Do Short-Sellers Profit From Mutual Funds? Evidence from Daily Trades

Salman Arif, Azi Ben-Rephael[†], and Charles M.C. Lee[§]

First Draft: September 15, 2014

Current Draft: May 21, 2015

Abstract

Daily mutual fund (MF) flows are highly persistent and price-destabilizing, and short-sellers (SSs) trade strongly in the opposite direction to these flows. This negative relation is associated with the expected component of MF flows (based on prior days' trading), as well as the unexpected component (based on same-day flows). The ability of SS trades to predict stock returns is up to 3 times greater when MF flows are in the opposite direction. The resulting wealth transfer from MFs to SSs is most pronounced for high-MF-held, low-liquidity firms, and is much larger during periods of high retail sentiment.

[*] We thank Yakov Amihud, Cliff Asness, Ekkehart Boehmer, Andrea Frazzini, Clifton Green, David Hirshleifer, Peter Kyle, Toby Moskowitz, Lasse Pedersen, Todd Pulvino, Adam Reed, Siew Hong Teoh, Xiaoyan Zhang, Lu Zheng, and seminar participants at Indiana University, MIT, UC Irvine, the Conference on Financial Economics and Accounting (CFEA), the NBER Market Microstructure Meeting, the University of Minnesota Empirical Conference, the Korean Securities Association Annual Conference, the AQR Insight Award Conference, and the State of Indiana Finance Conference for helpful suggestions and comments.

[†] Salman Arif and Azi Ben-Rephael are at the Kelley School of Business, Indiana University.
Salman Arif: arifs@indiana.edu, +1 (812) 856 – 1592. Azi Ben-Rephael: abenreph@indiana.edu, +1 (812) 856-4068.

[§] Charles M.C. Lee is at Stanford GSB. clee8@stanford.edu, +1 (650) 721 – 1295.

1 Introduction

Traditional rational expectation models with costly information feature agents who expend resources to become informed. These informed agents earn a return on their information acquisition efforts by trading against the uninformed, and as they do so, the information they possess is incorporated into prices.[1] Although such models offer broad insights into the informational role of prices, they are of less help in understanding the nature of the information possessed by the informed. A particular limitation is that informed traders in these models are typically identical (i.e., possess the same information and face the same cost constraints).

In real-world markets, price discovery is a much more complex process. A more realistic characterization of the world of professional investment management is one in which multiple groups of "heterogeneously informed" traders facing different cost constraints are seeking to earn a competitive return on their particular parcels of knowledge.[2] In such markets, efforts to understand price discovery calls for insights into the roles played by different groups, and the motives that each has for trading. A challenge to empiricists is to identify settings in which the actions of distinct investor groups can be identified and studied in isolation.

In this study, we use trade data at the daily level to examine the interaction between two important, yet largely orthogonal, investor groups – mutual funds (MFs) and short-sellers (SSs). Both groups are prominent in the U.S. equity market. MFs are professionally managed investment vehicles that charge an active management fee and cater primarily to a retail clientele. With close to $6 trillion in assets under management as of year-end 2012, they constitute a major source of active trading in the market.[3] Short-sellers are another important group of active investors, which prior studies consistently associate with superior information processing capabilities.[4]

[1] In equilibrium, the supply of traders with costly-to-collect information adjusts to provide just sufficient reward for information collection and processing. Thus the cost constraints faced by informed traders are reflected in the level of informational efficiency attained by the market. See for example, Admati (1985), Diamond and Verrecchia (1981), and Verrecchia (1982).

[2] Stefanini (2006) surveys investment strategies used by hedge funds. Difference-of-opinion models (e.g., Varian (1989), Harris and Raviv (1993), and Kandel and Pearson (1995)) may be viewed as an attempt to address this facet of reality. See Hong and Stein (2007) for a review of this literature.

[3] See the 2013 Investment Company Factbook, available at http://www.icifactbook.org

[4] Boehmer, Jones and Zhang (2008) report short-selling accounts for over 20% of the trading volume in the U.S. We discuss other related short-selling studies in Section 2.

Although MF managers tend to be regarded as sophisticated investors, they are also subject to a variety of regulatory and agency-related constraints that may impede fund performance. Prior evidence suggests that at least some subset of MF managers possess persistent stock-selection skill, although as a group MFs seem to curiously underperform.[5] Indeed, a number of recent studies (summarized in Section 2) show that MF trading can lead to predictable return patterns at the individual stock level. However, prior studies that examine institutional investor behavior typically rely on quarterly holdings culled from 13-F filings, which offer limited insights on daily trading activities (e.g., Kacperczyk, Sialm, and Zheng (2008) and Puckett and Yan (2011)). In addition, because these filings only reflect the long-side of investors' positions, no distinction can be made between the actions of MFs and SSs.

Using highly granular trading data, we provide the first close-up evidence on how these two investor groups interact with each other at the daily level, as well as the implications of their interaction for future stock returns. The two-folded focus of our investigation is on: (1) the responsiveness of daily SS trades to the direction of MF flows (i.e., whether SSs seem to detect and trade on patterns in MF flows), and (2) the implications of daily MF and SS interactions for future stock returns (i.e., the extent to which their interactions result in a wealth transfer from MFs to SSs).

Prior studies provide virtually no guidance on how these two groups of investors might interact at the daily level. Ex ante, a case might be made for either a positive or a negative correlation, or no correlation at all. For example, if MFs and SSs generally respond to similar information, the two groups may on average trade in the same direction. Conversely, short sellers may have superior information sets or higher processing speed relative to mutual funds. Moreover, if mutual fund trading pressure results in temporary price dislocations that are anticipatable by SSs, SSs may systematically exploit these patterns. In these latter scenarios, short-sale activities would be, on average, in the opposite direction to trades by mutual funds.

[5] Kacperczk et al. (2008) and Puckett and Yan (2011) show that the interim trades by MF managers are performance enhancing, even after costs, and that top MFs by this measure outperform consistently. Other studies show, taken as a whole, MFs tend to underperform (e.g., Gruber (1996), French (2008), Fama and French (2010)). Relatedly, Bennett, Sias and Starks (2003), Cai and Zheng (2004), and Yan and Zhang (2009) find institutional trades, inferred from changes in quarterly 13-F holdings, do not predict future returns. More recently, Del Guercio and Reuter (2014) show MFs that are directly-sold to investors do not underperform – i.e., the MF underperformance is driven primarily by funds sold through affiliated brokers.

To track the daily trades of mutual funds, we use information from a database provided by Ancerno Limited. Ancerno is a widely-recognized transaction-cost consulting firm to institutional investors, and our database contains all trades made by Ancerno's substantial base of clients. During our study period (January 2005 to July 2007), Ancerno's MF clients alone accounted for 13.65% of the average daily trading volume in our sample stocks.[6] We use this data to compute a measure of the daily directional flow across all MFs.[7] Specifically, for each stock, we compute "MF_t", defined as the number of shares purchased by MFs minus the number of shares sold by MFs on day t, divided by that day's total share volume traded.

We then compare the daily directional MF flow to the volume of newly-initiated short sales, computed using data from the NYSE Trade and Quote (TAQ) regulation SHO database.[8] The regulation SHO database contains tick-by-tick short-sale data for a cross-section of more than 3,800 individual stocks. We aggregate the short sales information for each stock to the daily level. In particular, we focus on "SS_t", a measure of the total number of shares traded in short-seller initiated transactions, expressed as a percentage of total daily share volume. During our sample period, a vast majority of mutual funds either do not take or are prohibited from taking short positions. We can therefore confidently exclude MF-initiated trades from those initiated by SSs in the SHO database.[9] Our research design thus provides a unique opportunity to compare and contrast the directional trading activities of two purportedly sophisticated sets of investors whose actions are mutually exclusive.

Our first main result is that daily SS and MF trades are highly interdependent. At the daily level, SSs trade strongly in the opposite direction to MFs. On days when MFs are net buyers

[6] Our sample period is limited to regulation SHO short-selling database availability (see Footnote 7). We discuss the Ancerno dataset in more detail in Section 2. Other studies that have used this database include: Chemmanur, He, and Hu (2009), Goldstein, Irvine, and Puckett (2011), Puckett and Yan (2011, 2013), Anand, Irvine, Puckett and Venkataraman (2012, 2013), Jame (2012), Busse, Green, and Jegadeesh (2012), Franzoni and Plazzi (2013), and Gantchev and Jotikasthira (2013). None of these studies examine the MF and SS interaction.

[7] We note that Ancerno provides trade level data on mutual fund trades and that the actual intraday execution times are not available.

[8] On June 23, 2004, the SEC adopted Regulation SHO to establish uniform locate-and-delivery requirements and establish a procedure to temporarily suspend the price tests for a set of pilot securities. At the same time, the SEC mandated that all self-regulatory organizations make tick data on short sales publicly available. This resulted in a short-sale Pilot period during which all short-initiated trades must be self-identified. Our study covers essentially the entire period of the regulated disclosure (the 626 trading days from January 3, 2005 to July 6, 2007, inclusively). See Diether, Lee, and Werner (2009) for additional details on this data.

[9] According to Chen, Desai, and Krishnamurthy (2013) the proportion of mutual funds that actually take *any* short position in a given year has increased recently, from 2% in 1994 to 7% in 2009. So during our sample period, only an extremely small minority of mutual funds engaged in any short selling.

(sellers) of a stock, we generally observe increased (decreased) SS activities. On days with extreme MF flows (i.e. those firm-days ranked in the top-quintile by MF, either strong buy or strong sell), SSs are on the opposite side of MF trades 71% of the time (see Panel 8.A). Even on days with less extreme MF flows (i.e., when we include all firm-day observations), SSs are still on the opposite side of MF flows 56% of the time.[10]

Both groups exhibit strong time-series persistence. Stocks that are strongly purchased (sold) by MFs continue to be strongly purchased (sold) by MFs for multiple days. The same is true for SS flows. These persistent time-series patterns can confound statistical inferences made from daily data. To address such concerns, we estimate a three-equation vector auto-regression (VAR) system. Specifically, we model daily SS trades, MF trades, and returns (RET) as dependent variables while controlling for lagged observations of each. The resulting cumulative impulse response functions show that a positive one standard deviation shock to MF increases SSs by 5% of daily volume, or roughly 30% of the average daily SS. Most of this response occurs in the next ten trading days. The MF reaction to SS is much more muted. Additional analyses show that it is possible to conclude daily MF trading "Granger cause" SS activities, but not vice versa.

To shed light on how SSs are able to detect and respond to MF flows, we parse each day's MF trading into two components – *ExpMF* (the expected amount of MF flow based on information available at the beginning of each day), and *UnexpMF* (the unexpected MF flow, based on same-day trades). If SSs are responding primarily to longer-term expected MF flows that are predictable in advance, we would expect a significantly negative coefficient on *ExpMF*. Conversely, if SSs are reacting primarily to same-day MF trades, the loading on *UnexpMF* should dominate.

Our results show that SSs are responsive to both *ExpMF* and *UnexpMF*. On average, a one standard deviation increase in *ExpMF* (*UnexpMF*) is associated with an 8.25% (6.0%) increase in the daily short-initiated volume. The larger effect associated with *ExpMF* suggests that daily SS trading is more sensitive to MF flows that were anticipatable by the beginning of trading each

[10] The SS variable is demeaned at the firm-level so we can make daily directional inferences. Note that although MFs and SSs disagree more often than they agree, their directional trades are far from a "zero-sum" game. Our results show are other sizable players in the market (e.g., retail investors, other institutions, or "short covers"), and on days when MF and SS are in directionally concordant, someone else is providing liquidity to both groups.

day. However, the economic and statistical significance of *UnexpMF* show that same-day MF buys also somehow are being telegraphed to SSs, who respond by increasing their short-sell volume.

We next investigate the implications of MFs and SSs flows for future stock returns. We find that directional MF flows are generally price destabilizing. Stocks experiencing strong MF buys (sells) on a given day have typically already been bought (sold) by MFs for the past 15 trading days. Moreover, extreme MF buys (sells) portend future negative (positive) abnormal returns over the next 63 days. Closer analyses show the "daily shock" to MF (*UnexpMF*) initially leads to short-term price continuation, lasting up to three days. However, over longer horizons, prices revert. These findings are consistent with MF herding leading to price destabilization in the short-run (Puckett and Yan (2013)). Indeed our evidence augments prior findings by showing that the MF herding phenomenon is pervasive, and has long-lasting implications for future returns.

Interacting *SS* with *MF*, we find that SSs benefit from the price reversals associated with MF trading – i.e., SSs earn higher profits when they trade against MFs. Nagel (2012) and So and Wang (2014) nominate the profitability of short-term price reversal strategies as a measure of the compensation earned by liquidity providers. Interpreted in this light, our findings are consistent with SSs serving as strategic liquidity providers to MFs, and earning a positive return from this activity over time. A large literature (see Section 2) suggests SSs possess superior ability to process fundamental information. Our findings show that the SSs' informational advantage is also related to their role as strategic liquidity providers to MFs.

Using weekly-aggregations, we confirm that MF-induced price reversals are a longer horizon phenomenon. A cash-neutral strategy based solely on betting against net MF flows yields an abnormal month return of 1.37% over a 63-day holding period.[11] Given the economic significance of these price reversals, we further examine whether SSs profit by betting against MF trades. Strikingly, we show that returns to the well-documented SS trading strategy (e.g. Boehmer et al 2008; Diether et al 2009) are up to three times larger when SSs trade against MFs (i.e., when they "disagree") than when SSs trade in the same direction as MFs (i.e., when they

[11] Consistent with prior literature, we also document that a long-short strategy based solely on SS yields an abnormal return of 1.60% over a 63-day holding period.

