase in *One-off* and *Completing* buy trades is concentrated among stocks where a fund likely holds a larger position. Instead, these additional quarter-end trades tend to occur among a fund's smaller positions (see Appendix Table C.1, Columns 2-3). In untabulated analyses, we also find no evidence that the quarter-end increase in *One-off* and *Completing* buy trades is concentrated in positions that are both larger and illiquid. We also find little evidence that a fund's past performance is associated with the observed quarterly trade dynamics (see Appendix Table C.2).[16]

[16] To conduct these cross-sectional tests, we first needed to estimate the daily start positions for each fund that executes a trade in the Ancerno data. Because the Ancerno data is anonymized, we cannot directly match funds to a separate database of disclosed holdings. Instead, we approximate daily positions by netting out the sell and buy trades in each security over the fund's entire trading history. We can then calculate the daily return of the fund based on those estimated start positions (setting any negative position to zero) and use these daily returns to calculate the compound return of the fund over a 12-month window prior to the trade. Additional details on how we conduct these cross-sectional tests are found in the notes of Appendix Tables C.1 and C.2. Our findings are similar if we instead estimate daily start positions and fund returns using a noisy matching of Ancerno's client-manager observations to mutual funds covered in the CRSP Mutual Fund Database. This matching process involves comparing quarterly fund-level position changes (as identified using the quarterly disclosures found in the CRSP Mutual Fund Data) to the position changes of individual Ancerno clients (as calculated using Ancerno trades), being careful to match on the dates of the reported portfolios, and then selecting the closest match in CRSP. Using these matches, we can then estimate an Ancerno client's daily positions and returns using the matched data found in CRSP.

Additional untabulated analysis also suggests other motives must be at play besides portfolio-pumping. For example, we find that sell trades where funds maintain a post-trade position contribute to the observed quarter-end increases in *One-off* and *Completing* trades. This finding is inconsistent with pumping as such trades would tend to depress the mark of the ongoing position. Likewise, the quarter-end increase in *One-off* buys is partly driven by trades in stocks the fund does not already hold, indicating that many of these are not trades designed to inflate an existing position.[17] Moreover, using the time stamps available in the Ancerno data, we find that excluding late-day trades (i.e., trades that occur in the last half-hour or hour of trade) has no impact on the quarterly trade dynamics we document. We also find no evidence that late-day trades become more frequent for any of the four trade types at quarter end. The lack of a quarter-end increase in late-day trades is consistent with evidence suggesting an absence of portfolio pumping trades in the Ancerno data in years following the publication of Carhart et al. (2002) (Duong and Meschke, 2020). Our findings are also robust to limiting the sample period to post-2002 trades.[18]

2.4.3.2 Managing disclosed information?

The observed quarter-end shift in trade dynamics might instead reflect funds managing the information they disclose through quarterly position reporting requirements. Such trades could be driven by either a desire to conceal or reveal a fund's positions. For example, disclosure obligations could cause funds to trade into positions at quarter-end that they do not plan to maintain or delay trades that they would otherwise execute. Such trades make disclosures less informative of future holdings. Alternatively, funds might accelerate the completion of planned positions or time their rebalancing trades to be completed prior to disclosure. Such shifts in the timing of trades can make reported positions more informative of future holdings.

[17] These tests use our earlier approximation of daily start positions, as discussed in Appendix Tables C.1 and C.2.
[18] Our findings with respect to time stamps should be interpreted with caution. While some studies do use the available time-stamp data in Ancerno (e.g., Duong and Meschke, 2020), others argue the time stamps provided in Ancerno are often inaccurate (e.g., Hu et al., 2013). For example, 35.34% of trades in our sample do not record a valid time stamp.

To analyze whether managing disclosed information contributes to the observed shift in trade types, we first examine whether funds are more likely to subsequently reverse the additional *Completing* and *One-off* trades executed on quarter-end days. An increase in such reversals would be consistent with funds executing these additional end-of-quarter *Completing* and *One-off* trades to conceal their fund's future positions. Continuing to hold the positions taken by these additional end-of-quarter *Completing* and *One-off* trades, however, would indicate these quarter-end trades make the reported disclosures more informative about future holdings.

We test for an increase in quarter-end reversals by modifying our trade-type indicators to differentiate between date *t* trades that are at least partially reversed over the next four weeks versus those that are not. Specifically, we define $Post\_Opposite_{ist}$ as an indicator equal to one when the sign of trade by fund *i*, in security *s*, over the four weeks following day *t* is opposite in sign to the trade on day *t*. We then use *Post_Opposite* to partition our two trade types for which future volume has a different sign as day *t* volume (i.e., *Completing* and *One-off* trades*). Completing* and *One-off* trades where $Post\_Opposite_{ist} = 1$ are labeled as *Completing (with subsequent reversal)* and *One-off (with subsequent reversal)*, respectively. The remaining *Completing* and *One-off* trades are those where the fund executes zero additional trades in the following four weeks (i.e., $Post\_Opposite_{ist} = 0$). We label these trades as *Completing (with zero subsequent trade)* and *One-off (with zero subsequent trade)*, respectively. We then re-estimate Equation (2) using these four new trade classifications as our dependent variables.[19] Table 5 reports these findings.

The observed shift in trade dynamics is consistent with funds timing their trading campaigns and rebalancing trades so that they are completed before disclosure deadlines, thus making disclosures more, not less, informative of future positions. The increase in quarter-end *Completing* trades is driven entirely by trades followed by zero subsequent trades (Table 5, Columns 1-2). In other words, the

[19] As we illustrate in Appendix B, *Completing* and *One-off* trades are the only trade types for which *Post_Opposite* can take a non-zero value. A full definition of these more refined trade classifications is provided in Appendix B.

additional quarter-end *Completing* trades are informative of a fund's holdings over at least the next four weeks. They do not reflect funds establishing positions in order to disclose them and then trading out of them shortly afterwards. Likewise, the increase in quarter-end *One-off* trades that are not subsequently reversed (and hence, informative of future holdings) is nearly three times larger than the increase in *One-off* trades that are at least partially reversed at the start of the quarter (Columns 3-4). These latter findings are consistent with funds using *One-off* trades to rebalance positions to their intended weights before reporting.

Another way in which funds could conceal their holdings from investors is by executing trades at quarter-end that reverse positions taken previously or by waiting until after positions are recorded to initiate the reversal of prior trades. We investigate this possibility by creating an indicator, $Pre\_Opposite_{ist}$, which equals one when the trade by fund i in security s in the four-week period preceding a date t trade is opposite in sign to date t trade. We then interact this indicator with the *Initiating* and *One-off* trade indicators to create two new dependent variables: *Initiating (reversal of prior position)* and *One-off (reversal of prior position)*. The remaining *Initiating* and *One-off* trades (i.e., those with $Pre\_Opposite_{ist} = 0$) are labeled as *Initiating (with zero prior trade)* and *One-off (with zero prior trade)*.[20] We then use these four new trade classifications as the dependent variables in our estimation of Equation (2). Table 6 reports these estimates.

We again find evidence that is largely inconsistent with funds seeking to conceal positions. For example, we find that the increase in *Initiating* trades at the beginning of the quarter is entirely concentrated in those preceded by zero volume (Table 6, Columns 1-2). In other words, there is no evidence the increase in *Initiating* trades at the start of each quarter is driven by trades that reverse positions taken at the end of the prior quarter. We see similar, although attenuated, results for other

[20] As we illustrate in Appendix B, *Initiating* and *One-off* trades are the only two trade type indicators for which *Pre_Opposite* can take non-zero values for some trades.

month-ends. Moreover, less than half of the quarter-end increase in *One-off* trades is driven by trades that reverse positions taken in the final weeks of the quarter (Columns 3-4).

The quarter-start spike in *Initiating* and *One-off* trades, however, could be driven by a different type of motive to deceive. In particular, funds may be shifting the timing of new purchases to conceal positions they intend to trade into and to manage investors' risk perceptions (e.g., see Haugen and Lakonishok, 1988; Musto, 1997, 1999). If true, these delayed trading campaigns will tend to make funds' disclosures less, rather than more, informative.

A number of our findings are consistent with this alternative form of managing information flow. For example, the quarter-start spike in *Initiating* purchases is nearly twice as large as the increase in *Initiating* sales (see Table 4). And in subsequent cross-sectional analysis, we find these delays are concentrated among stocks where a fund does not already hold a large position and among small-cap stocks, which Haugen and Lakonishok (1988) argue are perceived as riskier by investors. We now turn to this cross-sectional evidence and additional motives for delaying trades.

2.4.3.2 Avoiding the disclosure of incomplete positions?

One of the most salient findings in our analysis is funds' tendency to postpone *Initiating* trades until after the quarter-end. In addition to a potential desire to conceal intended trades, another possible motive for this delay is avoid reporting incomplete positions. This desire could lead funds to delay initiating positions until the next quarter so as to create more time to fully build the intended position before having to disclose it to investors. We analyze this possible motive using cross-sectional variation to understand the types of stocks funds delay trading in until after quarter-end and the funds that are more likely to delay trades.

There are a number of reasons why a fund might wish to initiate the building of a new position or the selling of an existing position slowly over multiple days and trades. One reason is market illiquidity, which can cause a fund's trades to exert price pressure if the new position is established in a short time. Because of this, a fund's value-weighted transaction price can be lower (higher) if they build (sell) positions slowly. A second reason is that the accumulation of information that determines how large of a position the fund wishes to build might occur slowly. For example, a fund might wish to establish an initial position after doing preliminary research but only deploy more capital as they learn more about the firm in the days and weeks that follow.

Because quarterly disclosures reveal a fund's current positions, they can interfere with this desire to slowly build or exit positions, especially in illiquid stocks and in companies where the fund is still acquiring information or seeking to establish a larger position change. For example, the disclosure of a toe-hold position might result in other funds attempting to front-run the position before the fund is able to finish building its position. Moreover, the disclosure might result in investors asking questions about the new position before the fund has had time to acquire all the information it seeks and to decide how large of a position to build. The same issues apply when funds seek to reduce or eliminate an existing position.

To examine these possible motives, we first test whether the delay in *Initiating* trades around quarter-ends is concentrated in illiquid securities. The desire to build (or exit) a position slowly so as to avoid exerting price pressure will be greater in illiquid stocks. To conduct this test, we construct each security's average illiquidity, using both the Amihud (2002) illiquidity measure and bid-ask spreads, over the twelve-month period preceding every trade date. We then percentile rank stocks for every trade date; for example, the most illiquid stock (using the prior twelve-months of trading data) receives a percentile rank of 1 for that day, while the least illiquid stock receives a percentile rank of 0. We then repeat our main test of Table 3 for *Initiating* trades after including interactions with a stock's illiquidity rank. Table 7 reports the findings.

Consistent with funds seeking to create more room to complete trades, funds are more likely to delay *Initiating* trades in illiquid securities at quarter-ends. The quarter-end decrease in *Initiating* trades is concentrated among the most illiquid stocks, as is the increase *Initiating* trades at the start of a quarter. This finding holds both when using the Amihud illiquidity measure (Table 7, Column 1) and when using bid-ask spreads as a measure of illiquidity (Column 2). We also find that the quarter-end shift in *Initiating* trades is concentrated among small cap stocks (Column 3). This finding could be driven by similar illiquidity reasons (as smaller cap stocks tend to be less liquid) or by a desire to avoid reporting small-cap positions (Lakonishok and Haugen, 1988).

Our earlier findings on how trade dynamics vary as a function of existing position sizes are also consistent with funds seeking to avoid the disclosure of new toe-hold positions before the fund has had time to complete the position. This incentive to avoid reporting a toe-hold position is not applicable to *Initiating* buy trades in stocks that the fund already maintains a large position (i.e., situations where a fund has decided to increase the size of an existing, large position). Consistent with the toe-hold explanation, we find that funds are less likely to delay initiating a larger position when they already hold large position in that stock (see Appendix Table C.1, Column 1). The delay only occurs for stocks in which they do not already hold a large position.

Next, we examine the fund characteristics that predict the quarter-end delay in *Initiating* trades. Smaller funds and funds that trade less frequently are likely less able to manage illiquidity through the employment of professional traders, sophisticated trading algorithms, and an ability to tap a larger network of brokers to execute their trades. Hence, we might expect such funds to be more likely to delay *Initiating* trades beyond the end of the quarter. To test this possibility, we calculate each fund’s average AUM over the last 12 months using our earlier approximation of daily start positions, and we create a fund-level measure of trade frequency by measuring the dollar value of securities traded by that fund over the last 12 months. We then percentile rank funds based on these size and trade frequency measures. The fund with the highest AUM receives a percentile rank of 1, while the smallest receives a percentile rank of 0. A similar percentile rank is created for a fund’s overall trading frequency. We then repeat our main test of Table 3 for *Initiating* trades after including interactions with a fund's size of trade-frequency rank.[21]

In further support of funds seeking to create more room to complete trades, funds less able to manage illiquidity are more likely to delay *Initiating* trades at quarter-ends. The quarter-end delay in *Initiating* trades is concentrated among the smallest funds (see Table 7, Column 4) and funds that tend to trade less frequently (Column 5).

Finally, we also find that quarter-beginning *Initiating* trades tend to be trades where the fund is building (or exiting) a larger position and seeking to break the planned trade into more pieces, consistent with funds delaying the start of new positions the fund knows will take more time to execute. In particular, the average quarter-beginning *Initiating* trade is associated with the fund buying (or selling) $8.78 million in the underlying security in that trade and through subsequent trades over the next 28 days, which is 9.2% larger than $8.04 million typically bought (or sold) for *Initiating* trades that occur on other days (p-value of difference = 0.03). The number of total trades in the sequence, 8.54, is 4.6% larger than that of other days (p-value = 0.01).

2.4.4 Portfolio informativeness around quarter-ends

The net impact of the observed quarterly trade dynamics on quarter-end portfolio informativeness is unclear. Funds' accelerated completion of planned trades at quarter-end will increase how informative the disclosed portfolio is about the future portfolio, but funds' delay in initiating new positions until quarter-start decreases the informativeness of disclosed positions.

To analyze how portfolio informativeness changes around disclosures, we test whether quarter-end positions explain more or less of a fund's future positions. To conduct this test, we start by identifying fund-date observations where we observe a trade. For each observation, we then

[21] The subsequent findings are similar if we instead estimate a fund's size using the CRSP Mutual Fund Data and the noisy matching process between Ancerno and CRSP that is described in Section 4.3.1.

approximate the relative size of the fund's end-of-day position in every possible security *s*, $Share(t)_{is}$, and the trading date that occurs 28 days later, $Share(t+28)_{is}$, where *i* indicates the fund that executed the trade on date *t* and *Share* is the proportion of the fund's portfolio that is held in security *s*. *Share* is calculated for every security, including ones that were not traded on day *t*, and set equal to zero when the fund holds no position in the security. We then run a cross-sectional regression of $Share(t+28)_{is}$ on $Share(t)_{is}$ for each date *t* and fund *i* in our sample.[22] We then extract the R-squared from these fund-date regressions, *Positions R_Squared*, and regress it on indicators for quarter- and month-end days. Specifically, we estimate

$$Positions\ R-Squared_t = \beta_0 + \beta_1 Qtr\_Beg_t + \beta_2 Qtr\_End_t + \beta_3 Mos\_Beg_t + \beta_4 Mos\_End_t + \epsilon_{it}. \quad (3)$$

If the quarterly trading dynamics change portfolio informativeness on quarter- or month-ends, we should detect a change in the *Positions R-squared* on those days. Table 8 presents the findings.

Consistent with the quarter-end trade dynamics increasing the informativeness of disclosures, portfolio positions are more informative on the last day of the quarter. The coefficient on Qtr_End_t loads with a positive and statistically significant coefficient, indicating that quarter-end positions explain more of a trading funds' longer-term positions than positions on other days that they execute trades (Table 8). Relative to average daily R-squared for other days (as given by the regression's intercept, 82.8%), quarter-end positions explain 0.025/0.828 = 2.97% more of the variation in a fund's positions 28 days later.[23]

---

[22] This approximation of relative end-of-day position sizes is done using the same method used in Appendix Tables C.1 and C.2. For this estimation, we drop observations from the first year of our sample, 1998, because observing such a short time-series of trades limits our ability to approximate portfolios.

[23] In an untabulated test, we also find that funds' quarter-end holdings do a better job of predicting future returns. In these tests, we instead estimate the *R-squared* variable of Eqn. (3) using a regression of day *t*+28 returns, as calculated using actual *t*+28 holdings, onto future returns, as predicted using current holdings. Similar to our findings for positions, quarter-end portfolios do a better job of predicting future returns, again indicating that quarter-end portfolios are more informative than portfolios from other days.

The informativeness of portfolio positions is lower on the first day of the quarter for funds executing trades. This finding suggests that the quarter-start decrease in *Completing* trades (i.e., trades not followed by subsequent trades) and quarter-start increase in *Initiating* trades (i.e., trades that will be followed by yet more trades that change the position) tend to make these quarter-start portfolios less informative of fund's future positions. We find little evidence of a change in portfolio informativeness around other month-ends.

2.4.5 Commissions paid around quarter-ends

The observed quarter-end trade dynamics suggest that funds are executing trades around quarter-ends for disclosure-related reasons rather than reasons involving the underlying value of securities. In particular, funds appear to accelerate the completion of existing positions and execute one-off rebalancing trades so as to make their quarterly disclosures more informative of their planned future holdings. At the same time, funds delay initiating new positions until the start of the next quarter so as to create more time to build positions before having to disclose them. Combined, these findings suggest quarter-end trades are less driven by newly acquired information. To test this possibility, we now analyze commissions paid around quarter-ends.

Commissions are often used by funds to compensate brokerages for information and research services, with industry estimates suggesting that such compensation accounts for about 40% of commissions (Blume, 1993). Moreover, anecdotal evidence suggests if an analyst motivates a trade by providing you some new information, than there is an expectation that the recipient will use that broker to execute the trade (e.g., see Blume, 1993; Irvine, 2001; Jackson, 2005). Because brokerages ration research services from funds that are not sufficiently good customers, funds have incentives to pay higher commissions when they receive information from analysts and/or salesmen (Groysberg and Healy, 2013). Funds also sometimes pay higher commissions knowing that the broker will pass part of it to a third party that provided research services (Blume, 1993). Consistent with these expectations and an allocation of trades varying with the provision of information, brokerage volume does vary with analyst following and/or the information content of analyst reports (e.g., see Irvine, 2001; Irvine, 2004; Jackson, 2005, Niehaus and Zhang, 2007, and Lehmer, Lourie and Shanthikumar, 2021).

As such, commissions can provide a potential proxy for the amount of information a manager obtained before executing the underlying trade. Therefore, if the trade dynamics we document are driven by disclosure-based motives rather than any new information acquired by the fund manager, we might also expect commissions to systematically decline around quarter-ends.

To test for quarter-end shifts in commissions, we estimate equation (2) using commissions per share as the dependent variable. We conduct our commission analysis at the fund-broker-security-date level as opposed to the fund-security-date level, which allows us to control for the broker and better identify the cause of any potential shift in commissions. The use of this less aggregated data adds approximately 15 million observations to our sample.

Consistent with quarter-end trades being less driven by information, commissions paid per share decline at quarter-end, and this decline is driven by a drop in commissions paid within a given fund-broker pair. Using the same fixed effect structure as in Tables 3 – 7, we find that commissions decline both at the end and beginning of quarters (Table 9, Column 1). Relative to the average commission per share of 2.33 cents, the magnitudes correspond to a drop of about 6.4% (3.0%) on the last (first) day of the quarter. We then modify the regression to include broker-by-fund fixed effects instead of just fund fixed effects. In doing this, the estimation now controls for any possible switch in brokers and directly tests whether the commission per share differs for given fund-broker combination around quarter ends. Our estimates are largely unchanged (Column 2). These findings confirm that funds are paying a lower commission to a given broker at quarter ends than they typically pay that same broker for trades executed at other points in the year.

Funds choosing to route their quarter-end trades through less expensive brokerages does not appear to contribute to the quarter-end decline in commissions per share. To illustrate this finding, we proxy for the ‘broker expensiveness’ using the average commissions per share received by the broker from all funds in a given year (*AvgCommPerShareOfChosenBroker*). We then use this average as the dependent variable for each executed trade instead of the actual commission paid. If funds strategically switch towards cheaper brokerages around quarter-ends, we should detect a drop in the average expensiveness of brokers chosen by funds around quarter-ends. However, we find no evidence of this (Table 9, Column 3).

Goldstein et al. (2009) argue that the compensation of brokers for information and services also has an ex-post settling up component, as the payments need not coincide with the trades accompanied by the high-quality services. Instead, funds can compensate brokers for their services over a longer window so that total commissions paid are proportional to the value of the services rendered by the broker. If such ex-post settling up occurs and if quarter-end trades are less driven by the timely provision of information from brokers, then we should also expect the fund to pay the broker lower total commissions over the course of a long window when a larger proportion of the trades executed with that broker occur on quarter ends.

Consistent with Goldstein et al. (2009), we find evidence of such ex-post settling up between funds and brokers. The proportion of a fund's trades executed with a given broker in a year that occur at quarter-end negatively predicts the total commissions paid by the fund to that broker for that year (Table 9, Column 4). The results also hold when we include fund-broker fixed effects, indicating that funds tend to pay the same broker less in years where a larger proportion of the trades executed through that broker were on the last day of the quarter (Column 5).

Overall, these findings are consistent with quarter-end trades being disclosure-driven rather than information-driven. Funds pay lower commissions to a given broker for trades executed on quarter ends, and the total commissions they pay a broker over the year are also lower when a larger proportion of trades executed with that broker occurred on quarter ends.[24]

---

[24] Furthermore, our finding that commissions vary around quarter ends for a given broker-fund pair is interesting and novel in its own right. Goldstein et al. (2009) found that 43.5% of client-broker pairs only used a single per-share commission

2.5 Price informativeness around quarter-ends

Our final test examines whether the cyclical trade patterns documented in the previous section associate with shifts in price informativeness. If disclosure- rather than information-based motives drive the quarter-end trade dynamics, price informativeness might decline at quarter-end.

To analyze whether price informativeness declines around disclosures, we test whether daily returns around quarter- and month-end days explain less of longer-term returns. Days on which less informed trading takes place should impound less information about long-term value into prices and explain less of future returns. To conduct this test, we run cross-sectional regressions of the thirty-day return, *Ret(t,t+30)*, on the daily return, *Ret(t)*, for each date t in our sample. We then extract the R-squared from these daily regressions, *Return R_Squared*, and regress it on indicators for quarter- and month-end days. Specifically, we estimate

$$Return\ R-Squared_t = \beta_0 + \beta_1 Qtr\_Beg_t + \beta_2 Qtr\_End_t + \beta_3 Mos\_Beg_t + \beta_4 Mos\_End_t + \epsilon_t. \tag{4}$$

If price informativeness declines around quarter- or month-ends, we should detect a decline in the daily *Return R-squared* for those days. Table 10 presents the findings of this estimation.[25]

during their sample period (1999-2003), and during our sample (1998-2010), this number is 35.4%. However, more than half of client-broker pairs do exhibit variation in commissions paid, and our findings show that some of this variation is driven by trades executed at quarter end. In untabulated findings, we also find the commission paid per share is higher within broker-fund pairs in the days around earnings announcements, consistent with funds compensating brokers for timely information provision around these announcements. Overall, our findings suggest that while funds do compensate brokers for timely information provision through the total commissions they pay and some forms of ex post settling up, it also appears that they sometimes do so on an individual trade level, providing yet additional evidence linking the level of commissions paid to brokers' information services.

[25] Since this analysis does not require trade-level classifications, as constructed from the Ancerno data, we extend the sample period for this and subsequent analysis to 1982-2018. However, the subsequent findings for price informativeness are robust to limiting our sample to the same period as our Ancerno sample, 1998-2010.

Consistent with the quarter-end trade dynamics being driven by disclosure- rather than information-based motives, price informativeness declines on the last day of the quarter. The coefficient on Qtr_End_t loads with a negative and statistically significant coefficient, indicating that returns on quarter-ends explain less of longer-term returns. Relative to average daily R-squared for other days (as given by the regression's intercept, 3.83%), the magnitude of the decline is sizable. Daily returns on the last day of the quarter are 0.0122/0.0382 = 32% less informative of the 30-day return relative to that of other days. There is little evidence of a change in the relative informativeness of daily returns on the first day of the quarter or on days around other month-ends.