"agree").[12] Specifically, over a 63-day holding period, returns to a SS strategy where MFs and SSs disagree earns 1.98%, while a SS strategy where MFs agree earns only 0.57%. This gap is consistent with SSs profiting from MF-induced price reversals. Taken together, these findings strongly suggest that SSs are able to detect and capitalize on MF trading activity.[13]

Finally, we examine several situations in which MFs might experience the greatest difficulty. First, consistent with a price-pressure explanation, we find that the wealth transfer from MFs to SSs is most pronounced in stocks with larger MF institutional ownership and lower overall liquidity. In addition, consistent with a behavioral-based explanation, we find this wealth transfer effect is much higher during periods of high retail investor sentiment.[14] During high sentiment periods, the volume of daily MF trading at the firm-level increases on average by 8.8% for large (top quintile) firms and 28% for small (bottom quintile) firms. At the same time, the implied wealth transfer from MFs to SSs increases dramatically relative to low sentiment periods (total losses to SSs average 2.10% higher per firm over the next 63-days). Further analyses show that this effect is directly linked to the increase in MF trading volume, and is not due to an increase in net MF buying during high sentiment periods.

Collectively, our findings provide at least a partial explanation for the MF performance puzzle. A curious finding from past studies is that active MFs consistently underperform their passive benchmark. We show that at least some of this underperformance is potentially attributable to a net wealth transfer between MFs and SSs, which is most pronounced when MFs trade stocks with high institutional ownership and low liquidity. Our results also provide a direct link between MF losses and retail investor sentiment. Consistent with the behavioral literature, MFs lose more to SSs when retail investors are overoptimistic about equities.

[12] The 'Disagree' portfolio consists of a long position in the portfolio of stocks with low short selling and high mutual fund selling and a short position in the portfolio of stocks with heavy short selling and heavy mutual fund buying. Thus, these portfolios consist of stocks where short sellers and mutual funds trade in opposite directions. Conversely, the 'Agree' portfolio consists of a long position in stocks with heavy mutual fund buying and light short selling, and a short position in stocks with heavy mutual fund selling and heavy short selling. In this case short sellers and mutual funds trade in the same direction.

[13] Two caveats are in order. First, because mutual fund trading data are not typically available in real time, this is not a tradable strategy. Second, we do not have data on when short-sellers close their positions, so we only estimate their profits based on hypothetical holding periods. Prior studies that estimate short-sale holding periods (e.g., Boehmer, Jones, and Zhang (2008)) report a median duration of 37 trading days, which is ample time for the short-sellers in our study to profit from trading in the opposite direction to MFs.

[14] We use the Ben-Rephael, Kandel and Wohl (2012) measure of retail investor sentiment, which captures the monthly flow of retail money from bond funds to equity funds within the same mutual fund family.

Our findings also shed new light on the predictive power of SS trades for future returns. We show that much of the SSs predictive power is due to their tendency to trade in the opposite direction to MFs. In addition, we find SSs respond both to expected MF flows (based on prior trading), and to unexpected shocks in MF trades on the same day. The former can be linked to the earlier literature on capital flow-induced MF trading.[15] The latter is a higher-frequency phenomenon associated with mutual fund herding. Despite efforts to engage in stealth trading and manage their costs through more skillful trading desks (e.g. Alexander and Peterson (2007), Anand et al. (2012)), evidently MFs are still telegraphing their trades to some SSs.

On a related note, our findings may also help to explain the main finding in Stambaugh, Yu and Yuan (2012; SYY). SYY report that the short-leg of multiple market pricing anomalies is only profitable during high sentiment periods. We find that it is precisely during these periods that the heightened trading activity of MFs becomes most vulnerable to SS activities. Thus it appears that the short-leg profitability documented by SYY may come in part at the expense of retail (MF) investors, who lose to SSs during such times.

Finally, our findings are related to the literature on predatory trading. Brunnermeier and Pedersen (2005) present a model in which some traders induce and/or exploit the need of other traders. In the same spirit, Chen, Hanson, Hong and Stein (2008) show that, in time series, the average return of 45 hedge funds are significantly higher in months when a larger fraction of MFs are in distress. Using monthly open short interest data, they find evidence that the short-sale ratio increases in advance of sales by distressed MFs. Our results are consistent with these findings, but we provide a much clearer view of the direct link between MF trades and SS activities.

The rest of the paper is organized as follows. Section 2 discusses related literature on why MF flows might be predictable. Section 3 describes the data and provides summary statistics. Section 4 presents our empirical results on the relationship between *MF* and *SS* trades. Section 5 reports the implications of these trading activities for future stock returns. Section 6 explores

[15] See, for example, Coval and Stafford (2007), Frazzini and Lamont (2008), Lou (2012), Shive and Yun (2013), and Khan, Kogan, and Serafeim (2012). According to this explanation, the combination of "dumb money" flows from retail investors and the "no leverage" restriction on MF funds conspire to generate predictable patterns in returns for individual stocks held by these funds . The no leverage constraint is important because it prevents MF managers from absorbing investor inflows and outflows by changing their leverage ratio.

short-term liquidity provision. Section 7 provides additional evidence on the return implications of the interaction between MFs and SSs in the cross-section and time-series. Section 8 concludes with a summary of the key results and a discussion of their implications for future research.

2 Related Literature

Prior studies suggest at least two reasons why the direction of daily MF trades might be predictable. First, MF trades are a function of investor flows in the retail market and are thus vulnerable to fluctuating investor sentiment. When market-wide sentiment is bullish (bearish), equity MFs experience inflows (outflows). These flows generate non-fundamental price pressure on aggregate stock prices that revert in the future.[16] At the same time, in the cross-section of mutual funds, poorly performing managers are vulnerable to redemption pressures, while high performing managers need to quickly equitize their new inflows. Thus the stocks held by MFs are prone to predictable directional flows that result in price pressure in the short-run, and return reversal in later periods. Prior studies show such flow-induced return patterns can be both statistically and economically significant (e.g., Frazzini and Lamont (2008), Coval and Stafford (2007), Lou (2012)). Indeed, the evidence in Coval and Stafford (2007), Lou (2012), Dyakov and Verbeek (2013) and Shive and Yun (2013) strongly suggest these predictable patterns are at least somewhat exploitable based on MF holdings as reported in quarterly 13-F filings.

Second, if the directional trading of individual MFs is correlated at the stock level (a phenomenon sometimes referred to as MF "herding"),[17] their collective actions can generate substantial short-term price pressure. Even if the past performance of a particular fund does not offer clear guidance as to the direction of future flows in a stock (e.g., if the particular MF in question is a mediocre performer in past months), the act of trading itself can still exert price pressure. If the buy-sell direction of MF trades in a given stock are positively correlated across funds (for example, due to common retail sentiment, or similarities in their investment strategies), these flows will again lead to short-term price pressure, which translates into higher trading costs for MFs, and subsequent return reversals for the stocks they trade.

[16] For example, see Baker and Wurgler (2000), Dichev (2007), Ben-Rephael et al. (2012), and Arif and Lee (2014).
[17] See, for example, Puckett and Yan (2013).

MFs and other institutional investors are, of course, aware of the price pressure problem. Prior studies on stealth trading show larger institutions (including MFs) attempt to hide their trades and reduce price impact by using mid-sized trades and by clustering in round amounts, such as 500, 1000, and 5000 shares (Alexander and Peterson (2007) and Chakravarty (2001)). Other institutions engage trading-desks and trade-cost consultants to help mitigate the problem (Anand, Irvine, Puckett, and Venkataraman (2012)). Nevertheless, given their size and the likelihood that their trades are directionally correlated over time, we expect MFs, as a group, to remain vulnerable to the price pressure problem.

At the same time, prior studies consistently find that short-sellers are highly sophisticated investors (e.g., Boehmer, Jones and Zhang (2013), Drake et al (2011), Engelberg, Reed, and Ringgenberg (2012), and Dechow et al. (2001)). At the intraday level, short-sale flows improve the informational efficiency of intraday prices (Boehmer and Wu (2013)). Globally, the introduction of short-selling in international markets is associated with a lowering of country-level costs-of-capital, an increase in market liquidity, and an improvement in overall pricing efficiency (Daouk et al. (2006), Bris et al. (2007)). In the cross-section, increased short selling activity has been associated with lower subsequent stock returns (Beneish et al. (2013), Diether et al (2009), Boehmer et al (2008)), and elevated levels of short selling has been observed prior to disappointing earnings announcements (Cristophe et al (2004)), analyst downgrades (Cristophe et al (2010)), disclosures of financial misconduct (Karpoff and Lou (2010)), and insider sales (Khan and Lu (2013)).

In this study, we are particularly interested in how short selling activities are affected by MF flows. Prior studies provide virtually no guidance on how the daily directional trades of these two groups might be related. Ex ante, a case might be made for either a positive or a negative correlation, or no correlation at all. For example, mutual funds and short sellers may on average trade in the same direction if they respond to similar information sets. Conversely, short sellers may have superior information sets or higher processing speed relative to mutual funds. Moreover, if mutual fund trading pressure results in temporary price dislocations, SSs may systematically exploit these patterns. In these latter scenarios, short-sale activities would be, on average, in the opposite direction to the trades by mutual funds. We explore each of these possibilities.

In sum, prior research suggests that the direction of daily MF trades may be predictable because of either: (1) lower frequency flow-induced trading associated with retail investor fund inflows and outflows, or (2) higher frequency problems associated with "crowded trades" at the daily level. We provide evidence on the relative importance of these two types of MF flows in explaining the level of daily SS activities. We also evaluate the extent to which these patterns in MF trading contribute to a wealth transfer from MFs to SSs.

3. Data and Summary Statistics

3.1 Data

3.1.1 Regulation SHO Short Sale Database

We obtain short sale data from the NYSE Trade and Quote (TAQ) Regulation SHO database. The data period ranges from January 3, 2005 to July 6, 2007 for NYSE-listed stocks and includes all intraday trades by short-sellers. Specifically, for each short sale transaction, the data includes the stock ticker, the number of shares traded, the execution price, and the date and time of the transaction. The data does not include information on short covering. In addition, the data includes an identification code for trades which are exempt from the price test rules. Usually, these trades (with the identification code "E") are executed by market makers (see, e.g., Evans, Geczy, Musto, and Reed, 2009). Following Boehmer et al (2008), since we are primarily interested in trades by informed short sellers, we exclude such trades from our analysis (they are only a minor fraction of the sample). We match the TAQ stock tickers to CRSP using link tables from WRDS.

3.1.2 Ancerno Institutional Trading Data

We obtain institutional trading data from Ancerno Ltd. Ancerno (formerly a unit of Abel/Noser Corp) is a widely-recognized consulting firm that provides consulting services to institutional investors to help them monitor their trading costs.[18] The data is available starting January 1999 and overlaps with our Reg-SHO 2005-2007 sample period. As mentioned in Puckett and Yan (2011) (hereafter, "PY"), Ancerno data has several appealing features for academic research. The data is supposed to be free of survivorship bias, self-reporting bias and backfill bias. In addition, PY find that the characteristics of stocks held and traded by Ancerno's institutions are not significantly different from the characteristics of stocks held and traded by the average 13F institution.

The Ancerno dataset provides data about trading by mutual funds and pension plans. Using Ancerno's client-type codes, we are able to focus on trades made by mutual funds. Our main variables include: the date of trade (*YY/MM/DD*), the stock ticker and *CUSIP*, the number of shares per trade, and a Buy or Sell indicator which specifies whether a trade is a buy (1) or a sell trade (-1). A detailed explanation about Ancerno variables can be found in the Appendix of PY. We note that the dataset provides trade level data on mutual fund trades and that the actual intraday execution times are not available. Accordingly, for each stock, we use the Ancerno dataset to compute the total daily mutual flow across all mutual funds. Finally, we match our sample to CRSP using both the stock ticker and *CUSIP*. To ensure that the match is made correctly, we require Ancerno's daily close-price variable to match CRSPs close-price for any given trade.

3.1.3 Other Variables and Final Sample

Stock prices, shares outstanding, daily volume and returns are obtained from the Center for Research in Securities Prices (CRSP). Book values and other accounting information are obtained from Compustat. We match the Reg SHO and Ancerno databases using CRSP's *permno* and *day*. We split-adjust all relevant variables using the CRSP adjustment factor. As part of our analysis, we explore the lead-lag relation between short sales, mutual fund trades and daily returns.

[18] Previous studies that use Ancerno data include: Chemmanur, He, and Hu (2009), Goldstein, Irvine, and Puckett (2011), Puckett and Yan (2011), Anand, Irvine, Puckett and Venkataraman (2012), Jame (2012), Busse, Green, and Jegadeesh (2012), Franzoni and Plazzi (2013), and Gantchev and Jotikasthira (2013).

To compute daily abnormal returns, we apply the Daniel, Grinblatt, Titman and Wermers (1997) characteristic-benchmark portfolio adjustment procedure (hereafter "*DGTW*"), which controls for firm size, B/M, and price momentum characteristics. Specifically, we construct our benchmark portfolios every year on June 30th, using NYSE size breakpoints to sort stocks into size quintiles. We then further conditionally rank on B/M and momentum, thus forming 125 benchmark portfolios. We compute daily returns for each of these 125 benchmark portfolios for every day in our sample. These portfolios are then used to calculate daily abnormal returns for each stock.

Finally, to reduce noise caused by microstructure issues and missing data, we apply the following filters: (1) stocks must have a previous day price of $5 and above; (2) stocks must be in the DGTW ranking sample. Our final sample includes 575,000 day-stock observations.

3.2 Variable Definitions and Daily Sample Statistics

The two key variables for our analyses are daily short sales for each stock (hereafter, "*SS*") and mutual funds' daily net purchases for each stock (hereafter, "*MF*"), each scaled by the stock's total daily trading volume. Specifically, *SS* is the number of shares sold short multiplied by -1, divided by total trading volume that day (expressed in %) in the stock. We multiply SS by minus 1 to reflect the fact that a short sale is a negative net purchase (i.e., from a directional perspective, it is a 'sell'). *MF* is the aggregate net number of shares purchased by mutual funds, divided by total trading volume that day (expressed in %). Aggregate net number of shares purchased by mutual funds is defined as the total number of shares bought minus the total number of shares of the stock sold by mutual funds on aggregate that day in the stock.