The quarter-end decline in price informativeness is also present in the days leading up to the quarter-end. This decline is shown in Figure 2, where we report the coefficients from a regression of *Return R_Squared* on indicators for each of the five trading days before and after quarter-ends. Similar to the quarter-end trade dynamics documented in Figure 1, we find a clear shift in price informativeness at quarter-ends. Price informativeness declines monotonically in the days preceding the quarter-end, but then returns to its average level at the start of the quarter.[26]

The quarter-end decline in price informativeness is also present for each quarter. Figure 3, which plots the coefficients from a regression *Return R_Squared* on indicators for each month-end, illustrates this pattern. Significant declines in price informativeness occur on each of the quarter-end months, and the three largest month-end indicators all correspond to quarter-ends.[27]

Tests that use return reversals as an alternative measure of price informativeness yield similar

[26] The absence of a quarter-start decrease in price informativeness indicates these price dynamics are not driven by an in-flow of cash to the financial system (e.g., Etula et al., 2020), which occurs both at the end and the start of quarters.
[27] The lower end-of-June *Return R-squared* is not explained by the reconstitution of Russell Investments' various indexes, which prior to 2004 occurred on the last trading day of June (e.g., see Ben-David, Franzoni, and Moussawi, 2019). In untabulated analysis, we find similar end-of-June decreases in price informativeness in years where Russell's reconstitution does not occur on the last day of June.

findings. Days when less information about long-term value gets impounded into prices should exhibit greater subsequent reversals (Campbell et al., 1993; Biais et al., 1999). Consistent with quarter-end returns including more ‘noise’ that subsequently flows out of price, we find that quarter-end days have return reversals that are 219% larger over the subsequent 30 trading days. Moreover, quarter-end return reversals are longer in duration than reversals on other days, with over half of the reversal occurring after the first day of the next quarter. Figure 4 , which plots the coefficients from regressions of $Ret(t+1,t+s)$ onto $Ret(t)$, Qtr_End, and $Qtr\_End \times Ret(t)$ for each value of s between 1 and 30, illustrates these larger quarter-end return reversals.

If funds execute less-informed trades in response to disclosures, then average illiquidity might also decrease on quarter-end days, as market makers have less incentive to price protect. In untabulated tests, this is exactly what we find. A stock’s Amihud measure of illiquidity is lower, on average, by 9.3% of a standard deviation on quarter-end days, and daily spreads are lower, on average, by 3.4% of a standard deviation. The lower quarter-end illiquidity is consistent with an increase in uninformed trading driving the quarter-end decrease in price informativeness.[28]

2.6 Conclusion

Using fund-level trades, we document that funds execute different types of trades around quarter-end dates, which is when most funds record positions for subsequent disclosures. Funds are more likely to start new trading campaigns after the quarter-end and more likely to complete existing trading campaigns before the quarter-end, consistent with funds shifting the timing of planned trades in response to upcoming disclosures. Trades that are not part of a trading campaign increase both before and after the quarter end, while trades in the middle of a campaign decrease.

[28] The decrease in average illiquidity is inconsistent with the quarter-end decline in price informativeness being driven by financial institutions drawing down their supply of liquidity in response to their own reporting requirements.

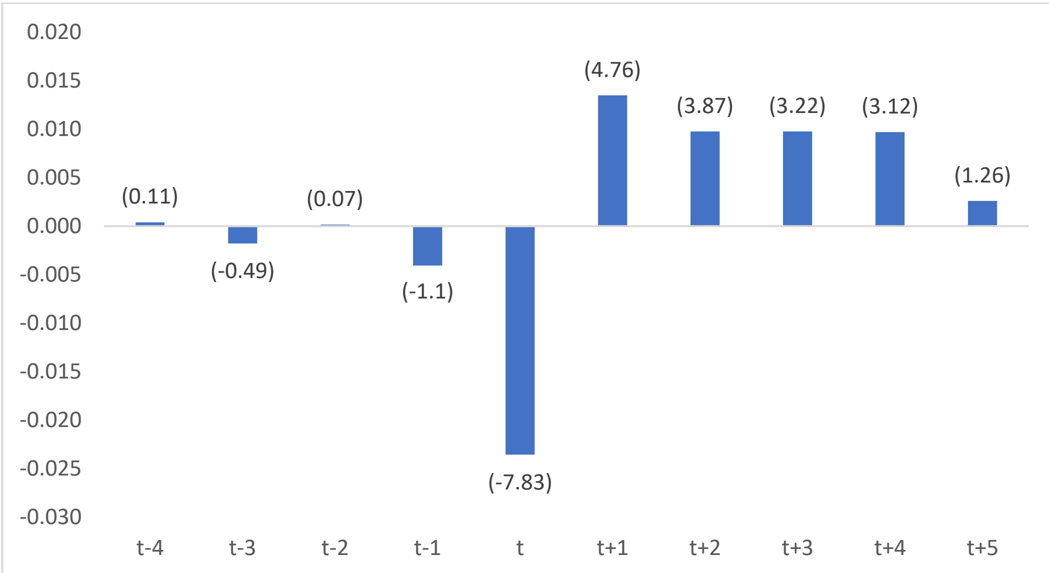
The documented patterns and additional findings suggest that funds seek to make their recorded positions more informative of their planned allocation strategy while simultaneously avoiding the disclosure of incomplete positions. For example, trades executed at quarter-end, including three-fourths of trades not part of a larger trading campaign, continue to be held by the fund in the the next quarter, thus making them informative of investors' future ownership. And the delay in initiating trading campaigns is concentrated in illiquid, small-cap stocks and among funds likely less able to quickly trade into new positions, consistent with funds delaying the start of trading campaigns that will require more time to build. Part of the delay might also be driven by a motive to avoid disclosing some positions entirely. Other disclosure-driven motives, such as portfolio-pumping, do not appear to be the key drivers of these quarter-end trade dynamics, and on net, we find that portfolio informativeness increases on quarter-end days.

Consistent with quarter-end shift in portfolio formation being driven by disclosure-related motives unrelated to stocks' intrinsic values, we also document that price informativeness declines at quarter-end. Returns on quarter-end days explain less of the variation in longer-term price changes than returns on other days, and this is true for each of the four calendar-year quarter-ends. Moreover, the price distortions associated with quarter-ends persist for several days.

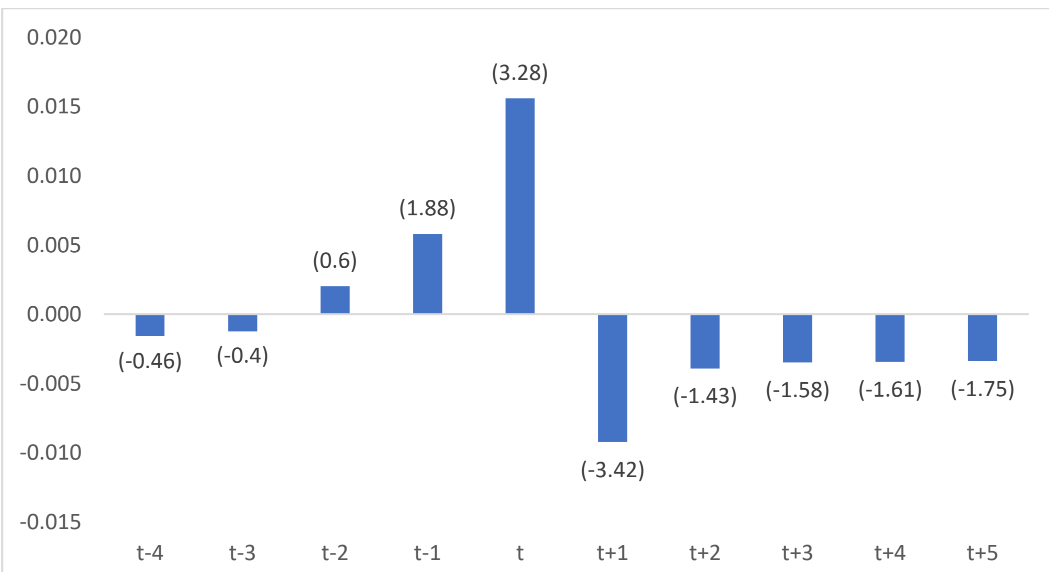
Our study makes three important contributions to the literature. First, we add to the literature on the consequences of reporting positions. Our findings suggest that funds adjust the timing of when they build, complete, and initiate new positions in response to the quarterly reporting cycle. Second, we show that some of the shifts in trade dynamics improve the informativeness of portfolio holdings prior to quarter-ends, whereas the prior literature has largely investigated disclosure-based motives where funds seek to deceive investors around quarter-end. Third, we document that these quarterly trade dynamics coincide with a quarter-end increase in portfolio informativeness and a decrease in price informativeness. Taken together, these results suggest that although funds trade into positions which tend to make portfolio disclosures more informative about future holdings, these trades simultaneously decrease price informativeness.

Figure 2.1 – Fund trading behavior around quarter-ends

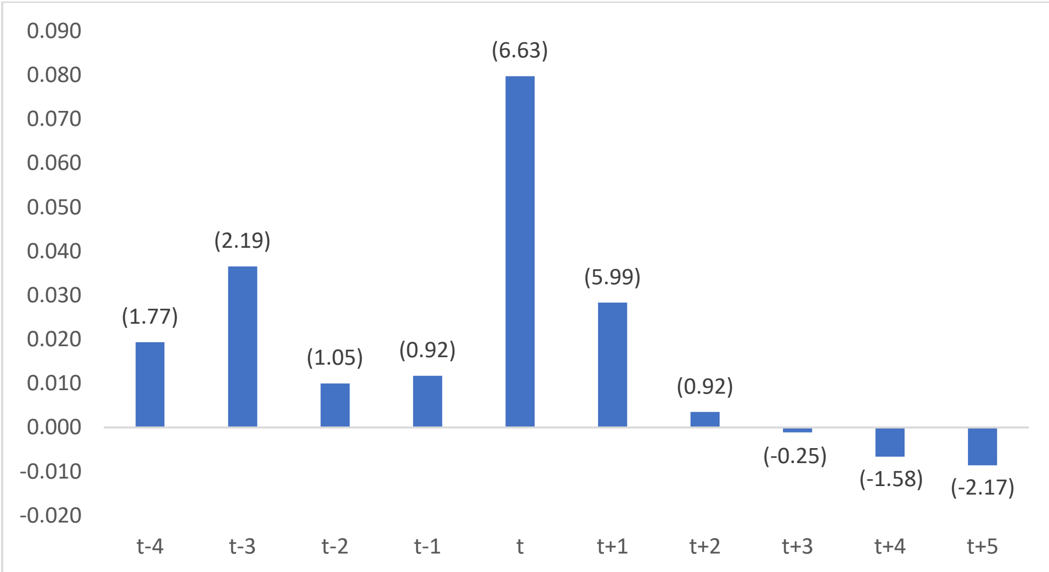
Panel A: Abnormal frequency of *Initiating* trades



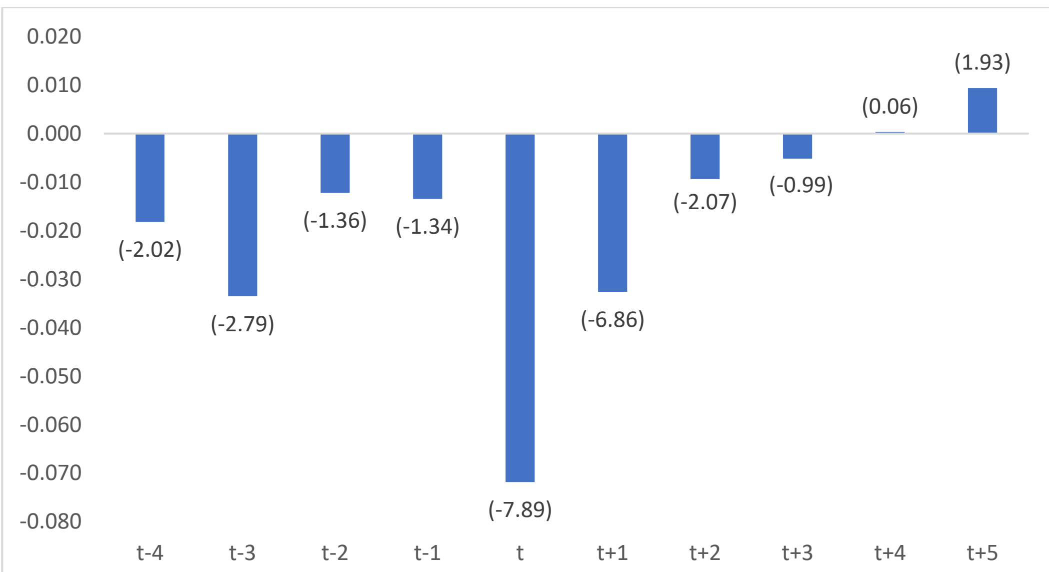
Panel B: Abnormal frequency of *Completing* trades