Table 1 Panel A presents summary statistics for our main variables. To construct this panel, we calculate the cross sectional mean, median and standard deviation for each day, and report the time series averages of these cross-sectional statistics. Consistent with prior work (e.g., Diether, Lee and Werner (2009) and Engelberg, Reed and Ringgenberg (2012)), short selling represents a substantial percentage of daily volume. On average, 18.79% of total daily trading volume is initiated by short-sellers. Mutual fund trade volume is also high: on average, mutual funds in our sample account for 13.65% of total daily volume (*MF VOL*). To provide a sense of the absolute magnitude of daily MF directional trading, we also compute *AbsMF*, defined as the absolute value of daily MF trading. The net directional trading by MFs is, of course, lower than their total daily volume (*MF VOL*). Nevertheless, it is still quite substantial, with an average of 9.28%.

Table 1 Panel B provides some preliminary evidence on the directional concordance / discordance of daily *MF* and *SS* trades. To construct this panel, we first demean SS at the firm-level by subtracting the average firm-level SS. We then group each firm-day observation by the sign of MF and the demeaned SS value independently. Table values in Panel 1.B represent the percentage of firm-day observations in each category, where "SS Buys" refer to days when SS-initiated volume is below firm-level mean, and "SS Sells" refer to days when SS-initated volume is above firm-level mean.

Panel 1.B shows that, more often than not, MFs and SSs are on opposite sides of daily trading. The off-diagonal cells show that in 56.4% (26.1% + 30.4%) of all firm-day observations, MFs and SSs directionally disagree. However, MF and SS trades are far from a "zero sum" game, whereby one provides liquidity for the other. Specifically, we observe that 43.6% of all firm-days (23.9% + 19.6%), MFs and SSs are directionally on the same side. On such days, someone else (perhaps retail investors, other institutions, or "short covers") is supplying the liquidity.

4. Mutual Fund Flows and Short Sales

4.1 Lead-Lag Relation between Daily Mutual Fund Flows and Short Sales

We now proceed with an analysis of the lead-lag relation between the level of daily trading by both groups. In Table 2 we report results with *SS* as the dependent variable. In Table 3, we conduct similar set of tests with MF as the dependent variable. In each case, we perform day-stock panel regressions, and include both firm and day fixed effects. Given the large number of observations, instead of using actual firm and day dummy variables, we de-mean all the variables of interest by firm and day. To control for additional unobservable effects, we also cluster the standard errors by firm and day. We also control for other explanatory variables nominated by prior studies such as firm-level trading volume, volatility, daily high and low prices, bid-ask spread, stock price, and firm size (see Diether, Lee and Werner (2009) for a detailed discussion).

Table 2 explores the daily relation between SS (the dependent variable) and lagged SS, lagged stock returns (*RET*) and lagged mutual fund net purchases (*MF*). Columns (1) and (2) confirm the findings in Diether, Lee and Werner (2009). Specifically, Column (1) documents strong positive persistence in short sale trading activity, with lagged short sales explaining 25% of the variation in *SS.* Column (2) documents a negative relation between lagged returns and *SS*, which indicates that SSs respond to short-term price changes in a contrarian fashion. Column (3) shows that lagged mutual fund net purchases negatively predict *SS*. This indicates that short sellers trade against the direction of past mutual fund flows: higher (lower) net purchases by mutual funds are followed by heavier (lower) short selling in the future. In Columns (4) through (7) we explore the partial effect of all variables after controlling for past returns and other firm characteristics. We find that all variables are important determinants in explaining *SS*. In particular, daily SS is negatively correlated with past MF even after controlling for past returns. Thus, SSs are not simply contrarian traders who respond to high returns in the past. Indeed, it appears they are also incrementally affected by MF flows. In subsection 4.2 we further explore the economic magnitude of the MF effect on SS in a VAR framework.

Table 3 presents similar analyses with *MF* as the dependent variable. Column (1) of Panel A shows directional MF flows are strongly persistent. As with SS, the Adjusted-*RSQ* is large (24.61%). Column (2) explores the relation between *MF* and past returns. Consistent with prior studies (e.g., Grinblatt, Titman, and Wermers (1995)) the mutual funds in our sample seem to engage in positive feedback trading – i.e. higher past returns portend stronger MF purchases. Column (3) shows that when the two time-series are considered in isolation, the first few lags of *SS* are negatively related to *MF*, but that the relation turns positive as the lags increase. Given the importance of past returns in explaining the actions of both groups, it is difficult to draw any conclusions about *SS* and *MF* interactions without controlling for *RET*. Columns (5) through (7) control for past *RET* as well as a host of other firm characteristics. These results show that the overall relation between lagged SS and current MF turns reliably positive beyond the first lag.

Figure 1 provides a graphic representation of the daily trading patterns for *MF* and *SS* for firms in the extreme *MF* deciles. To construct this figure, we rank all stocks in our sample each day into ten deciles based on *MF*. We then keep the firms in the top decile (heavily bought firms) and bottom decile (heavy sold firms). We denote the ranking day as day *t*, and compute daily trading activity by mutual funds and short sellers from day *t-14* to day *t+63*. Graphs 1.A and 1.B plot daily and cumulative *MF*, respectively, for the firms in the top and bottom decile of *MF*. Graphs 1.C and 1.D plot daily and cumulative *SS*, respectively, for the same firms (i.e. firms in the top and bottom deciles of *MF* ranked on day *t*).

The two top graphs show the strong persistence in MFs trades. For firms that were heavily bought by MFs, the buying began 14 days prior to day-*t*, and persists over the next three months. Graph 1.B shows that the total cumulative effect (a measure of cumulative net MF buying or selling over the entire period) is roughly 200% of average daily volume for the typical extreme decile stock. Graph 1.C (1.D) reports the daily (cumulative) *SS* for the same stocks, i.e. stocks in the extreme deciles of day-*t MF*. To facilitate interpretation, we plot daily *SS* demeaned by its long run mean. The effect of MF flows on SS is striking: SSs appear to respond to directional MF trades, both before and after day-*t*. Graph 1.D shows that in terms of long-run cumulative economic magnitude, SS increase their activity by 20-25% of daily volume in these stocks (relative to the average amount of daily SS for each firm).

4.2 Vector Auto Regression (VAR) Results

To assess the economic magnitude and dynamics of the relation between *RET*, *MF* and *SS*, we estimate a three equation VAR (Vector Auto Regression) system of *RET*, *MF* and *SS* with five lags of *RET*, *MF* and *SS* as follows:

$$
\begin{aligned}
RET_t &= \alpha_1 + \sum_{t=1}^{5}\gamma_{1i}RET_{t-i} + \sum_{t=1}^{5}\gamma_{1i}MF_{t-i} + \sum_{t=1}^{5}\delta_{1i}SS_{t-i} + \varepsilon_{1t} \\
MF_t &= \alpha_2 + \sum_{t=1}^{5}\gamma_{2i}RET_{t-i} + \sum_{t=1}^{5}\gamma_{2i}MF_{t-i} + \sum_{t=1}^{5}\delta_{2i}SS_{t-i} + \varepsilon_{2t} \qquad \text{(Eq. 1)} \\
SS_t &= \alpha_3 + \sum_{t=1}^{5}\gamma_{3i}RET_{t-i} + \sum_{t=1}^{5}\gamma_{3i}MF_{t-i} + \sum_{t=1}^{5}\delta_{3i}SS_{t-i} + \varepsilon_{3t}
\end{aligned}
$$

In our main Impulse Response Function analysis (hereafter, "*IRF*"), we set the contemporaneous Cholesky order to be *RET*, *MF*, and *SS*. This sequencing reflects our priors about the order of causality among the three endogenous variables. We set *RET* as the first variable because of extensive prior evidence that both MFs and SSs respond to past returns. We set *MF* as the second variable because the trading decisions of mutual funds are more constrained than short sellers. Thus it is less likely that MFs can respond quickly to daily SS trading activity, even if this activity was detectable by MFs.[19] On the other hand, it is much more likely that SSs can respond to same-day MFs trades. As a robustness check, we also provide the results for alternative order selection assumptions in Appendix A.[20]

Graph 2.A plots the accumulated response of *SS* to a positive one standard deviation shock in *MF* (i.e., the response of SSs when MFs are net buyers). The effect of *MF* on *SS* is economically and statistically significant. A positive one standard deviation shock to MF increases SSs by 5% of daily volume, or roughly 33% of the average daily SS. Most of the response occurs in the next ten trading days. Graph 2.B plots the accumulated response of MFs to a negative one standard deviation shock in SS (i.e., the response of MFs when SSs increase their short activity). A negative shock to SS has an initial weak positive effect on MF, but this reaction eventually turns negative, consistent with Columns (5) and (6) of Panel B in Table 3. Thus, when SSs increase their short selling activity, MFs also become net sellers 3-5 trading days later. Overall, a one standard deviation negative shock to *SS* decreases *MF* by 0.8% of daily volume, with most of this response occurring over the next ten trading days. Importantly, this relation does not seem to be stable. Graphs A.2 and A.3 of Appendix A show that changing the response order affects these results. Thus, we conclude that SS do not Granger cause MF.

4.3 The Contemporaneous Relation between *MF* and *SS*

Taken together, the results thus far establish a robust and economically significant lead-lag relation between MFs and SSs. We now examine the contemporaneous relation between daily *SS*, *MF*, and *RET* after taking into account the time-series patterns documented earlier.

[19] MFs are restricted in their use of leverage and do not tend to short. These constraints limit their options when confronted with daily retail investor flows (i.e. they must fully equitize inflows and redeem outflows).

[20] In Appendix A we show that the order of *RET* in that triplet does not affect the *IRF* cumulative responses of *MF* and *SS*. The order between *MF* and *SS* has an effect on the *IRF* magnitudes.

Table 4 reports results of panel regressions of *SS*, unexpected *SS* (*UnexpSS*), and expected *SS* (*ExpSS*), on selected contemporaneous variables. Panel A of Table 4 shows that daily *SS* is strongly negatively related to *MF* contemporaneously. This relation is robust across various model specifications. In Columns (1) through (5) the dependent variable is total daily short-selling, or *SS*. Column (1) shows that higher net purchases by mutual funds are associated with heavier short selling, even after controlling for *RET*. Column (2) shows that the coefficient on the interaction term (*Ret*MF*) is also negative, indicating that short sellers bet even more heavily against mutual funds when same-day returns are in the same direction as MF. Specification (3) shows that adding other stock control variables does not alter these results.

In Columns (4) and (5) we utilize our lead-lag analysis from Section 4.1 to explore the effect of the expected and unexpected *MF* components on *SS*. Specifically, we regress *MF* on five lags of *SS*, *MF* and *RET* and define expected mutual fund trade (*ExpMF*) as the fitted value from the regression. The residual from this regression is unexpected mutual fund trade (*UnexpMF*). Thus, *ExpMF* captures the expected amount of MF flow based on information available at the beginning of each day, while *UnexpMF* captures the unexpected MF flow, based on same-day trades. If SSs are responding primarily to longer-term expected MF flows that are predictable in advance, we would expect a significantly negative coefficient on *ExpMF*. Conversely, if SSs are reacting primarily to same-day MF trades, the loading on *UnexpMF* should dominate.

Interestingly, results in Columns (4) and (5) show that the coefficients on both *ExpMF* and *UnexpMF* are negative and highly significant, indicating that short sellers respond to both the expected and unexpected components of mutual fund trading. On average, a one standard deviation increase in *ExpMF* (*UnexpMF*) is associated with a 1.25% (1%) increase in daily SS, which translates into an 8.25% (6.0%) increase in the daily short-initiated volume.[21] Moreover, adding *ExpMF* as an additional explanatory variable significantly improves the adjusted R-Squared (the Adj-RSQ increases from 4.99% to 7.40%). The larger effect of *ExpMF* suggests that daily *SS* trading is more sensitive to *MF* flows that were anticipatable by the beginning of trading each day. However, the economic and statistical significance of *UnexpMF* show that

[21] A one standard deviation move in *ExpMF* is 6.9, while a one standard deviation move in *UnexpMF* is 12.07. To convert increases in daily SS as a percentage of daily volume into increases in daily short-initiated volume, recall that SS is around 18% of average daily volume.

same-day MF buys are also somehow being telegraphed to SSs, who respond by increasing their short-sell volume.

For completeness, we also decompose short selling (our dependent variable) into an expected component ("*ExpSS*") and an unexpected component ("*UnexpSS*"). These results are presented in Columns (6) through (11). The overall results are qualitatively similar to those reported for *SS*. In general, consistent with the lead-lag patterns reported earlier, *UnexpSS* responds negatively to *UnexpMF*, while *ExpSS* responds negatively to *ExpMF*.

Panel B of Table 4 extends Panel A's analysis and explores the sensitivity of daily *SS* to *MF* for various subsamples based on *MF*. To construct this panel, we first rank all firm-day observations into three tertiles based on either: *MF* (Specification 1), *ExpMF* (Specification 2), or *UnexpMF* (Specification 3). For each subpopulation of observations, we report the effect on daily SS (as a percentage of total daily volume) due to a one standard deviation change in the sort variable. This panel shows that SSs trade in the opposite direction of MFs regardless of whether mutual funds are selling (tertile 1), buying (tertile 3), or are relatively inactive (tertile 2). We obtain similar results when firms are sorted by *ExpMF* or *UnexpMF*.

In general, short sellers appear to trade more heavily against mutual funds when mutual funds are net sellers (*TER 1*) than when mutual funds are net buyers (*TER 3*). For example, a one standard deviation increase in selling by mutual funds is associated with a decline in short selling of 1.61% (as a percentage of total daily volume), while a one standard deviation increase in buying by mutual funds is associated with a 0.43% increase in short selling (as a percentage of total daily volume). Interestingly, the effect of buying vs. selling is more symmetric when stocks are sorted on the predicted MF component (*ExpMF*). The effect of a 1 SD change in expected mutual fund trading on SS is 1.01% for expected selling and 0.576% for expected buying, suggesting that both (predicted buys and sells) are important to SSs. Overall, we find that the negative relation between short-selling and mutual fund trading holds irrespective of the direction of mutual fund trade.