Panel C: Abnormal frequency of *One-off* trades

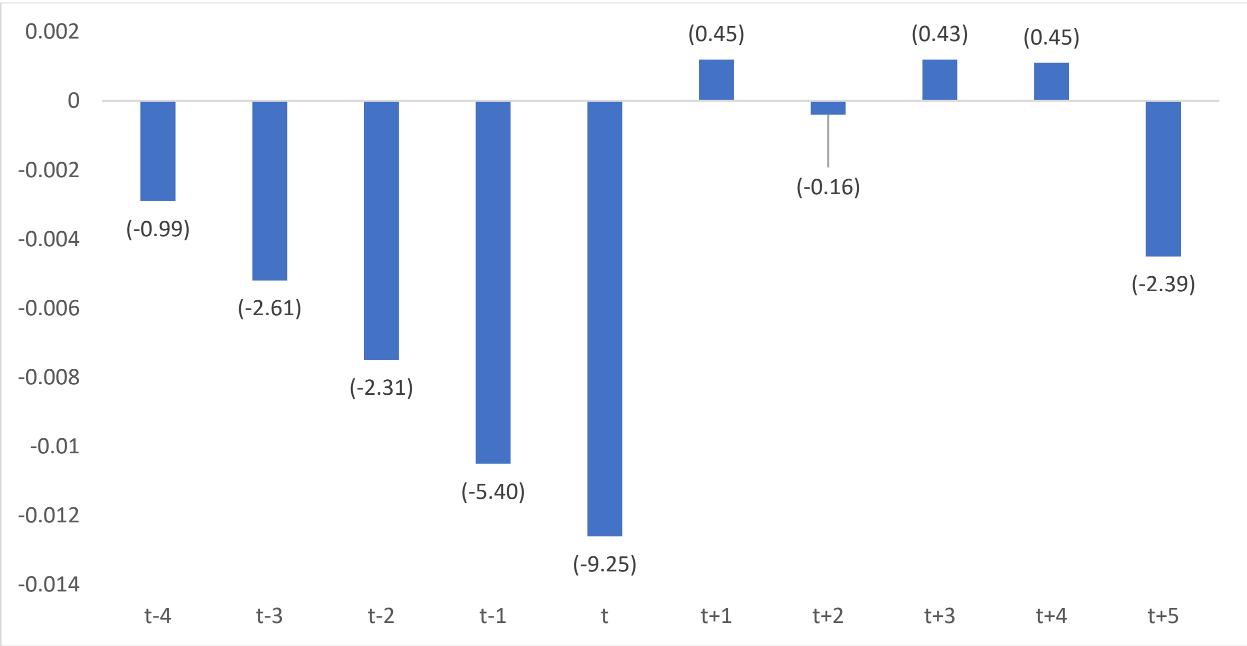


Panel D: Abnormal frequency of *Building* trades



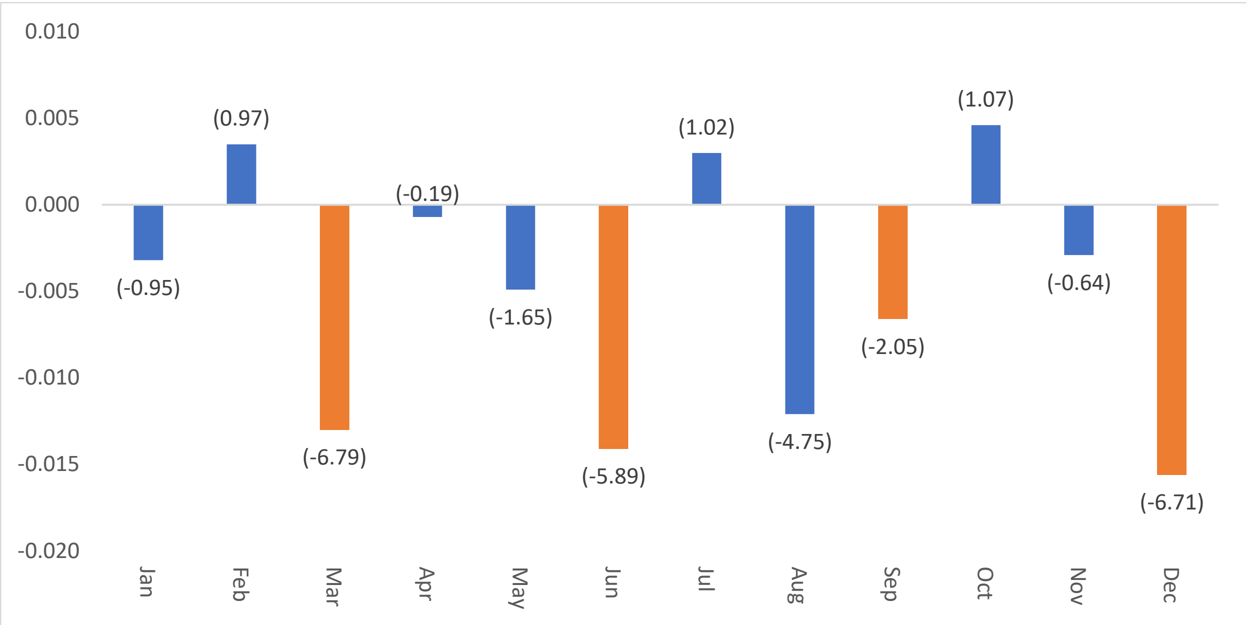
We compute each graph by regressing the trade category type indicator (unique at the fund-security-date level) on day indicators for each of the five days before and after the quarter-end using the Ancerno data from 1998 to 2010 and the estimation given by Equation (1). The bar represents the regression coefficient, and the *t*-statistics for each coefficient, computed by clustering two-ways on security and month-year, are provided in parentheses.

Figure 2.2 – Daily price informativeness, measured using Return R-squared, by day around quarter-ends



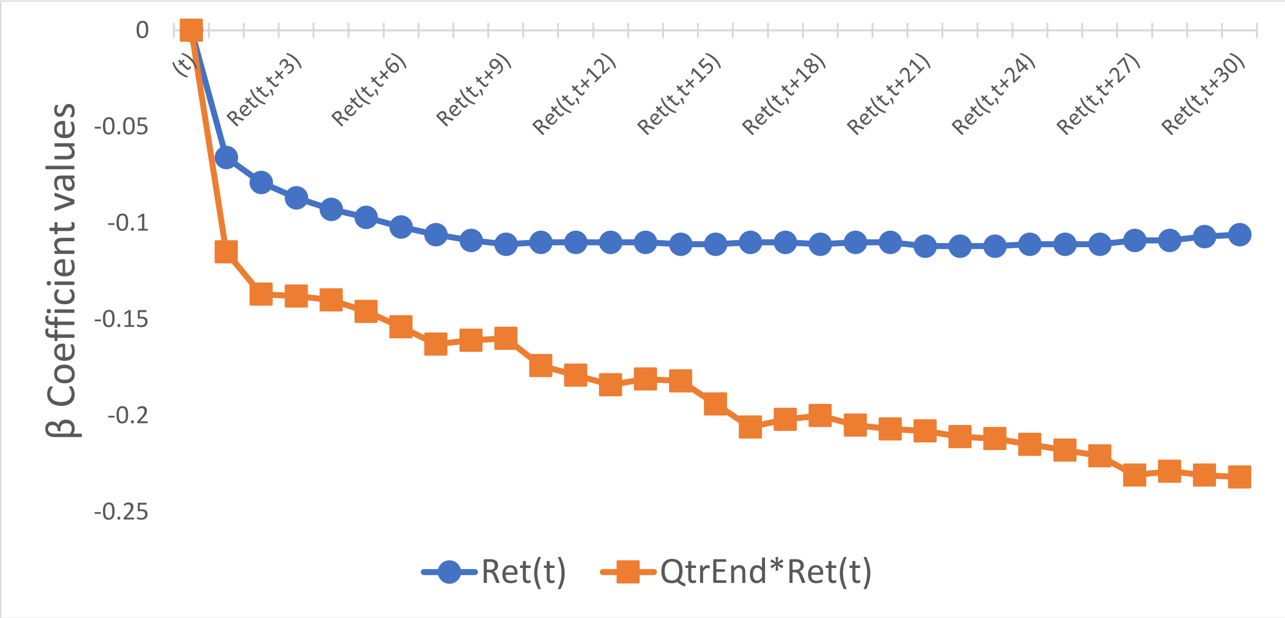
This figure plots the variation in the daily R-squared from running daily cross-sectional regressions of the thirty-day return, *Ret*(*t*, *t*+30), on daily returns, *Ret(t)* from 1982 to 2018. The R-squared from these daily regressions, *Return R-squared*, are then regressed on day indicators for each of the five days before and after the quarter-end dates. The bar represents the difference in R-squared on that day relative to that of other, non-quarter-end days, and the *t*-statistics associated with this variation, where standard errors clustered by month-year, are provided in parentheses.

Figure 2.3 – Variation in daily price informativeness, measured using Return R-squared, by month-ends



This figure plots how the average daily R-squared obtained from running daily cross-sectional regressions of the thirty-day return, *Ret*(*t*, *t*+30), on daily returns, *Ret(t)* from 1982 to 2018 varies on the last day of each month relative to all other non-month-end days. Each bar represents the average difference in the R-squared on that month-end relative to non-month-end days, and the *t*-statistics corresponding to this difference, where standard errors clustered by month-year, are provided in parentheses. Orange bars correspond to quarter-end indicators while blue bars correspond to other month-end indicators.

Figure 2.4 – Cumulative return reversals from t+1, t+30



This figure graphs the return reversal coefficients obtained by regressing future returns, *Ret(t+1, t+s)*, (where '*s*' varies from 1 to 30) on daily returns (*Ret(t)*), indicators for quarter-end (*Qtr_End*) indicators, and interactions of daily returns with the indicator variables.

Table 2.1 – Mutual fund disclosure date frequencies

	(1)	(2)	(3)
	Thomson Reuters S-12 value – weighted portfolio disclosures	CRSP value – weighted portfolio disclosures	
	1982 - 2018	2001 - 2007	2008 - 2018
Quarter End	80.89%	66.87%	45.48%
Other Month End	19.08%	33.13%	53.46%
All Other Dates	0.03%	0.00%	1.06%

This table tabulates the value weight of reported holdings disclosed using the Thomson Reuters (S12) and CRSP databases by quarter-end dates (i.e., the last trading days of March, June, September, and December), other month-end dates (i.e., the last trading days of all other months), and non-month end dates (i.e., all other trading days). The CRSP sample is divided into two time periods: 2001-2007 (during which disclosure data were sourced from Morningstar) and 2008-2018 (during which disclosure data were sourced from Lipper).

Table 2.2 – Trade characteristics by trade type

Trade type	Percentage buy	Absolute dollar volume	Absolute share volume	Dollar volume buy	Dollar volume sell
Initiating	49.1%	$747,511	27,585	$744,202	-$750,702
Completing	54.9%	$664,417	24,533	$612,447	-$727,565
Building	56.1%	$909,880	32,621	$823,705	-$1,019,857
One-off	47.2%	$505,925	18,969	$504,713	-$507,002

This table tabulates the descriptive statistics of the four trade types – *Initiating*, *Completing*, *Building* and *One-off* – using all transactions marked by Ancerno as 'good trades' over the period 1998 – 2010 after excluding trades from client managers that do not execute at least one trade in both the prior and subsequent month. The statistics reported are sample averages for each type of trade, and definitions for each of the four trade classifications can be found in Section 2 and Appendixes A and B.

Table 2.3 - Variation in trade-type frequency around quarter- and month-ends

	Initiating	*Completing*	*One-off*	*Building*
Qtr_End	-0.025305***	0.022436***	0.047503***	-0.044634***
	(-8.04)	(5.72)	(7.31)	(-8.63)
Qtr_Beg	0.014904***	-0.010826***	0.026225***	-0.030303***
	(4.67)	(-4.75)	(7.47)	(-7.62)
Month_End	-0.007429***	0.003438*	0.030542***	-0.026550***
	(-4.13)	(1.73)	(10.14)	(-9.53)
Month_Beg	0.007413***	-0.008256***	0.008085***	-0.007242***
	(3.85)	(-5.35)	(2.89)	(-3.00)
Fund FE	Yes	Yes	Yes	Yes
Security-by-month FE	Yes	Yes	Yes	Yes
Non-linear volume controls	Yes	Yes	Yes	Yes
Fund-flow controls and interactions	Yes	Yes	Yes	Yes
Two-way Clustered S.E	Firm & Month	Firm & Month	Firm & Month	Firm & Month
Observations	50,192,414	50,192,414	50,192,414	50,192,414
Adjusted R-squared	0.024	0.025	0.107	0.128

This table reports regressions of our four trade-type indicators (*Initiating*, *Completing*, *One-off*, *Building*) on indicators for dates around the change in months and quarters as well as controls. Specifically, we run the following regression: $Trade\_Cat_{ist} = \beta_1 Qtr\_End_t + \beta_2 Qtr\_Beg_t + \beta_3 Month\_End_t + \beta_4 Month\_Beg_t + X_{ist} + \delta_s \times MonthFE + \alpha_i + \varepsilon_{ist}$. We estimate this regression using all transactions marked by Ancerno as 'good trades' over the period 1998 – 2010 after excluding trades from client managers that do not execute at least one trade in both the prior and subsequent month. Standard errors are two-way clustered by security and month-year. *t*-statistics are reported in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.
Non-linear volume controls: *Signsharevol*$_{s,t}$, *ShareVol*$_{s,t}$, *Abs(ShareVol*$_{s,t}$*)*, *log(ShareVol*$_{s,t}$*)*, *DollVol*$_{s,t}$, *Abs(DollVol*$_{s,t}$*)* and *log(DollVol*$_{s,t}$*)*.
Fund-flow controls: *%FundFlows(t)* and *$FundFlows(t)*. We also include interactions of both with our four variables of interest.

Table 2.4 - Variation in buy and sell frequencies by trade-type around quarter-end

	(1) *Initiating*	(2) *Completing*	(3) *One-off*	(4) *Building*
*Qtr_End*Buy*	-0.01880***	0.01618***	0.04914***	-0.04652***
	(-4.88)	(3.84)	(6.50)	(-7.23)
*Qtr_End*Sell*	-0.03313***	0.03017***	0.04431***	-0.04136***
	(-6.72)	(5.20)	(5.94)	(-7.62)
*Qtr_Beg*Buy*	0.01998***	-0.01062***	0.02833***	-0.03769***
	(5.81)	(-3.50)	(7.87)	(-8.28)
*Qtr_Beg*Sell*	0.01016**	-0.01141***	0.02007***	-0.01882***
	(2.54)	(-4.30)	(3.37)	(-2.95)
Fund FE	Yes	Yes	Yes	Yes
Security-by-month FE	Yes	Yes	Yes	Yes
Non-linear volume controls	Yes	Yes	Yes	Yes
Fund-flow controls and interactions	Yes	Yes	Yes	Yes
Two-way Clustered S.E	Firm & Month	Firm & Month	Firm & Month	Firm & Month
Observations	50,192,414	50,192,414	50,192,414	50,192,414
Adjusted R-squared	0.023	0.025	0.107	0.128

This table reports regressions of our four trade-type indicators (*Initiating*, *Completing*, *One-off*, *Building*) on the interactions between indicators for dates around the change in quarters, *Qtr_End* and *Qtr_Beg*, and indicators for whether the trade was a purchase, *Buy*, or sale, *Sell*. We also include other controls (see below) and an indicator for *Buy*, but for brevity, we do not report the coefficients on these additional controls. Full variable definitions are provided in Appendix A. We estimate this regression using all transactions marked by Ancerno as 'good trades' over the period 1998 – 2010 after excluding trades from client managers that do not execute at least one trade in both the prior and subsequent month. Standard errors are two-way clustered by security and month-year. *t*-statistics are reported in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Non-linear volume controls: $Signsharevol_{s,t}$, $ShareVol_{s,t}$, $Abs(ShareVol_{s,t})$, $log(ShareVol_{s,t})$, $DollVol_{s,t}$, $Abs(DollVol_{s,t})$ and $log(DollVol_{s,t})$.

Fund-flow controls: *%FundFlows(t)* and *\$FundFlows(t)*. We also include interactions of both with our four variables of interest.

Table 2.5 – Abnormal frequency of *Completing* and *One-off* trades that are and are not subsequently reversed around quarter- and month-ends

	(1) *Completing (with zero subsequent trade)*	(2) *Completing (with subsequent reversal)*	(3) *One-off (with zero subsequent trade)*	(4) *One-off (with subsequent reversal)*
Qtr_End	0.0227***	-0.0003	0.0355***	0.0120***
	(6.32)	(-0.12)	(5.56)	(3.87)
Qtr_Beg	-0.0067***	-0.0042**	0.0123***	0.0139***
	(-4.87)	(-2.45)	(5.28)	(5.17)
Month_End	0.0066***	-0.0033**	0.0098***	0.0208***
	(5.23)	(-2.47)	(4.60)	(6.78)
Month_Beg	-0.0062***	-0.0021*	0.0048**	0.0033**
	(-5.90)	(-1.85)	(2.04)	(2.04)
Fund fixed effects	Yes	Yes	Yes	Yes
Security-by-month fixed effects	Yes	Yes	Yes	Yes
Non-linear volume controls	Yes	Yes	Yes	Yes
Fund-flow controls and interactions	Yes	Yes	Yes	Yes
Two-way clustered standard errors	Firm & Month	Firm & Month	Firm & Month	Firm & Month
Observations	50,192,414	50,192,414	50,192,414	50,192,414
Adjusted R-squared	0.075	0.062	0.224	0.060

This table reports regressions of the *Completing* and *One-off* trade indicators interacted with the *Post_Opposite* indicator [resulting in four trade classifications: *Completing (with zero subsequent trade)*, *Completing (with subsequent reversal)*, *One-off (with zero subsequent trade)*, and *One-off (with subsequent reversal)*] on indicators for dates around the change in months and quarters as well as controls. A full definition of the four trade classifications is provided in Section 3.3.2 and Appendixes A and B. We estimate this regression using all transactions marked by Ancerno as 'good trades' over the period 1998 – 2010 after excluding trades from client managers that do not execute at least one trade in both the prior and subsequent month. Standard errors are two-way clustered by security and month-year. *t*-statistics are reported in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Non-linear volume controls: $Signsharevol_{s,t}$, $ShareVol_{s,t}$, $Abs(ShareVol_{s,t})$, $log(ShareVol_{s,t})$, $DollVol_{s,t}$, $Abs(DollVol_{s,t})$ and $log(DollVol_{s,t})$.

Fund-flow controls: *%FundFlows(t)* and *$FundFlows(t)*. We also include interactions of both with our four variables of interest.

Table 2.6 – Abnormal frequency of *Initiating* and *One-off* trades that do and do not reverse prior positions around quarter- and month-ends

	(1) *Initiating (with zero prior trade)*	(2) *Initiating (reversal of prior position)*	(3) *One-off (with zero prior trade)*	(4) *One-off (reversal of prior position)*
Qtr_End	-0.0152***	-0.0101***	0.0245***	0.0230***
	(-6.40)	(-5.56)	(3.11)	(6.20)
Qtr_Beg	0.0158***	-0.0009	0.0182***	0.0080***
	(5.55)	(-0.51)	(5.99)	(2.88)
Month_End	-0.0047***	-0.0027***	0.0111***	0.0195***
	(-3.18)	(-2.71)	(5.77)	(6.99)
Month_Beg	0.0051***	0.0023	0.0042*	0.0039**
	(3.98)	(1.47)	(1.75)	(2.36)
Fund fixed effects	Yes	Yes	Yes	Yes
Security-by-month fixed effects	Yes	Yes	Yes	Yes
Non-linear volume controls	Yes	Yes	Yes	Yes
Fund-flow controls and interactions	Yes	Yes	Yes	Yes
Two-way clustered standard errors	Firm & Month	Firm & Month	Firm & Month	Firm & Month
Observations	50,192,414	50,192,414	50,192,414	50,192,414
Adjusted R-squared	0.074	0.060	0.222	0.063

This table reports regressions of the *Initiating* and *One-off* trade indicators interacted with the *Pre_Opposite* indicator [resulting in four trade classifications: *Initiating (with zero prior trade)*, *Initiating (reversal of prior position)*, *One-off (with zero prior trade)*, and *One-off (reversal of prior position)*] on indicators for dates around the change in months and quarters as well as controls. A full definition of the four trade classifications is provided in Section 3.3.2 and Appendixes A and B. We estimate this regression using all transactions marked by Ancerno as 'good trades' over the period 1998 – 2010 after excluding trades from client managers that do not execute at least one trade in both the prior and subsequent month. Standard errors are two-way clustered by security and month-year. *t*-statistics are reported in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Non-linear volume controls: $Signsharevol_{s,t}$, $ShareVol_{s,t}$, $Abs(ShareVol_{s,t})$, $log(ShareVol_{s,t})$, $DollVol_{s,t}$, $Abs(DollVol_{s,t})$ and $log(DollVol_{s,t})$.
Fund-flow controls: *%FundFlows(t)* and *$FundFlows(t)*. We also include interactions of both with our four variables of interest.

Table 2.7 – Heterogeneity in the quarter-end delay in *Initiating* trades

	(1) *Initiating*	(2) *Initiating*	(3) *Initiating*	(4) *Initiating*	(5) *Initiating*
Qtr_Beg	0.0032	0.0042	0.0252***	0.0427***	0.0389***
	(1.12)	(1.51)	(4.18)	(4.70)	(4.43)
Qtr_End	-0.0039	-0.0102***	-0.0478***	-0.0765***	-0.0794***
	(-1.61)	(-4.34)	(-7.68)	(-8.29)	(-7.83)
*Qtr_Beg*Rank(Amihud)*	0.0235***				
	(3.37)				
*Qtr_End*Rank(Amihud)*	-0.0433***				
	(-6.28)				
*Qtr_Beg*Rank(Spread)*		0.0215***			
		(3.74)			
*Qtr_End*Rank(Spread)*		-0.0311***			
		(-5.38)			
*Qtr_Beg*Rank(MarketCap)*			-0.0202***		
			(-2.88)		
*Qtr_End*Rank(MarketCap)*			0.0434***		
			(6.05)		
*Qtr_Beg*Rank(Fund AUM)*				-0.0311***	
				(-3.05)	
*Qtr_End*Rank(Fund AUM)*				0.0566***	
				(5.87)	
*Qtr_Beg*Rank(Fund Turnover)*					-0.0267***
					(-2.68)
Qtr_End Rank(Fund Turnover)*					0.0597***
					(5.62)
Fund fixed effects	Yes	Yes	Yes	Yes	Yes
Security-by-month fixed effects	Yes	Yes	Yes	Yes	Yes
Non-linear volume controls	Yes	Yes	Yes	Yes	Yes
Fund-flow controls and interactions	Yes	Yes	Yes	Yes	Yes
Observations	50,192,549	50,192,549	50,192,549	50,192,243	50,192,243
Adjusted R-squared	0.024	0.024	0.024	0.024	0.024

This table reports regressions of our *Initiating* trade indicators on the interactions between indicators for dates around the change in quarters, *Qtr_End* and *Qtr_Beg*, and proxies for the relative illiquidity of the underlying security [*Rank(Amihud)* and *Rank(Spread)*, Columns 1-2], relative market cap of the underlying security [*Rank(MarketCap)*, Column 3] and relative size and trade frequency of the fund executing the trade [*Rank(Fund AUM)* and [*Rank(Fund Turnover)*, Columns 4-5]. We also include other controls (see below) in each specification, including uninteracted controls for each aforementioned *Rank* variable, but for brevity, we do not report the coefficients on these additional controls. Full variable definitions are provided in Appendix A. We estimate this regression using all firm-fund-transactions marked by Ancerno over the period 1998 – 2010. Robust standard errors are clustered by security and month-year. *t*-statistics are reported in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Non-linear volume controls: $Signsharevol_{s,t}$, $ShareVol_{s,t}$, $Abs(ShareVol_{s,t})$, $log(ShareVol_{s,t})$, $DollVol_{s,t}$, $Abs(DollVol_{s,t})$ and $log(DollVol_{s,t})$. **Fund-flow controls:** *%FundFlows(t)* and *$FundFlows(t)*. We also include interactions of both with our four variables of interest.