We next investigate whether our results are driven by hard-to-borrow stocks. It is possible that when MFs sell hard-to-borrow, short sellers find it more difficult to short the stock because the availability of the stock in the lending market declines. This causes short selling to decline. Such a mechanism might lead to a mechanical negative relation between *MF* and *SS*. To examine this possibility, we supplement our main dataset with data from Data Explorers (DXL), which provides daily data on pricing and availability in the equity lending market. Specifically, we examine the contemporaneous relation between *SS* and *MF* within the subset of stocks that are hard-to-borrow versus the subset of stocks that are easy-to-borrow. In Appendix B, we investigate whether the negative relation between *SS* and *MF* is materially different for stocks with binding short-sale constraints. Following Beneish, Lee and Nichols (2013), we use the Daily Cost of Borrowing Score (DCBS) from the DXL dataset as a measure of short-sale constraints. In the DXL database, DCBS ranges between 1 and 10. Stocks with a DCBS value of 1 and 2 correspond to stocks that are easy-to-borrow ("General Collateral" or "GC") as defined in prior research (loan fees below 100 basis points), while stocks with a DCBS value of 3 or larger are considered hard-to-borrow ("HTB"). Note that HTB stocks represent only 2.26% of the stocks in the sample after we merge our main sample with DXL.

In Appendix B we present results for all stocks, as well as for *GC* and *HTB* subsamples. Columns (1) and (2) report results for all stocks with coverage in Data Explorer regardless of their DCBS values. The fact that the coefficients in these regressions are similar to the coefficients in Table 4 indicates that requiring DXL coverage does not affect our main results. Specification (2) shows that on average, more binding short-sale constraints are associated with a diminished sensitivity of SS to MF flows. This result is inconsistent with the idea that short selling activity in hard-to-borrow stocks is more sensitive to *MF* flows compared to stocks that are not hard-to-borrow. Columns (3) and (4) also show that there is a significantly negative relation between *SS* and *MF* within both *GC* stocks and within *HTB* stocks. Moreover, given the similarity in the MF coefficients (-0.112 vs. -0.104), we do not find evidence that our results are driven by stocks that have high short sale constraints.

5. ***MF*, *SS*, and Short-Term Future Stock Returns**

We next turn to explore the relation between *MF*, *SS* and future stock returns. We note that given the extensive literature on liquidity provision, short-term price effects (e.g. over a few days) may differ from long-term price effects (e.g. over several weeks). Specifically, liquidity provision refers to the willingness of market makers (or other traders) to absorb order imbalances. The compensation for liquidity provision is usually measured over a few days in the future (e.g., Lehmann 1990). Given the fact that SSs could engage in liquidity provision, it is important to understand the implications of the interaction between MFs and SSs over both short horizons and long horizons. Consequently, in this section we explore the relation between *SS* and *MF* trading decisions on day *t* and abnormal returns measured over relatively short future time periods. We explore the implications of the interaction between MF and SS for returns measured over longer horizons in Section 6.

We start with portfolio analysis (Table 5, Panel A) and continue with cross-sectional regressions (Table 5, Panel B). Panel A of Table 5 confirms the returns to a one-day-reversal strategy, which is well-documented in the literature (e.g., Pastor and Stambaugh (2003) and Nagel (2012)). Specifically, every day we rank stocks into deciles based on their DGTW adjusted returns on that day. We then keep the top decile (winners) and bottom decile (losers). On average, a portfolio which goes long day-*t* winners (Decile 10) and goes short day-*t* losers (Decile 1) earns a statistically significant return of -0.105% on day *t*+1. As suggested by prior literature, this return basically captures the premium for liquidity provision.

We also calculate the average rank of MF and SS for stocks in the winner and loser portfolios. Specifically, each day stocks are independently sorted into deciles based on day-*t* *DGTW(t)*. Columns (2) and (3) of Panel A in Table 5 report the average decile rank of *MF* (*SS*) that stocks in the winner and loser portfolios fall into. Consistent with Table 4, Panel A of Table 5 shows that MFs tend to be feedback traders while *SS* tend to be contrarian traders. In other words, MFs (SSs) tend to have sold (lightly shorted) losers, while MFs (SSs) tend to have bought (heavily shorted) winners.

Panel B of Table 5 analyzes future returns from a liquidity provision perspective in a Fama-MacBeth cross-sectional regression framework. We explore the gradual change in coefficient estimates from day *t*+1 to *t*+10. Since SS has a negative mean, we cross-sectionally demean SS and other explanatory variables. This gives our interaction variables a natural interpretation (i.e., positive or negative). Columns (1) and (2) explore the relation between Day *t*+1 abnormal returns and day-*t* explanatory variables. Column (1) shows there is a strong negative relation between day *t* and day *t*+1 returns. Specifically, the coefficient on *DGTW* (i.e. the DGTW-adjusted stock return on day *t*) is -1.81 (t-stat -4.42). This is the reversal strategy phenomenon documented in panel A of Table 5. Similar to Table 4, we also decompose MF into the expected (*ExpMF*) and unexpected (*UnexpMF*) components. Interestingly, *ExpMF* loads negatively when predicting one-day-ahead returns. Thus, high expected *MF* flows portend price reversals. Strikingly, the unexpected component, which captures the shock to MF trade, is positive and statistically significant, with a coefficient of 0.071 (t-stat 3.90). This indicates that a shock to MF demand is followed by a price continuation (and not a reversal) over the next day.

Column (2) explores the interaction between *SS*, *ExpMF* and *UnexpMF*. We find that the interaction between *SS* and *ExpMF* is negative and statistically significant. This indicates that the interaction between short sellers and mutual fund trades has incremental power to predict future returns. Specifically, the return of SSs strategies is larger when *ExpMF* and *SS* are in opposite directions.[22] This indicates that *SS* gain from *ExpMF* price reversals. However, the interaction between *SS* and *UnexpMF* is not statistically significant when predicting one-day-ahead returns (coefficient -0.002, *t*-statistic -0.71). Thus, on day *t*+1 SSs do not profit from the unexpected component of MF trade.

We continue and explore in more detail the effect of the unexpected component (*UnexpMF*) on future returns as the return window lengthens. This analysis provides insight into the dynamics of the expected and unexpected MF flows on returns. Specifically, Columns (3) through (10) analyze cumulative abnormal returns over the following 2, 3, 5 and 10 trading days. We find that the price reversal associated with *ExpMF* becomes even more pronounced over time. Specifically, the coefficient on *ExpMF* grows from -0.095 to -1.132 as the return window lengthens (Specifications 1, 3, 5, 7, and 9)). This indicates that the price reversals associated with expected MF trades are not limited to day *t*+1 alone; to the contrary, these return reversals persistent over much longer horizons. The fact that the return reversal persists over time is also consistent with the fact that there is a high level of persistence in net purchases by MFs, as documented in Figure 1B. Strikingly, we also find that the unexpected component (*UnexpMF*) becomes negative and significant after 10 trading days. In other words, in the long run, SSs profit by trading against both *ExpMF* and *UnexpMF*, since in the long run both signals ultimately have negative implications for future returns. In a similar manner, the interaction between SS and *UnexpMF* becomes negative and significant after 5 to 10 trading days.

[22] Note that when *SS* and *ExpMF* are of opposite sign (i.e., there is disagreement), their product is a negative number. Thus, a negative coefficient on the interaction term means that greater disagreement enhances the profitability of SSs' trades.

To summarize the results of this section, our analysis indicates that expected MF flows result in immediate price reversal over subsequent days, while unexpected shocks to MF flows result in short-term price continuations over the following few days, with a subsequent price reversal after about ten days. These results suggest that MFs exert price pressure when they trade, leading to price reversals in the future which SSs profit from. In Section 6 we continue and explore these price patterns at longer horizons and provide further evidence regarding the return implications of the interaction between MFs and SSs.

6. The Longer-Term Relation between *MF*, *SS* and Future Stock Returns

The results in Section 5 indicate that both *ExpMF* and *UnexpMF* are associated with a price reversal over the following ten trading days. Moreover, the magnitude of the reversal increases over time, which suggests that the documented return patterns are not short-lived. Consequently, in this section we are interested in the interaction between MFs and SSs over longer horizons and whether this plays a role in the long-term profitability of trading by SSs.

We note that previous literature documents a robust predictive relation between daily short selling activity and subsequent market returns (e.g. Boehmer et al (2008); Diether et al (2009); Engleberg et al (2012)). These papers find that stocks that are more heavily shorted earn lower future returns. In this section we provide evidence that part of the profitability associated with SS trades can be explained by long-term MF-induced price reversals.

In the analyses that follow, we average the trades of MFs and SSs over five day periods to investigate the implications of their interaction over longer horizons. This section is organized as follows. Subsection 6.1 explores the MF and SS lead-lag relation. Subsection 6.2 examines the individual profitability of MFs and SSs strategies. Subsection 6.3 explores the profitability of SSs and MFs strategies conditioned on the interaction between MFs and SSs in a cross-sectional Fama-Macbeth (1973) framework. Subsection 6.4 further investigates the profitability of strategies incorporating the interactive effect between MFs and SSs by forming hedge portfolios setting on the basis of independent double sorts.

6.1 The MF-SS lead-lag relation

We begin by exploring how MFs and SSs interact over periods longer than one day. As a result, in this subsection we re-estimate Tables 2 and 3 and explore the relation between *MF* and *SS* averaged over 5-day intervals.

Panel A of Table 6 presents regressions of short selling averaged over days *t* to *t+4* (*AveSS(t_t+4)*) on lagged explanatory variables averaged over days *t-5* to *t-1*. Consistent with the results presented in Table 2, we find a robust predictive relation between lagged mutual fund net purchases over the past 5 days, *AveMF(t-5_t-1)*, and future 5-day short selling, *AveSS(t_t+4)*. Interestingly, Column (4) shows that after controlling for *AveSS(t-5_t-1)*, 5-day lagged stock returns are no longer a statistically significant predictor of future short selling. This indicates that the contrarian behavior of SSs relative to stock returns documented in Diether, Lee and Werner (2009) is short-lived and is confined to the daily frequency. In contrast, as Columns (5) and (6) show, the negative lead-lag relation between *SS* and *MF* is robust, and plays out over multiple days in the future. Overall, Panel A indicates a robust predictive relation between lagged trading by mutual funds and future short selling: higher (lower) net purchases by mutual funds are followed by higher (lower) future short selling.

Panel B of Table 6 presents regressions of mutual fund flows averaged over days *t* to *t+4* (*AveMF(t_t+4)*), on lagged explanatory variables averaged over days *t-5* to *t-1*. Consistent with the results presented in Table 3, *MF* flows are strongly persistent. In addition, five-day lagged returns positively predict net purchases by MFs, which is consistent with MFs being feedback traders over longer horizons. Consistent with Table 3, Columns (5) and (6) show that after controlling for other variables, lagged 5-day *SS* positively predicts future 5-day *MF* flows. In sum, our tests exploring the lead-lag relation between MFs and SSs over longer horizons indicate that trades by MFs are an important predictor of trades by SSs.

6.2 Single-Sorted Portfolio Returns

Appendix C presents the returns to portfolio trading strategies formed using extreme deciles of *AveSS(t-5_t-1)* and *AveMF(t-5_t-1)* over holding periods of 10, 21, 42 and 63 days. A reader who is familiar with the implications of short selling for future returns and the price pressure induced by mutual fund trading may skip this subsection.

We compute returns to the decile portfolios by equal-weighting the DGTW-adjusted returns of the stocks in each portfolio. Following Diether, Lee and Werner (2009) we skip one day when measuring future returns to avoid bid-ask bounce (i.e., we start compounding returns starting on day $t+1$). We note that the sample period ends on July 6th, 2007. Therefore, returns to portfolios constructed during the last three months of our sample (May-July 2007) will span the August 2007 "quant meltdown" period. Prior studies have shown that returns to standard trading strategies are highly unusual during this period.[23] To isolate the effect of August 2007, we report results for three separate time periods: the pre-meltdown period, from January 3, 2005 to April 30, 2007, a total of 579 trading days; the meltdown period, May 1, 2007 to July 6, 2007, a total of 47 trading days; and the total sample period, from January 3, 2005 to July 6, 2007, a total of 626 trading days.

Consistent with prior studies, Panel C.1 of Appendix C documents that stocks with the heaviest short selling (*SS*1) underperform stocks with the lightest short selling *(SS10)* in the future. The return differential over the following 63 days between the extreme SS deciles is 1.59%, with a *t*-statistic of 5.72. The symmetric return pattern following high and low short selling activity is consistent with the results in Boehmer, Huszar and Jordan (2010). Column (5) explores the Quant Meltdown period. The return differential between the top and bottom deciles is 0.58% (1/3 of the "normal" period) and not statistically significant.

Panel C.2 of Appendix C provides evidence that MFs tend to trade in the wrong direction. Specifically, future returns are in the opposite direction to MF flows. Consistent with a trade-induced price pressure effect, we find that stocks heavily sold (bought) by mutual funds subsequently outperform (underperform). A long-short trading strategy based on MF flows earns a statistically significant negative return of -1.37% over the following 63 days (*t*-statistic 7.05). Column (5) explores the Quant Meltdown period. Strikingly, the difference between the top and bottom MF deciles during this period is positive with an average of 1.07% with and *t*-statistic of 1.66. Consequently, the spread during the entire sample period (Column (6)) is -1.18% with a *t*-statistic of 5.13.

Figure 3 plots the time series of cumulative abnormal returns of the top and bottom *SS* and *MF* decile portfolios. Graph 3.A (3.B) depicts the SS (MF) portfolio. In general, these graphs

[23] The quant meltdown started on August 6th, 2007. See Khandani and Lo (2008) regarding the hedge-fund meltdown and institutional trading in the summer of 2007.

show that the returns to extreme portfolios formed on the basis of both *SS* and *MF* continue to grow over the next 3 months. However, in the case of *MF* flows, the price reversal is much more muted following MF buys than after MF sells. Overall, the actions of these two groups of market participants are strikingly informative about future abnormal returns, but in opposite directions.

6.3 Multivariate Cross-Sectional Regressions

In Table 7 we report results of return predictability tests based on daily Fama-MacBeth cross-sectional regressions. This allows us to explore the interaction between MF and SS while controlling for other variables. The dependent variable is *DGTW_10* (or *DGTW_21*), the DGTW-adjusted stock return over the subsequent 10 (21) days. The independent variables are *AveMF(t-5_t-1)* and *AveSS(t-5_t-1)*, each cross-sectionally demeaned using daily means.[24] The first two rows of Table 7 show that both *AveSS(t-5_t-1)* and *AveMF(t-5_t-1)* have individually incremental predictive power for future returns, even after controlling for past returns and other firm- level explanatory variables. Consistent with Appendix C and Figure 3, *SS* and *MF* predict future stock returns with opposite signs. That is, SSs trade in the right direction relative to future returns, while heavy trading by MFs is followed by price reversals.