Table 2.8 – Portfolio informativeness around quarter-ends

	(1) *Positions* *R-Squared*
Qtr_Beg	-0.042***
	(-3.68)
Qtr_End	0.025***
	(3.71)
Month_Beg	0.002
	(0.18)
Month_End	0.69
	(0.18)
Intercept	0.827***
	(164.57)
Clustered standard errors	Month
Observations	2,568,249
Adjusted R-squared	0.001

This table reports regressions of *Positions R-squared* on indicators for dates around the change in months and quarters. To conduct this test, we start by identifying fund-date observations where we observe a trade. For each observation, we then approximate the relative size of the fund's end-of-day position in every possible security *s*, $Share(t)_{is}$, and the trading date that occurs 28 days later, $Share(t+28)_{is}$, where *i* indicates the fund that executed the trade on date *t* and *Share* is the proportion of the fund's portfolio that is held in security *s*. *Share* is calculated for every security, including ones that were not traded on day *t*, and set equal to zero when the fund holds no position in the security. We then run a cross-sectional regression of *Share(t+28)* on *Share(t)* for each date *t* and fund *i* in our sample and use the resulting R-squared, *Positions R-squared*, as the outcome variable in the tabulated regression. Standard errors are clustered by month-year. *t*-statistics are reported in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2.9 – Commissions

	(1)	(2)	(3)	(4)	(5)
	Commissions PerShare	*Commissions PerShare*	*AvgComm PerShareOf ChosenBroker*	*Sum Commissions*	*Sum Commissions*
Qtr_Beg	-0.0007***	-0.0004***	0.0001		
	(-4.87)	(-4.07)	(0.43)		
Qtr_End	-0.0015***	-0.0011***	0.0003		
	(-5.24)	(-4.99)	(0.59)		
Scaled_Vol_Qtr_Beg				0.0170	0.0040
				(1.12)	(0.20)
Scaled_Vol_Qtr_End				-0.0388*	-0.0405**
				(-2.06)	(-2.43)
Security-by-month fixed effects	Yes	Yes	Yes	No	No
Fund-by-broker fixed effects	No	Yes	No	No	Yes
Fund fixed effects	Yes	No	Yes	Yes	No
Broker fixed effects	No	No	No	Yes	No
Year fixed effects	No	No	No	Yes	Yes
Clustered standard errors	Firm & Month	Firm & Month	Firm & Month	Year	Year
Adjusted R-squared	0.549	0.665	0.040	0.952	0.967
Observations	65,597,203	65,458,362	65,458,362	618,912	618,912

This table reports the variation in commissions paid by funds to brokers around quarter beginnings and ends. Columns 1 and 2 use commissions per share at the fund-firm-transaction-broker level as the dependent variable. Column 3 uses the average commissions paid by all funds to the broker for a stock over the entire year as the dependent variable. Columns 4 and 5 use the total commissions paid by the fund to the broker across all stocks over the entire year as the dependent variable and the scaled volume of transactions conducted on quarter-beginning and ending days as the independent variables. Full variable definitions are provided in Appendix A. We estimate all the regressions using all firm-fund-broker-transactions over the period 1998 – 2010. Standard errors are two-way clustered by security and month-year in columns 1-3 and by year in columns 4-5. *t*-statistics are reported in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively

Table 2.10 – Price informativeness around quarter- and month-ends

	Return R-squared
Qtr_Beg	0.0015
	(0.58)
Qtr_End	-0.0122***
	(-9.10)
Month_Beg	0.0018
	(1.26)
Month_End	-0.0013
	(-0.99)
Intercept	0.0382***
	(81.59)
Sample	1982-2018
Clustered standard errors	Month
Adjusted R-squared	0.003
Observations	9329

This table reports variation in the relative informativeness of daily returns around quarter-end days over the period 1982 to 2018. We measure the informativeness of daily returns using *Return R-squared*, which is the daily R-squared obtained from daily cross-sectional regressions of the thirty-day return, *Ret*(*t*, *t*+30), on daily returns, *Ret(t)*. Our sample to compute the daily R-squareds consists of all firm-security days from 1982 – 2018 having (i) a listing on NYSE, AMEX or Nasdaq, (ii) exchange code 10 or 11, and (iii) a market capitalization of at least $10 million. Robust standard errors are clustered by month-year. *t*-statistics are reported in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Appendix 2.A – Variable definitions

Variable Name	Variable Description
Change-of-quarter and month-end indicators (Tables 2-10)	
Qtr_End_t	Indicator variable set equal to one if the date *t* is the last trading day of a quarter (i.e., the last trading day of March, June, September, and December).
Qtr_Beg_t	Indicator variable set equal to one if date *t* is the first trading day of a quarter (i.e., the first trading day of January, April, July, and October).
$Month\_End_t$	Indicator variable set equal to one if the date *t* is the last trading day of a month that does not correspond to the change in a calendar quarter (i.e., the last trading day all months, except March, June, September, and December).
$Month\_Beg_t$	Indicator variable set equal to one if the date *t* is the first trading day of a month that does not correspond to the change in a calendar quarter (i.e., the first trading day all months, except January, April, July, and October).
Trade-type dependent variables (Tables 2-4, Table 7, Figure 1, and Appendix Tables A1-A2)	
$Initiating_{i,s,t}$	Indicator variable set equal to one if the trade initiates a new position. Specifically, we set the indicator equal to one if the sign of fund *i*'s trade on date *t* (i.e., buy or sell) in security *s* [i.e., $Sign(Vol_{i,s,t})$] equals the sign of trading volume in that security by that fund over the next four weeks [i.e., $Sign(\Sigma_{i=1\ to\ 28}Vol_{i,s,t+i})$] but does not equal the sign of trade volume over the past four weeks [i.e., $Sign(\Sigma_{i=-28\ to\ -1}Vol_{i,s,t-i})$].
$Completing_{i,s,t}$	Indicator variable set equal to one if the trade completes the funds position in a security. Specifically, we set the indicator equal to one if the sign of fund *i*'s trade on date *t* (i.e., buy or sell) in security *s* [i.e., $Sign(Vol_{i,s,t})$] equals the sign of trading volume in that security by that

	fund over the past four weeks [i.e., $Sign(\Sigma_{i=-28\ to\ -1}Vol_{i,s,t-i})$] but does not equal the sign of trade volume over the next four weeks [i.e., $Sign(\Sigma_{i=1\ to\ 28}Vol_{i,s,t+i})$].
$Building_{i,s,t}$	Indicator variable set equal to one if a trade continues to build a position. Specifically, we set the indicator equal to one if the sign of fund *i*'s trade on date *t* (i.e., buy or sell) in security *s* [i.e., $Sign(Vol_{i,s,t})$] equals the sign of trading volume in that security by that fund over the next four weeks [i.e., $Sign(\Sigma_{i=1\ to\ 28}Vol_{i,s,t+i})$] and the past four weeks [*i.e.*, $Sign(\Sigma_{i=-28\ to\ -1}Vol_{i,s,t-i})$].
$One\text{-}off_{i,s,t}$	Indicator variable set equal to one if the shift in a funds position is unrelated to the sign of either past or future trades. Specifically, we set the indicator equal to one if the sign of fund *i*'s trade on date *t* (i.e., buy or sell) in security *s* [i.e., $Sign(Vol_{i,s,t})$] does not equal the sign of trading volume in that security by that fund over the next four weeks [i.e., $Sign(\Sigma_{i=1\ to\ 28}Vol_{i,s,t+i})$] or the past four weeks [i.e., $Sign(\Sigma_{i=-28\ to\ -1}Vol_{i,s,t-i})$].
Trade-type explanatory variables (Table 4 and Appendix Tables A1-A2)	
$Buy_{i,s,t}$	Indicator variable set equal to one when the trade by fund *i*, in security *s*, on date *t* is a purchase.
$Sell_{i,s,t}$	Indicator variable set equal to one when the trade by fund *i*, in security *s*, on date *t* is a sale.
Trade-type dependent variables (Table 5)	
$Post\_Opposite_{i,s,t}$	Indicator variable set equal to one when the sign of trade by fund *i*, in security *s*, over the four weeks following day *t* [$Sign(\Sigma_{i=1\ to\ 28}Vol_{i,s,t+i})$] is opposite in sign to the trade on day *t* [$Sign(Vol_{i,s,t})$].
Completing (with zero subsequent trade)$_{i,s,t}$	Indicator variable set equal to one when the trade is both a *Completing* trade and has a *Post_Opposite* value equal to 0.

Completing (with subsequent reversal)$_{i,s,t}$	Indicator variable set equal to one when the trade is both a *Completing* trade and has a *Post_Opposite* value equal to 1.
One-off (with zero subsequent trade)$_{i,s,t}$	Indicator variable set equal to one when the trade is both a *One-off* trade and has a *Post_Opposite* value equal to 0.
One-off (with subsequent reversal)$_{i,s,t}$	Indicator variable set equal to one when the trade is both a *One-off* trade and has a *Post_Opposite* value equal to 1.
Trade-type dependent variables (Table 6)	
Pre_Opposite$_{i,s,t}$	Indicator variable set equal to one when the sign of trade by fund *i*, in security *s*, over the four weeks preceding day *t* [$Sign(\Sigma_{i=-28\ to\ -1}Vol_{i,s,t-i})$] is opposite in sign to the trade on day *t* [$Sign(Vol_{i,s,t})$].
Initiating (with zero prior trade)$_{i,s,t}$	Indicator variable set equal to one when the trade is both an *Initiating* trade and has a *Pre_Opposite* value equal to 0.
Initiating (reversal of prior position)$_{i,s,t}$	Indicator variable set equal to one when the trade is both an *Initiating* trade and has a *Pre_Opposite* value equal to 1.
One-off (with zero prior trade)$_{i,s,t}$	Indicator variable set equal to one when the trade is both an *One-off* trade and has a *Pre_Opposite* value equal to 0.
One-off (reversal of prior position)$_{i,s,t}$	Indicator variable set equal to one when the trade is both an *One-off* trade and has a *Pret_Opposite* value equal to 1.
Fund- and firm-characteristic explanatory variables (Table 7)	
Rank(Amihud)$_{s,m}$	Percentile rank of a security's Amihud illiquidity over the last 12 months. To construct this measure, we begin by calculating the average Amihud illiquidity measure for each security *s* in the previous 12 months, *Amihud*, by calculating the security's absolute return divided by dollar

	volume on a daily basis and then taking the average of that daily ratio over the previous 12 months. Using this *Amihud*, we then rank securities in the given month *m* by constructing *Rank(Amihud)*, where the most illiquid stock (i.e., the stock with the highest *Amihud*) receives a *Rank(Amihud)* equal to one for that month, while the least illiquid stock receives a *Rank(Amihud)* value of 0.
$Rank(Spread)_{s,m}$	Percentile rank of a security's average bid-ask spread over the last 12 months. To construct this measure, we begin by calculating the average bid-ask spread for each security *s* in the previous 12 months, *Spread*, where the spread is calculated as the difference between the ask and the bid prices divided by the average of these prices. Then, using this *Spread*, we rank securities in the given month *m* by constructing *Rank(Spread)*, where the most illiquid stock (i.e., the stock with the highest average bid-ask spread in the previous 12 months) receives a *Rank(Spread)* equal to one for that month, while the least illiquid stock receives a *Rank(Spread)* value of zero.
$Rank(MarketCap)_{s,m}$	Percentile rank of a security's market capitalization as of prior month's last trading date. To construct this measure, we begin by calculating the market cap for each security *s* on the last trading date of the previous month, *MarketCap*. Then, using this *MarketCap*, we rank securities in the given month *m* by constructing *Rank(MarketCap)*, where the security with the largest *MarketCap* (i.e., the stock with the highest market cap at the end of the prior month) receives a *Rank(MarketCap)* equal to one for that month, while the stock with the smallest market cap receives a value of zero.
$Rank(Fund\ AUM)_{i,m}$	Percentile rank of the AUM for the fund executing a trade using the estimated average AUM of that fund over the last 12 months. To estimate the AUM, we approximate the daily start position of each fund *i* by netting out the sell and buy trades in each security over the fund's entire trading history. We then use stock prices from CRSP to estimate a daily AUM from these start positions

	(setting any negative position to zero) and take the average of these over the last 12 months as our proxy for a fund's average AUM, *Fund AUM*. Using this *Fund AUM*, we then rank funds in the given month *m* by constructing *Rank(Fund AUM),* where *Rank(Fund AUM)* equals 1 for the fund with the highest *Fund AUM* that month, while *Rank(Fund AUM)* equals 0 for the fund with the lowest *Fund AUM* that month.
Rank(Fund Turnover)$_{i,m}$	Percentile rank of fund turnover for the fund executing a trade using the dollar value of securities traded over the last 12 months. To construct this measure, we calculate the dollar value of securities traded over the last 12 months for each fund *i* as our proxy for a fund's trade frequency, *Fund Turnover*. Using this *Fund Turnover*, we then rank funds in the given month *m* by constructing *Rank(Fund Turnover)*, where the fund with the greatest turnover over the last 12 months (i.e., the fund with the highest *Fund Turnover*) receives a *Rank(Fund Turnover)* equal to one for that month, while the fund with the lowest turnover receives a value of 0.
Portfolio informativeness dependent variable (Table 8)	
Positions R-squared$_{it}$	The R-squared obtained for fund *i* on date *t* from running a cross-sectional, security-level regression of the fund's position sizes 28 days later, *Share(t+28)*$_i$, on the fund's current position sizes, *Share(t)*$_{is}$, where *Share* is the proportion of the fund *i*'s holdings in security *s*. Position sizes are estimated using a fund's entire Ancerno trading history, and *Share* is set to zero if the fund does not have a position in the security.
Commissions dependent and explanatory variables (Table 9)	
CommissionsPerShare$_{i,q,s,t}$	Commissions paid per share for trading in security *s* by fund *i* on trade date *t* to broker *q*. Winsorized at ten cents per share and zero cents per share.
AvgCommPerShareOfChosenBroker$_{s,q,y}$	Average commission per share paid by all funds to broker *q* for trades in security *s* averaged over the calendar year *y*. Winsorized at ten cents per share and zero cents per share.