Similar to Table 5, we include an interaction term between *AveSS(t-5_t-1)* and *AveMF(t-5_t-1)* to explore whether SSs benefit from longer-term MF-induced price reversals. Columns (4) and (8) document the incremental effect of the interaction between short sales and mutual fund trades (i.e., *Ave SS*MF*). Notably, the coefficient on the interaction term is negative and significant in both specifications, indicating that SS strategies are more profitable when SSs trade in the opposite direction of MFs even over longer horizons.[25] This suggests that SSs exploit MF-induced long-term reversal price effects. We explore this interactive effect in more detail in the following section to identify the source of the incremental returns.

[24] As done in Table 5, we demean these variables so their interaction term can be more easily interpreted. The fact that SS is always negative presents a problem when we interact MF with SS. To overcome this issue, each day, we cross-sectionally demean our explanatory variables. This transformation allows the interaction term (*Ave SS*MF*) to preserve rank order.

[25] As in Table 5, when *SS* and *MF* are of opposite sign (i.e., there is disagreement), their product is a negative number. Thus, a negative coefficient on the interaction term means that greater disagreement enhances the profitability of SSs' trades.

6.4 Double-Sorted Portfolio Returns

In this section, we explore the return implications of the interaction between MFs and SSs in more detail by parsing the effect of SS and MF on future returns in a portfolio setting. We sort firms each day independently into quintiles on the basis of both *AveSS(t-5_t-1)* and *AveMF(t-5_t-1).* This results in a total of 25 portfolios. We then keep the top and bottom quintile of each group (i.e., *MF1*, *MF5*, *SS1*, and *SS5*). Panel A of Table 8 reports the time series average future return and the average number of stocks in each portfolio. Specifications (1)-(3) present averages for three different holding periods (21, 42 and 63 days). Specifications (4) and (5) analyze these averages over the quant meltdown period and over the non-meltdown periods.

Given the results documented in Table 7, we are particularly interested in the differential profitability of SS strategies when short-sellers are trading *with* or *against* MFs. Accordingly, in Panel B we construct two hedge portfolios, i.e. 'Disagree' and 'Agree' portfolios. The 'Disagree' portfolio consists of a long position in the portfolio of stocks with light short selling (*SS5*) and heavy mutual fund selling (*MF1*) and a short position in the portfolio of stocks with heavy short selling (*SS1*) and heavy mutual fund buying (*MF5*). In other words, the 'Disagree' portfolio is a cash-neutral bet on stocks where short sellers and mutual funds trade in *opposite* directions. Conversely, the 'Agree' portfolio consists of a long position in stocks with heavy mutual fund buying and light short selling, and a short position in stocks with heavy mutual fund selling and heavy short selling. In this case short sellers and mutual funds trade in the *same* direction.

Strikingly, we find sharp return differences between the Disagree and Agree hedge portfolios. For example, the Disagree strategy earns abnormal returns that are more than triple the returns of the Agree strategy over the 63 days following portfolio formation (1.98% vs. 0.57%), and the 1.41% return differential between the two portfolios is statistically significant (*t*-statistic of 3.46). The number of stocks in each of the four portfolios (Panel A) shows that SS and MF disagree more than twice as often as they agree. This is evidence is consistent with the notion that SSs are aware of the implications of MF trades for future returns. Henceforth, we call the Disagree-minus-Agree portfolio the "*DMA*" portfolio (we use the acronym "*DMA"* to denote the fact that this portfolio measures the difference in return between the disagree portfolio and the agree portfolio). Returns to the *DMA* portfolio reflect the wealth transfers between MFs and SSs. We examine this portfolio in more detail in Section 7.

Panel C explores the returns to alternative strategies and evaluates the profitability of SS and MF strategies after controlling for the level of buying or selling by MFs. Specifically, we examine a "pure" MF-based strategy (i.e. hedged returns to extreme MF quintiles within the same SS quintile). Our results show MF flows portend negative returns even after controlling for SS. For example, within the first quintile of short sales (*SS1*), a strategy that buys stocks when mutual funds are heavy buyers (*MF5*) and shorts stocks when mutual funds are heavy sellers (*MF1*) earns a negative abnormal return of -0.66% over the following 63 days.[26] Similarly, we find that SS continues to predict returns after controlling for MF trades.

Figure 4 plots the cumulative abnormal returns of the returns earned by the Disagree and Agree portfolios over 63 days following portfolio formation. The returns to both the long and short sides of the portfolios are plotted. This figure shows that the hedge returns to the Agree portfolios are always less than the hedge returns to the Disagree portfolio. Moreover, the hedge returns to the Disagree portfolios continue to increase over time, while the hedge returns to the Agree portfolios are relatively constant after about 25 days. Overall, these results suggest that the incorporation of information into prices is faster when SSs and MFs are on the same side.

7. *DMA* (Disagree-minus-Agree) Portfolio Returns in the Cross-Section and Time-Series

The results in the preceding sections indicate that SSs profit from MF trade-induced price pressure effects. Specifically, Tables 5, 7 and 8 indicate that short sellers earn higher profits when they trade against MFs by benefitting from future price reversals. Of course, other alternative explanations could be consistent with these findings. For example, SSs may trade against MFs to hide their trades, or they may respond faster to information than MFs and trade in the correct direction prior to other investors.

Thus, if MF price pressure effects are indeed the reason behind the observed differences in the profitability of short selling strategies when conditioned on the actions of MFs, we would expect to find stronger results in cases where trading by MFs creates greater price pressure effects. In this section, we provide robust evidence indicating that the wealth transfer from MFs

[26] The -0.66% return to this strategy can be computed from the results presented in Column (3) of Panel A, since it equals the return to the (MF5, SS1) portfolio minus the (MF1, SS1) portfolio, i.e. -0.84% minus -0.18% = -0.66%.

to SSs (captured by the *DMA* portfolio) are stronger in stocks where MF ownership is higher, MFs are more active, and in small and illiquid stocks where the price impact of MF trading is greater. We also find that the results are stronger during high sentiment periods, consistent with SYY (2012).

7.1 DMA returns in the cross-section

Panels A through C of Table 9 explore whether the wealth transfer from mutual funds to short sellers varies according to firm characteristics. Specifically, if the hypothesized MF-induced price pressure channel is correct, we expect to find a stronger effect in stocks that have higher mutual fund ownership or in stocks that mutual funds trade more actively. In addition, the MF price pressure effect may be more pronounced in small and less liquid stocks, since the stock prices of such firms are likely to be more sensitive to trading activity. In the analyses that follow, *MFH* is the aggregate mutual fund holding of a given stock at the end of quarter *t-1*, scaled by shares outstanding. *MFSD* is the standard deviation of aggregate *MF* quarterly changes in holdings of a given stock over quarters *t-5* to *t-1*. Aggregate quarterly change in holdings is calculated following Sias, Stark and Titman (2006) as the difference between total shares held by mutual funds at the beginning of the quarter and total shares held by mutual funds at the end of the quarter divided by shares outstanding (in %). Mutual funds' aggregate quarterly holdings are derived from the Thomson Reuters CDA/Spectrum mutual fund holdings (S12) database.

Panel A (B) presents results for *MFH* (*MFSD*). Since size and institutional holdings are likely to be positively correlated, we directly control for size. We first sort stocks into tertiles based on market capitalization (*Size*). Then, within each *Size* tertile, we further sort stocks into tertiles by aggregate *MFH* (*MFSD*). To construct the *DMA* portfolios in Panels A and B, within of each of the nine portfolios (i.e., *Size-MFH* and *Size-MFSD*) we further sort the stocks based on *AveSS* and *AveMF* tertiles. We then keep the intersection of the top and bottom tertiles. Panels A and B present the results for all size groups and *MFH* and *MFSD* top (tertile 3) and bottom (tertile 1) portfolios. We find that after controlling for firm size, the *DMA* portfolio returns are more pronounced when MF ownership is larger and when MFs trade more actively.

Panel C of Table 9 further investigates the magnitude of the wealth transfer from mutual funds to short sellers after single-sorting firms into tertiles based on our selected firm characteristics. Specifically, within each tertile of the selected firm characteristics, we construct our *DMA* portfolio (using MF and SS quintiles as in Table 8) and calculate the "*Diff- in- DMA"* (i.e., the return difference between the *DMA* portfolios of the top and bottom sorting tertiles). Notably, we find significant differences in our *Diff-in-DMA* portfolios across tertiles of firm characteristics. The difference in *DMA* returns across tertiles of *MFH* is 1.62% with a *t*-statistic of 1.77. Similarly, the difference in *DMA* returns across tertiles of *MFSD* is 0.99% with a *t*-statistic of 1.64. *Size* and the *Relative Spread* are associated with *DMA* differences of -3.05% and 2.71% with *t*-statistics of 2.88 and 2.87, respectively. In untabulated results, we sort the stocks in our sample based on past returns (*AveRET (t-5_t-1)*), turnover (*AveTurnover(t-27_t-6*)), and standard deviation of returns (over *t*-27 to *t*-6). However, the differences in *DMA* returns are not economically or statistically significant. The average differences and *t*-statistics of the diff-in-DMA portfolios are -0.18% with a *t*-statistic of 0.29, 0.42% with a *t*-statistic of 0.56 and -0.64% with a *t*-statistic of 0.62, respectively. Thus, our analysis indicates that wealth transfers do not depend on past stock returns, turnover or standard deviation of returns.

In sum, the wealth transfer is larger among firms with higher mutual fund ownership, higher standard deviation of mutual fund ownership, smaller market capitalization and higher relative spread.

7.2 Investor sentiment and the time series of DMA returns

Table 10 examines *DMA* returns conditional on retail investor sentiment. Following Ben-Rephael, Kandel and Wohl (2012), we measure retail investor sentiment using the monthly net flows from bond mutual funds to equity mutual funds.[27] Panel A presents tests of whether mutual fund trading activity is different in periods of high retail sentiment than in periods of low retail sentiment. We find that periods of higher retail sentiment are associated with higher trading volume by mutual funds. For example, we find that mutual fund trading volume increases by 16% (28%) across all stocks (small stocks) when retail sentiment is in the highest tertile ('bullish' sentiment) versus when retail sentiment is in the bottom tertile ('bearish' sentiment).

[27] These flows are measured within the same mutual fund family and are classified by the ICI Company as exchanges in and exchanges out. Such transfers from bond to equity funds represent retail investors' appetite for equity which are distinct than net flow-induced trades.

Thus, during periods of high sentiment, mutual funds trade more actively. However, we do not find evidence that the net purchases of mutual funds differ across periods of higher or lower retail sentiment. Specifically, *MF* (which measures net purchases) is not different across high and low sentiment periods.

Panel B shows that the profitability of SSs is higher during periods of high retail sentiment. There is also some evidence that MFs exert higher price pressure during periods of higher sentiment than in periods of lower sentiment, although the difference is not statistically significant.

Panel C examines whether the profitability of the *DMA* portfolio varies with the level of retail sentiment. Strikingly, we find that the wealth transfer from mutual funds to short sellers is sharply higher in high sentiment months than in low sentiment months. Specifically, the return to the *DMA* portfolio is 2.27% during high sentiment periods (*t*-statistic 4.62), while during low sentiment periods it is only 0.17% (*t*-statistic 0.26), and the 2.10% differential (i.e., diff-in-*DMA*) is statistically significant. These results suggest that mutual fund-driven price pressure is particularly pronounced during periods of high retail investor sentiment, and that the profits earned by short sellers are particularly pronounced in periods of high retail investor sentiment.

Overall, the collective evidence presented in Tables 9 and 10 supports our hypothesis that *MF* price pressure effects are an important source of the profitability of trades by short sellers. The profitability of SSs is more pronounced in stocks which are widely held by MFs and in which *MF* trade volatility is high, and during periods of bullish retail investor sentiment. These findings are consistent with the view there is a wealth transfer from mutual funds to short sellers in stocks most susceptible to trade-induced price pressure, and in times of buoyant retail sentiment.

8. Conclusion

In this study, we explore the daily trading patterns of MFs and SSs to better understand how each group fares in higher frequency exchanges. Specifically, we evaluate the proposition that SSs can profitably exploit the predictability in MF trading patterns. Our results show that on a typical day and in a typical stock, MFs and SSs are on the opposite sides of the trade. When

MFs increase their net purchases, SSs increase their net short-selling activities. Conversely when MFs are net sellers, SSs decrease their short-selling activities.

We show in a VAR framework that it is the MF flows that “Granger cause” *SS* flows. Parsing daily *MF* flows into its expected and unexpected components, we show that *SS* flows are sensitive to the expected component, indicating that the *SS* activity is substantially related to lower frequency predictability in *MF* flows. However, we also find evidence that MFs are telegraphing their flows during the day, as SSs seem to also respond strongly to the unexpected component of daily *MF* flows.

Analyzing the return predictability of each group, we find that SSs trade in the right direction (i.e., price continuation) while MFs cause long-term price reversals when they trade. Exploring the interaction between these groups, our analysis of subsequent returns over the next three months shows that the general discordance in the directional trades of these two groups tend to resolve itself in favor of the SSs. Specifically, we explore the effect of MFs on SSs profitability using SSs trades which are in the *same* or *opposite* direction of MFs trades (which we term “Agree” and “Disagree” portfolios, respectively). We find that the returns to SS-based strategies are more than triple when SSs trade in the opposite direction of MFs. For example, over the next 63 trading days, a typical long-short SS strategy which systematically bets against MFs earns a return of 1.98% while a strategy in which SSs trade in the same direction as MFs trades earns a return of 0.57%. Thus, SSs seem to exploit and benefit from MF-induced price reversals.

Consistent with the MF price reversal explanation, in further analysis, we show that this effect is most pronounced for firms that have a large proportion of MF institutional ownership and lower overall market liquidity. We also find these results are significantly higher in periods of high retail investor sentiment. This evidence suggests that at least part of the MFs woes are likely to be due to flow-induced problems arising from retail sentiment. Collectively, our results point to a substantial wealth transfer between MFs and SSs.

In sum, our results contribute to the literature on short-selling. We show that part of the profitability of trading by short sellers is the ability to exploit the price effects of MFs directional trades. Put differently, a significant element in the profitability of SSs is derived from predictability in MF trading patterns. Prior studies have shown that SSs appear to have an advantage in processing fundamental news. Our findings suggest they also profit from “strategic liquidity provision” in relation to MF flows.

Finally, our results also shed some light on the persistent underperformance of mutual funds. Specifically, our results show that MF trades are collectively price destabilizing, resulting in short-term price continuation (lasting up to three days) in the direction of MF flows, followed by a protracted period of price reversal (lasting 60 days). The strongly persistent pattern of daily directional MF flows that we document is reminiscent of an elephant herd moving slowly. As our results show, stock that are being strongly bought (sold) by MFs have typically been bought (sold) for at least 3 weeks, and will continue to be bought (sold) by MFs for at least another 60 trading days in the future.

Our results show this predictable pattern of directional MF trading is resulting in substantial losses to MFs. While our analysis cannot clearly adjudicate between longer-term retail-flow induced problems and shorter-term clustered trading issues, we do find that SSs seem to respond to both types of MF flows. It does appear MFs are telegraphing their trades to SSs even at a daily basis. As a minimum, our evidence suggests MFs would do well to better understand (and attempt to mitigate) the problems associated with their correlated directional trades.

Appendix A – The Impulse Response Function based on Alternative Order Selections

Appendix A reports the accumulated impulse response functions of *SS* and *MF* under alternative order selection assumptions. Specifically, we estimate a three-equation *VAR* system of *RET*, *MF* and *SS* with five lags of *RET*, *MF* and *SS* as follows:

$$RET_t = \alpha_1 + \sum_{t=1}^{5} \gamma_{1i} RET_{t-i} + \sum_{t=1}^{5} \gamma_{1i} MF_{t-i} + \sum_{t=1}^{5} \delta_{1i} SS_{t-i} + \varepsilon_{1t}$$

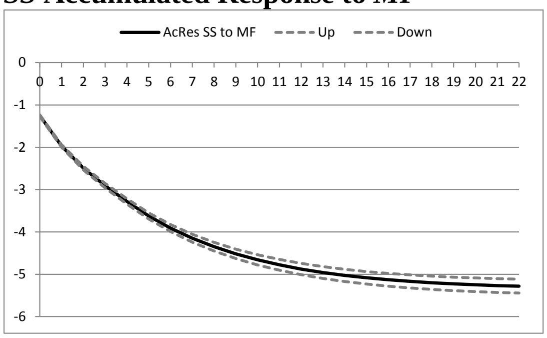
$$MF_t = \alpha_2 + \sum_{t=1}^{5} \gamma_{2i} RET_{t-i} + \sum_{t=1}^{5} \gamma_{2i} MF_{t-i} + \sum_{t=1}^{5} \delta_{2i} SS_{t-i} + \varepsilon_{2t}$$

$$SS_t = \alpha_3 + \sum_{t=1}^{5} \gamma_{3i} RET_{t-i} + \sum_{t=1}^{5} \gamma_{3i} MF_{t-i} + \sum_{t=1}^{5} \delta_{3i} SS_{t-i} + \varepsilon_{3t}$$

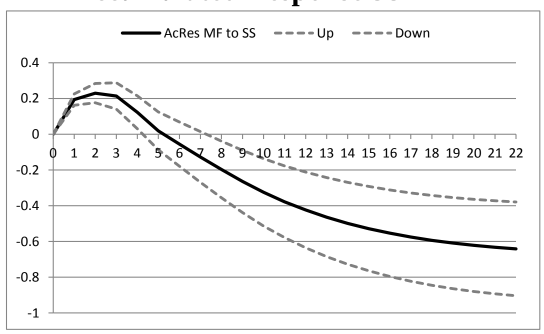
In each graph the solid black line represents the impulse response and the dashed gray lines represent the 5% confidence intervals.

Graph A.1 - Cholesky Ordering: *MF SS RET*

SS* Accumulated Response to *MF

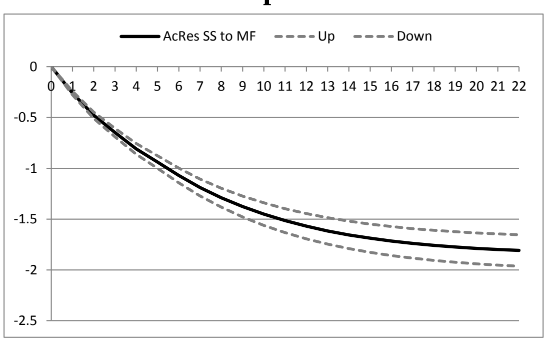


MF* Accumulated Response *SS

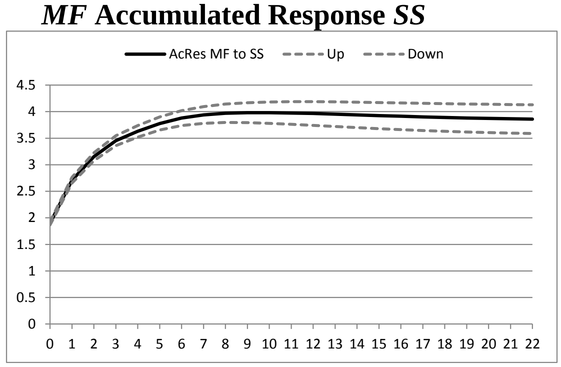


Graph A.2 - Cholesky Ordering: *RET SS MF*

SS* Accumulated Response to *MF

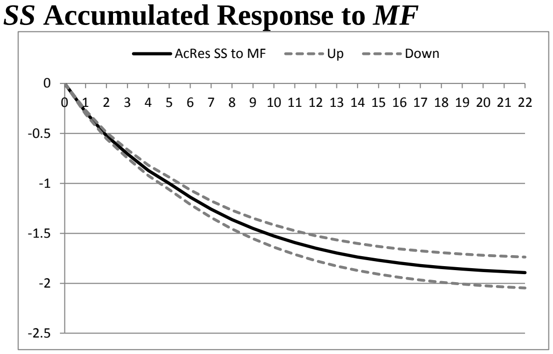


MF* Accumulated Response *SS

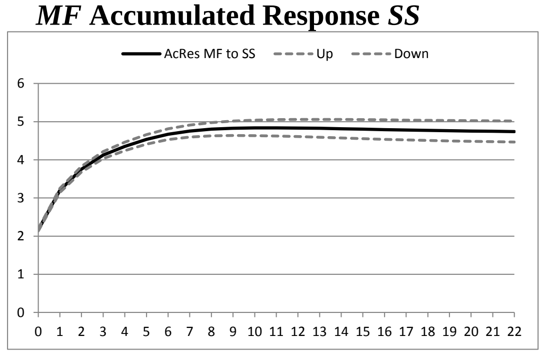


Graph A.3 - Cholesky Ordering: *SS MF RET*

SS* Accumulated Response to *MF



MF* Accumulated Response *SS



Appendix B – Short Sale Constraints and the MF-SS relation

Appendix B extends the analysis in Table 4 and estimates the effect of short-sale constraints on the relation between *MF* and *SS*. *SS*, *MF*, and *RET* are as defined in Table 4 and expressed in percentages. Following Beneish, Lee and Nichols (2013), we use the Daily Cost of Borrowing Score (DCBS) from the DXL dataset to measure short sale constraints. DCBS ranges from 1 to 10. Stocks with a DCBS value of 1 and 2 correspond to stocks that are easy-to-borrow ("General Collateral" or "GC" in Column (3)), and stocks with a DCBS value of 3 or larger are considered hard-to-borrow ("HTB" in Columns (4)). Stocks with a DBCS score of less than 3 account for 98% of our sample. The sample includes 389, 685 Day-Stock observations from January 3, 2005 to July 6, 2007. Other stock controls are not reported for brevity. All regressions include firm and time fixed effects using the demean procedure. ***t***-statistics below the coefficients are clustered by firm and day.

	SS			
	ALL	*ALL*	*GC*	*HTB*
Variables	(1)	(2)	(3)	(4)
MF	-0.111	-0.118	-0.112	-0.104
	54.61	27.42	54.46	9.31
RET	-0.800	-0.800	-0.821	-0.315
	34.56	34.71	37.33	3.52
HTB		0.162		
		1.64		
*MF*HTB*		0.006		
		2.32		
N	389,685	389,685	380,872	8,813
% Obs	100%	100%	97.74%	2.26%
AdjRSQ	6.82%	6.83%	6.96%	3.01%

Appendix C – Cumulative Abnormal Return for *AveSS* and *AveMF* Single-Sorted Portfolios

Appendix C reports the average cumulative abnormal returns to daily single-sorted equally-weighted portfolios based on *AveSS* (Panel A) and *AveMF* (Panel B). *SS* is the daily ratio of the stock's shorting volume to total trading volume multiplied by negative one (in %). *MF* is the daily ratio of net purchases by mutual funds to total trading volume (in %). *AveSS* (*AveMF*) is the average of *SS* (*MF*) over days *(t-1)* to *(t-5)*. To construct this table, stocks are sorted each day into deciles based on *AveSS* (Panel A) and *AveMF* (Panel B). We then construct equally-weighted portfolios and calculate their time-series average returns. *SS1* and *MF1* (*SS10* and *MF10*) refer to the bottom (top) decile portfolio. *SS10-SS1 (MF10-MF1)* is the difference in returns between the top and bottom deciles.

Table values present average future cumulative abnormal returns for holding periods up to 63 trading days following portfolio formation. Daily abnormal returns are defined as the stock's CRSP returns minus its *DGTW(1997)-matched* daily benchmark portfolio returns. In both panels 10, 21, 42, and 63 refer to the 10, 21, 42, and 63-day cumulative *DGTW* returns, starting from day *t*+1. *t*-statistics below the portfolio averages are adjusted for serial correlation using Newey-West (1987) correction, where the number of lags is set to the number of the dependent variable's overlapping days.

Portfolios constructed during the last three month of our sample (May-July 2007) include the August 2007 quant meltdown crisis. This time period is quite unusual in terms of the profitability of SS strategies. Consequently, we report results for three time periods: January 3, 2005 to April 30, 2007 a total of 579 trading days (Specifications (1) – (4)); May 1, 2007 to July 6, 2007 a total of 47 trading days (Specification (5)); and January 3, 2005 to July 6, 2007 a total of 626 trading days (Specification (6)).

Panel C.1 – Top and Bottom Deciles based on *AveSS (t-5_t-1)*

	AveSS Sort					
	10	*21*	*42*	*63*	*63 - Aug 2007*	
	(1)	(2)	(3)	(4)	(5)	(6)
*SS*1 (Heavily shorted)	-0.16%	-0.31%	-0.57%	-0.79%	-1.39%	-0.84%
	2.64	2.83	2.99	2.94	2.45	3.28
*SS*10 (Lightly shorted)	0.31%	0.53%	0.71%	0.80%	-0.81%	0.68%
	5.50	6.22	4.75	3.85	2.63	3.10
*SS*10 - *SS*1	0.47%	0.84%	1.28%	1.59%	0.58%	1.52%
	6.15	6.75	7.12	5.72	0.89	4.08
N	579	579	579	579	47	626

Panel C.2 – Top and Bottom Deciles based on *AveMF (t-5_t-1)*

	AveMF Sort					
	10	*21*	*42*	*63*	*63 - Aug 2007*	
	(1)	(2)	(3)	(4)	(5)	(6)
*MF*1 (Sell)	0.30%	0.46%	0.76%	1.09%	-0.41%	0.98%
	5.82	4.34	3.11	3.63	1.26	3.33
*MF*10 (Buy)	-0.10%	-0.18%	-0.20%	-0.27%	0.66%	-0.20%
	2.07	2.27	1.67	1.87	2.02	1.26
*MF*10 - *MF*1	-0.40%	-0.64%	-0.96%	-1.37%	1.07%	-1.18%
	6.63	6.24	5.51	7.05	1.66	5.13
N	579	579	579	579	47	626

References

Admati, A. R., 1985, A noisy rational expectations equilibrium for multi-asset securities markets, *Econometrica* 53, 629-657.

Alexander, G. J., and M. A. Peterson, 2007, An analysis of trade-size clustering and its relation to stealth trading, *Journal of Financial Economics* 84, 435-471.

Anand, A., Irvine, P., Puckett, A., Venkataraman, K., 2012, Performance of institutional trading desks: an analysis of persistence in trading costs, *Review of Financial Studies* 25, 557–598.

Anand, A., Irvine, P., Puckett, A., Venkataraman, K., 2013, Institutional trading and stock resiliency: Evidence from the 2007-2009 financial crisis, *Journal of Financial Economics* 108, 773–797.

Arif, S. and C. M. C. Lee, 2014, Aggregate investment and investor sentiment, *Review of Financial Studies*, forthcoming.

Baker, M., and J. Wurgler, 2000, The equity share in new issues and aggregate stock returns, *Journal of Finance* 55, 2219-2257.

Beneish, M., Lee, C. M. C., and D. C., Nichols, 2013, In short supply: Equity Overvaluation and Short Selling, Indiana University, Syracuse University, and Stanford University working paper, November.

Ben-David, I., F. Franzoni, and R. Moussawi. 2012. Hedge fund stock trading in the financial crisis of 2007–2008. *Review of Financial Studies* 25:1–54.

Ben-Rephael, A., S. Kandel, and A. Wohl, 2011, The price impact of aggregate mutual fund flows, *Journal of Financial and Quantitative Economics* 46, 585-603.

___________________. 2012, Measuring investor sentiment with mutual fund flows, *Journal of Financial Economics* 104, 363-382.

Boehmer, E., C. Jones and X. Zhang, 2008, Which Shorts are Informed? *Journal of Finance* 63, 491-527.

___________________. 2012. Shackling short sellers: The 2008 shorting ban. Working Paper, Singapore Management University, Columbia Business School, and Purdue University.

___________________. 2013. What do short sellers know? Working Paper, Singapore Management University, Columbia Business School, and Purdue University.