SumCommissions$_{i,q,y}$	Log of total commissions paid by fund *i* to broker *q* over the entire year calendar *y*. Winsorized at 1 and 99 percent.
Scaled_Vol_Qtr_Beg$_{i,q,y}$	Proportion of volume traded on the first day of quarter to the total volume traded over the entire year *y* by fund *i* through broker *q*.
Scaled_Vol_Qtr_End$_{i,q,y}$	Proportion of volume traded on the last day of quarter to the total volume traded over the entire year *y* by fund *i* through broker *q*.
Price informativeness dependent variable (Table 10 and Figures 2-3)	
Return R-squared$_t$	The R-squared obtained for date *t* from running a daily cross-sectional security-level regression of thirty-day returns, *Ret(t, t+30)*, on daily returns, *Ret(t)*.
Stock-level return reversal variables (Figure 4)	
Ret(t)	Return on trade date *t*.
Ret(t+1, t+s)	Compound return if held from trading day *t+1* to trading day *t+s*.
Ancerno analysis control variables (Tables 3 – 7)	
%FundFlows$_{i,t}$	We subtract buy dollar volume from sell dollar volume across all trades made by fund *i* at date *t*, and then divide by the sum of buy and sell volume across trades, to capture the flow of funds on date *t*.
*$FundFlows*$_{i,t}$	We subtract buy dollar volume from sell dollar volume across all trades made by fund *i* on date *t*. We then take the log of the absolute value of dollar volume and multiply by the sign of the trade (i.e., we take the log of signed $ flows to reduce the influence of outliers).
SignShareVol$_{s,t}$	Sign of share volume in security *s* on date *t* (i.e., one for buy trades and negative one for sell trades).
ShareVol$_{s,t}$	Share volume in security *s* on date *t*.

Abs(ShareVol$_{s,t}$)	Absolute value of share volume in security *s* on date *t*.
log(ShareVol$_{s,t}$)	Log of the absolute value of share volume in security *s* on date *t*, multiplied by the sign of share volume.
DollVol$_{s,t}$	Signed dollar volume in security *s* on date *t*.
Abs(DollVol$_{s,t}$)	Absolute value of dollar volume in security *s* on date *t*.
log(DollVol$_{s,t}$)	Log of the absolute value of dollar volume in security *s* on date *t*, multiplied by the sign of share volume.

Appendix 2.B – Trade type definitions

In our primary classification scheme, we classify trades based on the similarity of a fund's date *t* trade in security *s* with the cumulative trade by that fund in that security over the prior and subsequent four weeks. Using S to denote a fund's trade volume over a four-week interval having the same sign as the day *t* trade and NS to denote trade volume that does not have the same sign, there are four possible classifications for each date *t* trade: S-S, NS-S, S-NS and NS-NS, where the first (second) label indicates the sign of prior (subsequent) four-week trade volume. For example, NS-S indicates a trade on date *t* that does not have the same sign as trade volume in the prior four weeks but does have the same sign as trades in the subsequent four weeks. We label these four trade *t* classifications as *Building*, *Initiating*, *Completing*, and *One-off*, respectively.

The trade-type classifications can be expanded by differentiating whether the NS trades reflect trades of the opposite sign as trade date *t* volume (O) and those with zero volume (Z), resulting in a total of nine classifications. For example, a *Completing* trade (S-NS) can be subdivided into *Completing* trades that are at least partially reversed over the next four weeks (S-O) and *Completing* trades that are followed by zero trade volume (S-Z). And, *Initiating* trades (NS-S) can be subdivided into *Initiating* trades that begin the reversal of a prior trading direction (O-S) and *Initiating* trades that reflect the beginning of trades in the security (Z-S). The labels we assign to these nine possible trade classifications are provided in the below table:

Trade classifications	***Pre_Opposite* = 1**	***Post_Opposite* = 1**
S-S *[Building]*	NO	NO
S-Z *[Completing (with zero subsequent trade)]*	NO	NO
S-O *[Completing (with subsequent reversal)]*	NO	YES
Z-S *[Initiating (new position)]*	NO	NO
O-S *[Initiating (reversal of prior trade)]*	YES	NO
Z-Z *[One-off (preceded and followed by zero trade)]*	NO	NO
Z-O *[One-off (with subsequent reversal)]*	NO	YES

O-Z *[One-off (reversal of prior trade)]*	YES	NO
O-O *[One-off (preceded and followed by opposing trades)]*	YES	YES

We use these additional classifications in Tables 5-6 when we investigate whether the quarterly variation in trade types we document is concentrated in trades that reverse a prior position or are subsequently reversed. Specifically, in Table 5 we investigate whether the quarter-end increase in date *t* trades with NS post-trade volume (i.e., *Completing* and *One-off* trades) is driven by an increase in trades that are subsequently reversed by the fund (i.e., S-O, Z-O, and O-O trades) or not (i.e., S-Z, Z-Z, and O-Z trades). In Table 6, we investigate whether the increase in date *t* trades with NS pre-trade volume (i.e., *Initiating* and *One-off*) at the start of each quarter is driven by trades that reverse previous trades (i.e., O-S, O-Z, and O-O trades) or instead have zero prior trade volume (i.e., Z-S, Z-Z, and Z-O trades).

Appendix 2.C – Additional tables

Table 2.C.1 – Relative magnitude of position within a fund and trade-type frequency around quarter-ends

	(1) *Initiating*	(2) *Completing*	(3) *One-off*	(4) *Building*
*Qtr_End*Buy*	-0.1034***	0.0428***	0.1039***	-0.0432***
	(-8.24)	(3.73)	(5.18)	(-3.17)
*Qtr_End*Sell*	-0.0271***	0.0442***	0.0662***	-0.0833***
	(-2.85)	(2.83)	(4.37)	(-8.83)
*Qtr_Beg*Buy*	0.0383***	-0.0355***	0.0381***	-0.0410***
	(3.83)	(-4.41)	(3.27)	(-3.94)
*Qtr_Beg*Sell*	0.0316***	-0.0382***	0.0469***	-0.0402***
	(4.16)	(-8.18)	(4.87)	(-4.04)
*Qtr_End*Buy*Rank(Position)*	0.1202***	-0.0367***	-0.0836***	0.0001
	(8.80)	(-2.79)	(-3.94)	(0.01)
*Qtr_End*Sell*Rank(Position)*	-0.0033	-0.0310*	-0.0373**	0.0717***
	(-0.32)	(-1.66)	(-2.21)	(6.76)
*Qtr_Beg*Buy*Rank(Position)*	-0.0246**	0.0341***	-0.0147	0.0052
	(-2.05)	(3.91)	(-1.05)	(0.42)
*Qtr_Beg*Sell*Rank(Position)*	-0.0382***	0.0477***	-0.0483***	0.0388***
	(-4.29)	(8.69)	(-4.29)	(3.45)
Fund FE	Yes	Yes	Yes	Yes
Security-by-month FE	Yes	Yes	Yes	Yes
Non-linear volume controls	Yes	Yes	Yes	Yes
Fund-flow controls and interactions	Yes	Yes	Yes	Yes
Two-way clustered SE	Firm & Month	Firm & Month	Firm & Month	Firm & Month
Adjusted R-squared	0.038	0.033	0.113	0.135
Observations	50,192,549	50,192,549	50,192,549	50,192,549

This table reports regressions of our four trade type indicators (*Initiating*, *Completing*, *One-off*, *Building*) on the interactions between indicators for dates around the change in quarters, *Qtr_End* and *Qtr_Beg*, indicators for whether the trade was a purchase, *Buy*, or sale, *Sell*, and the normalized rank of the security's position in a fund's portfolio at the start of the trading day, *Rank(Position)*. We also include other controls (see below), including *Buy* and the interactions of the *Buy* and *Sell* indicators with *Rank(Position)*, but for brevity, we do not report the coefficients on these additional controls. To calculate *Rank(Position)*, we first approximate daily positions by netting out the sell and buy trades in each security over the fund's trading history, setting any negative position to zero. Next, we create a normalized daily percentile rank of each fund's positions. A fund's position with the estimated largest value at the beginning of a given trading day receives a *Rank(Position)* value of 1 for that day, while the fund's smallest position receives a *Rank(Position)* value of 0. Standard errors are two-way clustered by firm and month-year. *t*-statistics are reported in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.
Non-linear volume controls: $Signsharevol_{s,t}$, $ShareVol_{s,t}$, $Abs(ShareVol_{s,t})$, $log(ShareVol_{s,t})$, and $log(DollVol_{s,t})$.
Fund-flow controls: *%FundFlows(t)* and *$FundFlows(t)*. We also include interactions of these with our four variables of interest.

Table 2.C.2 – Relative past performance of a fund and trade-type frequency around quarter-ends

	(1) *Initiating*	(2) *Completing*	(3) *One-off*	(4) *Building*
*Qtr_End*Buy*	-0.0226**	0.0271*	0.0516***	-0.0560***
	(-2.42)	(1.88)	(2.95)	(-3.81)
*Qtr_End*Sell*	-0.0427**	0.0384	0.0657***	-0.0614***
	(-2.36)	(1.33)	(3.82)	(-6.02)
*Qtr_Beg*Buy*	0.0138*	-0.0035	0.0342**	-0.0445***
	(1.90)	(-0.37)	(2.35)	(-3.19)
*Qtr_Beg*Sell*	0.0186*	-0.0004	0.0027	-0.0209
	(1.70)	(-0.05)	(0.17)	(-1.58)
*Qtr_End*Buy*Rank(Return)*	0.0073	-0.0199	-0.0053	0.0179
	(0.54)	(-0.84)	(-0.20)	(0.96)
*Qtr_End*Sell*Rank(Return)*	0.0184	-0.0149	-0.0413*	0.0378**
	(0.66)	(-0.33)	(-1.69)	(2.37)
*Qtr_Beg*Buy*Rank(Return)*	0.0112	-0.0133	-0.0112	0.0134
	(0.96)	(-0.94)	(-0.46)	(0.60)
*Qtr_Beg*Sell*Rank(Return)*	-0.0158	-0.0203*	0.0318	0.0043
	(-0.84)	(-1.79)	(1.24)	(0.21)
Fund fixed effects	Yes	Yes	Yes	Yes
Security-by-month fixed effects	Yes	Yes	Yes	Yes
Non-linear volume controls	Yes	Yes	Yes	Yes
Fund-flow controls and interactions	Yes	Yes	Yes	Yes
Two-way clustered SE	Firm & Month	Firm & Month	Firm & Month	Firm & Month
Adjusted R-squared	0.023	0.025	0.107	0.128
Observations	50,170,968	50,170,968	50,170,968	50,170,968

This table reports regressions of our four trade type indicators (*Initiating*, *Completing*, *One-off*, *Building*) on the interactions between indicators for dates around the change in quarters, *Qtr_End* and *Qtr_Beg*, indicators for whether the trade was a purchase, *Buy*, or sale, *Sell*, and the normalized rank of the fund's past performance, *Rank(Return)*, and its interaction with the quarter indicators. We also include other controls (see below), including *Buy* and the interactions of the *Buy* and *Sell* indicators with *Rank(Return)*, but for brevity, we do not report the coefficients on these additional controls. *Rank(Return)* is computed as the monthly percentile rank of value-weighted return of the fund over a 12-month period ending prior to the month of the trade. The fund with the best performance of the last 12 months receives a rank of 1 for that month, while the worst-performing fund receives a rank of 0. The controls also include non-linear volume controls, fund flow controls and their interactions with the quarter indicators. Standard errors are two-way clustered by firm and month-year. *t*-statistics are reported in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Non-linear volume controls: $Signsharevol_{s,t}$, $ShareVol_{s,t}$, $Abs(ShareVol_{s,t})$, $log(ShareVol_{s,t})$, $DollVol_{s,t}$, $Abs(DollVol_{s,t})$ and $log(DollVol_{s,t})$.

Fund-flow controls: *%FundFlows(t)* and *$FundFlows(t)*. We also include interactions of both with our four variables of interest.

References

Agarwal, V., Gay, G.D. and Ling, L., 2014. Window dressing in mutual funds. The Review of Financial Studies, 27(11), 3133-3170.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of financial markets, 5(1), 31-56.

Anand, A., Gatchev, V.A., Madureira, L., Pirinsky, C.A. and Underwood, S., 2011. Geographic proximity and price discovery: Evidence from NASDAQ. Journal of financial markets, 14(2), 193-226.