Boehmer, E., Z. R. Huszar and B. D. Jordan, 2010, The good news in short interest, *Journal of Financial Economics* 96, 80-97.

Boehmer, E., and J. J. Wu, 2013, Short selling and the price discovery process, *Review of Financial Studies* 26(2), 287-322.

Bris, A., W. N. Goetzmann, and N. Zhu, 2007, Efficiency and the Bear: Short sales and markets around the world, *Journal of Finance* 62(3), 1029-1079.

Brunnermeier, M., and L. Pedersen, 2005, Predatory trading, *Journal of Finance* 60, 1825-1863.

Carhart, M. M., R. Kaniel, D. K. Musto, and A. V. Reed, 2002, Leaning for the Tape: Evidence of Gaming Behavior in Equity Mutual Funds, *Journal of Finance* 57, 661-693.

Chakravarty, S., 2001, Stealth-trading: which traders' trades move stock prices? *Journal of Financial Economics* 61, 289-307.

Chemmanur, T. J., S. He, and G. Hu, 2009, The Role of Institutional Investors in Seasoned Equity Offerings, *Journal of Financial Economics* 94, 384–411.

Chen, H., H. Desai, and S. Krishnamurthy, 2013, A first look at mutual funds that use short sales, *Journal of Financial and Quantitative Analysis* 48(3), 761-787.

Chen, J., S. Hanson, H. Hong, and J. Stein, 2008, Do Hedge Funds Profit from Mutual Fund Distress? NBER Working Paper 13786, February.

Christophe, S., M. Ferri, and J. Angel, 2004, Short-Selling Prior to Earnings Announcements, *Journal of Finance* 59, 1845-1875.

Christophe, S., Ferri, M., Hsieh, J., 2010, Informed trading before analyst downgrades: evidence from short sellers, *Journal of Financial Economics* 95, 85–106.

Coval, J., and E. Stafford, 2007, Asset fire sales (and purchases) in equity markets, *Journal of Financial Economics* 86, 479-512.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers, 1997, Measuring Mutual Fund Performance with Characteristic-Based Benchmarks, *Journal of Finance* 52, 1035-1058.

Daouk, H., C. M. C. Lee, and D. Ng, 2006, Capital market governance: how do security laws affect market performance? *Journal of Corporate Finance* 12, 560-593.

Dechow, P. M., A. P. Hutton, L. Meulbroek, and R. G. Sloan, 2001, Short-sellers, fundamental analysis, and stock returns. *Journal of Financial Economics* 61 (1), 77–106.

Del Guercio, D., and J. Reuter, 2014, Mutual fund performance and the incentive to generate alpha, *Journal of Finance*, forthcoming.

Diamond, D. W., and R. E. Verrecchia, 1981, Information aggregation in noisy rational expectations model, *Journal of Financial Economics* 9, 221-235.

Diether, K., Lee, K., and I. Werner, 2009, Short-Sale Strategies and Return Predictability, *Review of Financial Studies* 22, 575-607.

Dichev, I., 2007, What Are Stock Investors' Actual Historical Returns? Evidence from Dollar-Weighted Returns, *American Economic Review* 97(1), 386-401.

Drake, M. S., L. Rees, and E. P. Swanson, 2011, Should Investors Follow the Prophets or the Bears? Evidence on the Use of Public Information by Analysts and Short Sellers, *The Accounting Review* 86, 101-130.

Dyakov, T. and M. Verbeek, 2013, Front-running of mutual fund fire-sales, *Journal of Banking & Finance* 37(12), 4931-4942.

Engelberg, J. E., A. V. Reed, and M. C. Ringgenberg, 2012, How are shorts informed? Short sellers, news, and information processing, *Journal of Financial Economics* 105, 260-278.

Evans, R., C. Geczy, D. Musto, and A. Reed, 2009, Failure is an Option: Impediments to Short-Selling and Options Prices, *Review of Financial Studies* 22(5),

Fama, Eugene F., and French, Kenneth R., 2010, Luck versus skill in the cross-section of mutual fund returns, *Journal of Finance* 65, 1915–1947.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607-636.

French, Kenneth R., 2008, The cost of active investing, *Journal of Finance* 63, 1537–1573.

Franzoni, F., and A. Plazzi, 2012, Hedge Funds' Liquidity Provision and Trading Activity, University of Lugano and Swiss Finance Institute Working Paper, November.

Frazzini, A., and O. Lamont, 2008, "Dumb money: Mutual Fund Flows and the Cross-Section of Stock Returns", *Journal of Financial Economics* 88(2), 299-322.

Gantchev, N., and C. Jotikasthira, 2013. Hedge Fund Activists: Do They Take Cues from Institutional Exit? Working paper.

Goldman Sachs. 2008. Goldman Sachs hedge fund trend monitor. February 20.

Goldstein, M. A., P. Irvine, and A. Puckett, 2011, Purchasing IPOs with commissions, *Journal of Financial and Quantitative Analysis* 46, 1193-1225.

Griffin, J. M., and J. Xu, 2009, How smart are the smart guys? A unique view from hedge fund stock holdings, *Review of Financial Studies* 22, 2531-2570.

Grinblatt, M., S. Titman, and R. Wermers, 1995, Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior, *American Economic Review* 85, 1088–1105.

Gruber, Martin J., 1996, Another puzzle: The growth in actively managed mutual funds, *Journal of Finance* 51, 783–810.

Harris, M. and A. Raviv, 1993, Differences of opinion make a horse race, *Review of Financial Studies* 6, 473-506.

Hanson, S. G., and A. Sunderam. 2014. The growth and limits of arbitrage: evidence from short interest, *Review of Financial Studies* 27 (4), 1238-1286.

Hong, H., and J. C. Stein, 2007, Disagreement and the stock market, *Journal of Economic Perspectives* 21:2, 109-128.

Jame, R., 2012, Pension Fund Trading and Stock Returns, University of New South Wales working paper, May.

_____________, 2013, How do hedge fund “stars” create value? Evidence from their daily trades, University of New South Wales working paper, June.

Kandel, E., and N. D. Pearson, 1995, Differential interpretation of public signals and trade in speculative markets, *Journal of Political Economy* 103, 831-872.

Karpoff, J., and X. Lou, 2010, Short sellers and financial misconduct, *Journal of Finance* 65 (5), 1879–1913.

Khan, M., L. Kogan, and G. Serafeim, 2012, Mutual Fund Trading Pressure: Firm-Level Stock Price Impact and Timing of SEOs, *Journal of Finance* 67 (4), 1371-1395.

Khan, M. and H. Lu, 2013, Do short sellers front-run insider sales? *The Accounting Review*, 88(5), 1743-1768.

Lehmann, B. N., 1990, Fads, martingales, and market efficiency, *Quarterly Journal of Economics* 105, 1–28.

Lou, D., 2012, A flow-based explanation for return predictability, *Review of Financial Studies* 25(1), 3457-3489.

Nagel, S., 2012, Evaporating liquidity, *Review of Financial Studies* 25:7, 2005-2039.

Newey, W. K. and K. D. West, 1987, A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica* 55, 703–708.

Puckett, A., X. Yan, 2011, The interim trading skills of institutional investors, *Journal of Finance* 66, 601–633.

_____________, 2013, Short-term institutional herding and its impact on stock prices, University of Missouri working paper.

Sharpe, W., F., 1991, The arithmetic of active management, *Financial Analysts Journal* 47:1, January/February, 7-9.

Shive, S. and H. Yun, 2013, Are mutual funds sitting ducks? *Journal of Financial Economics* 107, 220-237

So, E. C., and S. Wang, 2014, News-driven return reversals: liquidity provision ahead of earnings announcements, *Journal of Financial Economics*, forthcoming.

Stambaugh, R. F., J. Yu, and Y. Yuan, 2012. The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* 104(2), 288-302.

Stefanini, F., 2006, *Investment strategies of hedge funds*, John Wiley & Sons Ltd., West Sussex, England.

Varian, H., R., 1989, Differences of opinion in financial markets, in CC. Stone, ed., *Financial risk: theory, evidence and implications: Proceedings of the 11th annual economic policy conference of the Federal Reserve Bank of St. Louis,* Kluwer Academic Publishers, Boston MA.

Verrecchia, R., 1982, Information acquisition in a noisy rational expectations economy, *Econometrica* 50, 1415-1430.

Table 1 – Summary Statistics of Main Variables

This table reports the time-series averages of the daily cross-sectional statistics for our main variables. The sample consists of daily observations from January 3, 2005 to July 6, 2007, a total of 626 trading days. Panel 1.A reports summary statistics for key variables, each expressed as a percentage of daily total trading volume for each stock. *SS* is the total number of shares traded in short-seller initiated transactions multiplied by negative one. *MF* is net directional trading by mutual funds, computed as the daily total shares purchased minus shares sold across all MFs in our sample. *AbsMF* is the absolute value of *MF*, and provides a sense of the absolute magnitude of daily MF directional trading. *MF Vol* is daily total mutual fund trading volume (buys plus sells). Panel 1.B examines the directional concordance/discordance of daily MF and SS trades. To construct this panel, we first demean SS at the firm-level (i.e. control for the average firm-level SS). We then group each firm-day observation by the sign of MF and the demeaned SS value independently. Table values in Panel 1.B represent the percentage of firm-day observations in each category, where "SS Buys" refer to days when SS-initiated volume is below firm-level mean, and "SS Sells" refer to days when SS-initated volume is above firm-level mean.

Panel 1.A Descriptive Statistics

Variables	Mean	Median	SD
As Percentage of Daily Share Volume			
SS	-18.79	-17.48	9.01
MF	0.29	0.19	14.08
AbsMF	9.28	4.79	11.62
MF Vol	13.65	8.62	14.85

Panel 1.B Directional Concordance/Discordance

	MF Buys	***MF Sells***	
"SS Buys"	26.0%	28.3%	54.3%
"SS Sells"	28.0%	17.7%	45.7%
	54.0%	46.0%	

Total Disagree 56.5%
Total Agree 43.5%

Table 2 –Panel Regressions of *SS* on Lagged Explanatory Variables

This table reports results from panel regressions of daily *SS* on lagged explanatory variables. Sample includes 575,000 Day-Stock observations from January 3, 2005 to July 6, 2007. *SS* is the daily ratio of the stock's short-initiated volume to total trading volume multiplied by negative one. *MF* is the daily ratio of net purchases by mutual funds to total trading volume. *RET* is the daily CRSP stock return. All three variables are expressed in percentages. In the table, *(t-j)* refers to the j_{th} lag of the corresponding variable. "*Stock Controls*" (Specification 7) controls for: five lags of *TO*, where *TO* is the daily stock turnover; five lags of *HLtH*, where *HLtH* is the ratio between the stock's daily high-and-low price difference and the daily high price; five lags of *HBAS*, where *HBAS* is the relative half bid-ask spread calculated as [(Ask-Bid)/Midpoint]/2 using *CRSP* end of day quotes; *SD (t-27_t-6)*, the standard deviation of daily returns from day *t-27* to *t-6*; *LnPRC (t-27_t-6)*, the log of the stock's average price from day *t-27* to *t-6*; *LnSizeM (t-27_t-6)*, the log of the stock's average size in millions of dollars from day *t-27* to *t-6*; and *LnBM*, the log of the stock's book-to-market ratio. For brevity, results for individual *Stock Controls* are not reported in this Table. All regressions include firm and time fixed effects using the demean procedure. *t*-statistics below the coefficients are clustered by firm and day.

***SS(t)* as Dependent Variable**

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SS (t-1)	0.349			0.447	0.364	0.330	0.329
	136.57			143.25	138.32	168.41	128.41
SS (t-2)	0.119				0.176	0.118	0.117
	60.92				79.53	69.72	58.52
SS (t-3)	0.068					0.071	0.070
	36.50					41.30	35.66
SS (t-4)	0.055					0.058	0.058
	31.00					34.34	31.11
SS (t-5)	0.061					0.064	0.064
	36.10					39.06	36.13
RET (t-1)		-0.514		-0.087	-0.184	-0.215	-0.209
		40.30		9.15	18.35	24.07	20.10
RET (t-2)		-0.359			0.010	-0.069	-0.066
		35.14			1.43	10.54	8.43
RET (t-3)		-0.270				-0.021	-0.018
		31.35				3.48	2.75
RET (t-4)		-0.199				0.023	0.026
		24.49				4.02	3.88
RET (t-5)		-0.173				0.042	0.043
		22.11				7.43	6.75
MF (t-1)			-0.059	-0.025	-0.020	-0.022	-0.022
			49.73	26.21	22.70	25.44	23.91
MF (t-2)			-0.021		-0.003	-0.002	-0.002
			22.43		3.42	2.58	2.55
MF (t-3)			-0.013			0.000	0.000
			13.67			0.13	0.03
MF (t-4)			-0.012			0.000	0.000
			13.85			0.22	0.14
MF (t-5)			-0.014			0.001	0.001
			13.62			1.60	1.54
Stock Controls							YES
AdjRSQ	25.01%	2.12%	2.35%	21.30%	23.75%	25.39%	25.48%

Table 3 –Panel Regressions of *MF* on Lagged Explanatory Variables

This table reports results from panel regressions of daily *MF* on lagged explanatory variables. Sample includes 575,000 Day-Stock observations from January 3, 2005 to July 6, 2007. *SS* is the daily ratio of the stock's short-initiated volume to total trading volume multiplied by negative one. *MF* is the daily ratio of net purchases by mutual funds to total trading volume. *RET* is the daily CRSP stock return. All three variables are expressed in percentages. In the table, *(t-j)* refers to the j_{th} lag of the corresponding variable. "*Stock Controls*" (Specification 7) controls for: five lags of *TO*, where *TO* is the daily stock turnover; five lags of *HLtH*, where *HLtH* is the ratio between the stock's daily high-and-low price difference and the daily high price; five lags of *HBAS*, where *HBAS* is the relative half bid-ask spread calculated as [(Ask-Bid)/Midpoint]/2 using *CRSP* end of day quotes; *SD (t-27_t-6)*, the standard deviation of daily returns from day *t-27* to *t-6*; *LnPRC (t-27_t-6)*, the log of the stock's average price from day *t-27* to *t-6*; *LnSizeM (t-27_t-6)*, the log of the stock's average size in millions of dollars from day *t-27* to *t-6*; and *LnBM*, the log of the stock's book-to-market ratio. For brevity, results for individual *Stock Controls* are not reported in this Table. All regressions include firm and time fixed effects using the demean procedure. *t*-statistics below the coefficients are clustered by firm and day.