Ben-David, I., Franzoni, F. and Moussawi, R., 2019. An improved method to predict assignment of stocks into russell indexes. Unpublished working paper. Ohio State University.

Biais, B., Hillion, P. and Spatt, C., 1999. Price discovery and learning during the preopening period in the Paris Bourse. Journal of Political Economy, 107(6), 1218-1248.

Black, Fischer. “Noise.” The journal of finance 41, no. 3 (1986): 528-543.

Blocher, J., Engelberg, J. and Reed, A.V., 2012. The long and the short of it: Evidence of year-end price manipulation by short sellers. Unpublished working paper. Vanderbilt University

Blume, M.E., 1993. Soft dollars and the brokerage industry. Financial Analysts Journal, 49(2), 36-44.

Brunnermeier, Markus K., Christian Gollier, and Jonathan A. Parker. “Optimal beliefs, asset prices, and the preference for skewed returns.” American Economic Review 97, no. 2 (2007): 159-165.

Campbell, J.Y., Grossman, S.J. and Wang, J., 1993. Trading volume and serial correlation in stock returns. The Quarterly Journal of Economics, 108(4), 905-939.

Carhart, M.M., Kaniel, R., Musto, D.K. and Reed, A.V., 2002. Leaning for the tape: Evidence of gaming behavior in equity mutual funds. The Journal of Finance, 57(2), 661-693.

Chakrabarty, B., Moulton, P.C. and Trzcinka, C., 2017. The performance of short-term institutional trades. Journal of Financial and Quantitative Analysis, *52*(4), pp.1403-1428.

Chava, Sudheer. “Environmental externalities and cost of capital.” Management Science 60, no. 9 (2014): 2223-2247.

Coval, Joshua D., and Tobias J. Moskowitz. “Home bias at home: Local equity preference in domestic portfolios.” The Journal of Finance 54, no. 6 (1999): 2045-2073.

Cremers, M. and Pareek, A., 2016. Patient capital outperformance: The investment skill of high active share managers who trade infrequently. Journal of Financial Economics, 122(2), 288-306.

Cremers, K.M. and Petajisto, A., 2009. How active is your fund manager? A new measure that predicts performance. The review of financial studies, 22(9), 3329-3365.

D'Allegro, J., 2016. It's time for a tricky year-end portfolio balancing act. CNBC, 13th October 2016, viewed 03rd October 2021. <https://www.cnbc.com/2016/10/13/rebalancing-season-brings-out-best-and-worst-from-investors.html>.

Diamond, R. (2019, April 29). CalSTRS Tackles Opioid Crisis. Chief Investment Officer. https://www.ai-cio.com/news/calstrs-tackles-opioid-crisis/

Di Mascio, R., Lines, A. and Naik, N. Y., 2017. Alpha Decay. Unpublished working paper. Columbia Business School.

Di Giuli, Alberta, and Leonard Kostovetsky. "Are red or blue companies more likely to go green? Politics and corporate social responsibility." Journal of Financial Economics 111, no. 1 (2014): 158-180.

Duong, T.X. and Meschke, F., 2020. The rise and fall of portfolio pumping among US mutual funds. Journal of Corporate Finance, 60, p.101530.

Duran, R. (2013, April 12). CalSTRS Divests of Certain Firearms Holdings. CalSTRS Pension Sense Blog. https://www.calstrs.com/news-release/calstrs-divests-certain-firearms-holdings

Durden, T. 2018. Why stocks are soaring: A massive $64 billion buy order. Zero-hedge, December 27, 2018, viewed 25 August 2019. <http://web.archive.org/web/20190825023348/https://www.zerohedge.com/news/2018-12-26/why-stocks-are-soaring-massive-64-billion-buy-order>

Engelberg, Joseph, R. David McLean, and Jeffrey Pontiff. "Anomalies and news." The Journal of Finance 73, no. 5 (2018): 1971-2001.

Etula, E., Rinne, K., Suominen, M. and Vaittinen, L., 2020. Dash for cash: Monthly market impact of institutional liquidity needs. The Review of Financial Studies, 33(1), 75-111.

Fama, Eugene F., and Kenneth R. French. "Dissecting anomalies with a five-factor model." The Review of Financial Studies 29, no. 1 (2016): 69-103.

Frank, M. M., Poterba, J. M., Shackelford, D. A., & Shoven, J. B. (2004). Copycat funds: Information disclosure regulation and the returns to active management in the mutual fund industry. The Journal of Law and Economics, 47(2), 515-541.

Friedman, M. (2007). The social responsibility of business is to increase its profits. In Corporate ethics and corporate governance (pp. 173-178). Springer, Berlin, Heidelberg

Goldstein, M.A., Irvine, P., Kandel, E. and Wiener, Z., 2009. Brokerage commissions and institutional trading patterns. The Review of Financial Studies, 22(12), 5175-5212.

Gormley, Todd A., Zachary Kaplan, and Aadhaar Verma. "More informative disclosures, less informative prices? Portfolio and price formation around quarter-ends." Journal of Financial Economics (2021).

Green, T.C., Jame, R., Markov, S. and Subasi, M., 2014. Access to management and the informativeness of analyst research. Journal of Financial Economics, 114(2), 239-255.

Groysberg, B., Healy, P. M., 2013. Wall Street Research: Past, Present and Future. Stanford University Press

Harris, L.E., Hartzmark, S.M. and Solomon, D.H., 2015. Juicing the dividend yield: Mutual funds and the demand for dividends. Journal of Financial Economics, 116(3), 433-451.

Hartzmark, S.M. and Solomon, D.H., 2013. The dividend month premium. Journal of Financial Economics, 109(3), 640-660.

Hartzmark, S.M. and Sussman, A.B., 2019. Do investors value sustainability? A natural experiment examining ranking and fund flows. The Journal of Finance, 74(6), 2789-2837.

Haugen, R.A. and Lakonishok, J., 1987. The incredible January effect: The stock market's unsolved mystery. Irwin Professional Pub.

Hong, Harrison, and Marcin Kacperczyk. "The price of sin: The effects of social norms on markets." Journal of financial economics 93, no. 1 (2009): 15-36.

Hu, G., McLean, R.D., Pontiff, J. and Wang, Q., 2014. The year-end trading activities of institutional investors: Evidence from daily trades. The Review of Financial Studies, 27(5), 1593-1614.

Hu, G., Jo, K.M., Wang, Y.A. and Xie, J., 2018. Institutional trading and Abel Noser data. Journal of Corporate Finance, 52, 143-167.

Huberman, Gur. "Familiarity breeds investment." The Review of Financial Studies 14, no. 3 (2001): 659-680.

Irvine, P.J., 2000. Do analysts generate trade for their firms? Evidence from the Toronto stock exchange. Journal of Accounting and Economics, 30(2), 209-226.

Irvine, P.J., 2004. Analysts' forecasts and brokerage-firm trading. The Accounting Review, 79(1), 125-149.

Jackson, A.R., 2005. Trade generation, reputation, and sell-side analysts. The Journal of Finance, 60(2), 673-717.

Kacperczyk, M., Sialm, C. and Zheng, L., 2008. Unobserved actions of mutual funds. The Review of Financial Studies, 21(6), 2379-2416.

Kansas, D. 2011. Quarter End: Window-Dressing Targets. Wall Street Journal, 28th March 2011, viewed 03 October 2021. https://blogs.wsj.com/marketbeat/2011/03/28/quarter-end-window-dressing-targets

Kozlowski, R. (2016, July 15). New York City Employees to divest some gun retailer holdings. Pensions & Investments. https://www.pionline.com/article/20160715/ONLINE/160719915/new-york-city-employees-to-divest-some-gun-retailer-holdings

Kozlowski, R. (2018, Aug 22). Yale adopts investment ban on assault weapon retailers. Pensions & Investments. https://www.pionline.com/article/20180822/ONLINE/180829905/yale-adopts-investment-ban-on-assault-weapon-retailers

Krüger, Philipp. "Corporate goodness and shareholder wealth." Journal of financial economics 115, no. 2 (2015): 304-329.

Lakonishok, J., Shleifer, A., Thaler, R. and Vishny, R., 1991. Window Dressing by Pension Fund Managers. The American Economic Review, 81(2), 227-231.

Larsen, R. and Valentini, F. (2016, May 23). Axa to Divest its Tobacco Industry Assets Worth $2 billion. Bloomberg. https://www.bloomberg.com/news/articles/2016-05-23/axa-to-sell-2-billion-of-tobacco-assets-as-it-divests-industry

Lee, W. (2000, June 16). U-M to divest its holdings in tobacco manufacturing companies. University of Michigan. http://ns.umich.edu/Releases/2000/Jun00/r061600i.html

Lehmer, T, Lourie, B, and Shanthikumar, D. M, 2021. Broker Trading Volume and Analysts' Earnings Forecasts: A Conflict of Interest? Review of Accounting Studies, In Press.

Leuz, C. and Wysocki, P.D., 2016. The economics of disclosure and financial reporting regulation: Evidence and suggestions for future research. Journal of accounting research, 54(2), 525-622.

Lewin, T. (1990, May 24). Harvard and CUNY Shedding Stocks in Tobacco. The New York Times. https://www.nytimes.com/1990/05/24/us/harvard-and-cuny-shedding-stocks-in-tobacco.html

Meier, I. and Schaumburg, E., 2004. Do funds window dress? Evidence for US equity mutual funds. Unpublished working paper. Northwestern University.

Manchiraju, Hariom, and Shivaram Rajgopal. "Does corporate social responsibility (CSR) create shareholder value? Evidence from the Indian Companies Act 2013." Journal of Accounting Research 55, no. 5 (2017): 1257-1300.

Moyer, L. (2018, Feb 22). State pensions and fund companies feel heat over their investments in gun makers. CNBC. https://www.cnbc.com/2018/02/22/state-pensions-and-fund-companies-feel-heat-over-their-gun-stock-investments.html

Musto, D.K., 1997. Portfolio disclosures and year-end price shifts. The Journal of Finance, 52(4), 1563-1588.

Musto, D.K., 1999. Investment decisions depend on portfolio disclosures. The Journal of Finance, 54(3), 935-952.

Niehaus, G. and Zhang, D., 2010. The impact of sell-side analyst research coverage on an affiliated broker's market share of trading volume. Journal of Banking & Finance, 34(4), 776-787.

Novy-Marx, Robert. "The other side of value: The gross profitability premium." Journal of financial economics 108, no. 1 (2013): 1-28.

Offerman, M. (2017, October 30). Investor coalition calls on 10 firms to assess their risks related to opioids. Pensions & Investments. https://www.pionline.com/article/20171030/ONLINE/171039966/investor-coalition-calls-on-10-firms-to-assess-their-risks-related-to-opioids

Riedl, Arno, and Paul Smeets. "Why do investors hold socially responsible mutual funds?" The Journal of Finance 72, no. 6 (2017): 2505-2550.

Schwarz, C.G. and Potter, M.E., 2016. Revisiting mutual fund portfolio disclosure. The Review of Financial Studies, 29(12), 3519-3544.

Sebastian, T. and Staley T. (2018, June 19). Beshear: Stop Sending State Dollars to Opioid Companies. Kentucky.gov. https://kentucky.gov/Pages/Activity-stream.aspx?n=AttorneyGeneral&prId=592

Sensoy, B.A., 2009. Performance evaluation and self-designated benchmark indexes in the mutual fund industry. Journal of Financial Economics, 92(1), 25-39.

Shiller, Robert J. "Stock prices and social dynamics." Brookings papers on economic activity 1984, no. 2 (1984): 457-510.

Skypala, P. (2018, May 13). Pharma investors mobilise on reputational risk concerns. Financial Times. https://www.ft.com/content/3ad0f62a-2dd5-11e8-97ec-4bd3494d5f14

Solomon, D.H., Soltes, E. and Sosyura, D., 2014. Winners in the spotlight: Media coverage of fund holdings as a driver of flows. Journal of Financial Economics, 113(1), 53-72.

Spector, M. and Terlep, S. (2012, December 18). Talk of Selling Gun Maker Started Just After Shooting. Wall Street Journal. https://www.wsj.com/articles/SB10001424127887324907204578187623794707396

Van Zee, A. (2009). The promotion and marketing of oxycontin: commercial triumph, public health tragedy. American journal of public health, 99(2), 221-227.

Wermers, Russ. "The potential effects of more frequent portfolio disclosure on mutual fund performance." Perspective 7, no. 3 (2001): 1-11.

Wermers, R., 2011. Performance measurement of mutual funds, hedge funds, and institutional accounts. Annual Review of Financial Econ., 3(1), 537-574.