***MF(t)* as Dependent Variable**

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MF (t-1)	0.392			0.467	0.403	0.385	0.385
	130.15			136.88	136.18	129.70	129.49
MF (t-2)	0.094				0.137	0.097	0.097
	41.33				57.63	42.36	42.33
MF (t-3)	0.053					0.054	0.054
	27.90					28.55	28.54
MF (t-4)	0.038					0.039	0.039
	19.53					20.17	20.01
MF (t-5)	0.041					0.042	0.042
	22.54					22.91	22.86
RET (t-1)		0.699		0.263	0.322	0.341	0.342
		33.21		20.85	24.37	25.23	25.18
RET (t-2)		0.393			-0.017	0.030	0.028
		22.99			1.49	2.59	2.93
RET (t-3)		0.240				-0.031	-0.031
		16.94				2.95	2.07
RET (t-4)		0.184				-0.013	-0.016
		13.47				1.24	1.41
RET (t-5)		0.149				-0.023	-0.023
		10.89				2.11	2.06
SS (t-1)			-0.177	-0.020	-0.013	-0.012	-0.010
			45.71	7.88	4.83	4.52	3.83
SS (t-2)			-0.041		0.008	0.010	0.011
			15.35		3.06	3.72	3.96
SS (t-3)			-0.014			0.006	0.006
			5.23			2.11	2.29
SS (t-4)			0.001			0.010	0.010
			0.37			3.61	3.69
SS (t-5)			0.008			0.004	0.004
			2.96			1.46	1.62
Stock Controls							YES
AdjRSQ	24.61%	1.02%	1.38%	22.50%	23.95%	24.80%	24.81%

Table 4 –Panel Regressions of *SS* on Contemporaneous Explanatory Variables

The table reports results of panel regressions of *SS* on selected contemporaneous variables. The sample includes 575,000 Day-Stock observations from January 3, 2005 to July 6, 2007. *SS* is the daily ratio of the stock's short-initiated volume to total trading volume multiplied by negative one. *MF* is the daily ratio of net purchases by mutual funds to total trading volume. *RET* is the daily CRSP stock return. All three variables are expressed in percentages. Specifically, Panel A reports results of panel regressions of *SS, Unexpected SS,* and *Expected SS* on selected contemporaneous variables. *UnexpSS* (*ExpSS*) is the residual (predicted value) from a regression of *SS* on five lags of *SS*, *MF* and *RET*. Analogously, *UnexpMF* (*ExpMF*) is the residual (predicted value) from a regression of *MF* on five lags of *SS*, *MF* and *RET*. *Ret*MF* is the daily interaction between *RET* and *MF*. *Ret*Unexp* and *Ret*ExpMF* are constructed in a similar manner. Columns (1) to (5) present the results for *SS* as a dependent variable; Columns (6) to (8) present the results for *UnexpSS* as a dependent variable; and Columns (9) to (11) present the results for *ExpSS* as a dependent variable. "*Stock Controls*" controls for: *HLtH*, where *HLtH* is the ratio between the stock's daily high-and-low price difference and the daily high price; *HBAS*, where *HBAS* is the relative half bid-ask spread calculated as [(Ask-Bid)/Midpoint]/2 using *CRSP* end of day quotes; *SD (t-27_t-6)*, the standard deviation of daily returns from day *t-27* to *t-6*; *LnPRC (t-27_t-6)*, the log of the stock's average price from day *t-27* to *t-6*; *LnSize (t-27_t-6)*, the log of the stock's average size in millions of dollars from day *(t-27)* to *(t-6)*; and *LnBM*, the log of the stock book-to-market ratio. For brevity, results for each *Stock Controls* variable are not reported individually. Panel B extends Panel A's analysis, and estimates the relation between *SS* and *MF*, *ExpMF* and *UnexpMF* within *MF*, *ExpMF* and *UnexpMF* tertiles, respectively. Specifically, each day stocks are sorted into three tertiles from negative-to-positive, based on three MF trading measures (*MF*, *ExpMF* and *UnexpMF*). We control for the same variables as in Panel A and use dummy interaction variables to estimate three slope coefficients. In Column (1), stocks are sorted on the basis of *MF*. In column (2), stocks are sorted on the basis of *UnexpMF*. In column (3), stocks are sorted on the basis of *ExpMF*. *TER1 - Sell*, *TER2* and *TER3-Buy* are tertiles 1, 2 and 3, respectively. Instead of presenting the regression coefficient, we multiply each coefficient by its respective standard deviation. Thus, the numbers in the table represent the effect of a 1 standard deviation (SD) change in the dependent variable. Panels A and B's regressions include firm and time fixed effects using the demean procedure. *t*-statistics below the coefficients are clustered by firm and day.

Panel 4.A - Panel Regressions of *SS, UnexpSS,* and *ExpSS* on Selected Contemporaneous Variables

	SS					*UnexpSS*			*ExpSS*		
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
MF	-0.112	-0.112	-0.111								
	64.95	64.78	65.04								
RET	-0.795	-0.801	-0.783	-0.878	-0.826	-0.871	-0.871	-0.875	0.050	0.051	0.051
	39.78	40.24	40.18	41.97	40.35	41.66	41.65	41.87	10.32	10.31	10.34
*Ret*MF*		-0.007	-0.006	-0.008	-0.007						
		8.95	7.17	9.45	9.04						
UnexpMF				-0.088	-0.088	-0.088	-0.088	-0.088		-0.001	
				65.51	60.70	65.80	65.80	65.71		1.21	
ExpMF					-0.181		0.000		-0.181	-0.181	-0.181
					53.51		0.05		81.34	81.35	81.34
*Ret*UnexpMF*								-0.005			
								5.62			
*Ret*ExpMF*											0.001
											2.61
Stock Controls			YES								
AdjRSQ	6.87%	6.91%	7.56%	4.99%	7.40%	7.11%	7.11%	7.13%	9.51%	9.51%	9.51%

Panel 4.B – *MF* effect by Flow Tertiles

Dependent Variable	*SS*		
Exp. Sorting Variables	*MF*	*ExpMF*	*UnexpMF*
Sorting Tertiles	(1)	(2)	(3)
TER 1 - Sell	-1.613	-1.010	-1.336
	63.56	38.76	58.67
TER 2	-0.183	-0.197	-0.060
	8.41	9.61	3.35
TER 3 - Buy	-0.430	-0.576	-0.269
	11.38	16.98	4.58

Table 5 – *MF, SS* and Short-Term Future Stock Returns

The table reports results of short-term future returns analyses using single sorted portfolios (Panel A) and Fama-Macbeth (1973) cross-sectional regressions (Panel B) from January 3, 2005 to July 6, 2007, a total of 626 trading days. *RET* is the daily CRSP stock return (in %). *DGTW* is the stock return (*RET)* minus the *DGTW* (1997)-matched daily benchmark portfolio return. *SS* is the daily ratio of the stock's shorting volume to total trading volume multiplied by negative one (in %). *MF* is the daily ratio of net purchases by mutual funds to total trading volume (in %).

Panel A presents results of single sorted portfolios based on previous day *DGTW* adjusted returns. Specifically, stocks are sorted each day into deciles based on day *t's DGTW*-adjusted abnormal returns. We then construct equally-weighted portfolios and calculate their time-series average returns. *DGTW1-Losers* (*DGTW10-Winners*) refers to the bottom (top) decile portfolio. *D10-D1* is the difference in returns between the top and bottom deciles. *MF Decile Rank* (*SS Decile Rank*) is the average decile rank of the stock when ranked on *MF* (*SS*). Specifically, each day stocks are independently sorted into deciles based on day *t MF* (*SS*). The table then reports the *MF* (*SS*) average decile rank of stocks in the top and bottom *DGTW* portfolios.

Panel B presents results of daily Fama-Macbeth (1973) cross-sectional regressions of cumulative *DGTW* adjusted stock returns from day *t*+1 to *t*+10 on day-*t* explanatory variables. All coefficients are multiplied by 100 for ease of presentation. *UnexpMF* (*ExpMF*) is the residual (predicted value) from a regression of *MF* on five lags of *SS*, *MF* and *RET*. *SS*ExpMF* (*SS*UnexpMF*) is the daily interaction between *SS* and *ExpMF* (*Un*exp*MF*). All other interaction terms are constructed in a similar manner. *Stock Controls* are the same controls used in Table 2. ***t*-statistics below the coefficients are adjusted for serial correlation using the Newey-West (1987) correction, where the number of lags is set to the number of the dependent variable's overlapping days.

Panel 5.A – Top and Bottom Deciles based on *DGTW (t)*

	Dgtw t+1	*MF Decile Rank*	*SS Decile Rank*
	(1)	(2)	(3)
Dgtw 1 - Losers	0.060%	4.84	6.05
	3.68		
Dgtw 10 - Winners	-0.045%	6.07	4.29
	3.12		
D10 - D1	-0.105%	1.23 ***	-1.75 ***
	4.00		

Panel 5.B - Cross Sectional Regressions of Cumulative *DGTW* on day-*t* Explanatory Variables

	DGTW t+1		*DGTW t+1_t+2*		*DGTW t+1_t+3*		*DGTW t+1_t+5*		*DGTW t+1_t+10*	
Variables - time *t*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DGTW	-1.818	-1.514	-1.617	-1.115	-1.794	-1.171	-1.302	-0.446	0.985	2.288
	4.42	3.63	2.78	1.89	2.64	1.70	1.55	0.52	0.82	1.83
ExpMF	-0.095	-0.187	-0.214	-0.318	-0.332	-0.463	-0.552	-0.689	-1.132	-1.580
	2.97	2.81	4.06	2.91	4.76	3.14	5.27	3.10	6.03	4.90
UnexpMF	0.071	0.081	0.082	0.068	0.077	0.056	0.049	0.011	-0.149	-0.264
	3.90	1.95	2.88	1.21	2.17	0.80	0.51	0.12	2.69	2.02
SS		0.410		0.619		0.763		1.036		1.614
		12.34		11.95		10.88		9.50		9.19
*SS*ExpMF*		-0.010		-0.012		-0.016		-0.018		-0.041
		2.98		2.36		2.21		2.15		3.14
*SS*UnexpMF*		-0.002		-0.004		-0.005		-0.008		-0.015
		0.71		1.42		1.59		1.78		2.21
Stock Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AdjRSQ	3.24%	3.41%	3.27%	3.43%	3.13%	3.27%	2.97%	3.13%	2.70%	2.86%

Table 6 – Panel Regressions of *SS* and *MF* averaged over 5 days on Lagged Explanatory Variables

This table reports results from panel regressions of *SS* (Panel A) and *MF* (Panel B) averaged over 5 days on lagged explanatory variables. Sample includes 575,000 Day-Stock observations from January 3, 2005 to July 6, 2007. *AveSS (t_t+4*) is defined as the average of *SS(t)* to *SS(t+4)*. In a similar manner, the prefix "Ave" refers to the average of the specified period. For example, *Ave MF(t-5_t-1*) is the average of *MF(t-5)* to *MF(t-1)*. *SS* is the daily ratio of the stock's short-initiated volume to total trading volume multiplied by negative one. *MF* is the daily ratio of net purchases by mutual funds to total trading volume. *RET* is the daily CRSP stock return. All three variables are expressed in percentages. In the table, *(t-j)* refers to the j_{th} lag of the corresponding variable. "*Stock Controls*" (Specification 6) controls for: five lags of *TO*, where *TO* is the daily stock turnover; five lags of *HLtH*, where *HLtH* is the ratio between the stock's daily high-and-low price difference and the daily high price; five lags of *HBAS*, where *HBAS* is the relative half bid-ask spread calculated as [(Ask-Bid)/Midpoint]/2 using *CRSP* end of day quotes; *SD (t-27_t-6)*, the standard deviation of daily returns from day *t-27* to *t-6*; *LnPRC (t-27_t-6)*, the log of the stock's average price from day *t-27* to *t-6*; *LnSizeM (t-27_t-6)*, the log of the stock's average size in millions of dollars from day *t-27* to *t-6*; and *LnBM,* the log of the stock's book-to-market ratio. All regressions include firm and time fixed effects using the demean procedure. *t*-statistics below the coefficients are clustered by firm and day.

Panel 6.A – *AveSS (t_t+4)* as Dependent Variable

Variables	(1)	(2)	(3)	(4)	(5)	(6)
AveSS (t-5_t-1)	0.446			0.445	0.439	0.431
	95.17			91.77	88.23	88.65
AveRET (t-5_t-1)		-0.731		-0.026	-0.005	0.029
		22.42		1.21	0.23	1.03
AveMF (t-5_t-1)			-0.079		-0.016	-0.016
			31.79		8.92	8.88
AveTO (t-5_t-1)						10.337
						2.61
AveHLtH (t-5_t-1)						-6.305
						1.85
SD (t-27_t-6)						15.749
						5.67
LnSizeM (t-27_t-6)						2.800
						12.03
LnBM						0.351
						2.98
AveHBAS (t-5_t-1)						-3.739
						0.12
LnAvePRC (t-27_t-6)						-0.957
						4.27
AdjRSQ	19.96%	0.86%	1.82%	19.96%	20.03%	20.49%

Panel 6.B – *AveMF (t_t+4)* as Dependent Variable

Variables	(1)	(2)	(3)	(4)	(5)	(6)
AveMF (t-5_t-1)	0.330			0.331	0.338	0.338
	78.15			77.41	78.22	78.43
AveRET (t-5_t-1)		0.562		-0.060	0.010	0.000
		12.82		1.62	0.27	0.01
AveSS (t-5_t-1)			-0.088		0.053	0.059
			12.99		9.68	10.81
AveTO (t-5_t-1)						-21.862
						4.36
AveHLtH (t-5_t-1)						25.740
						5.23
SD (t-27_t-6)						-13.523
						3.07
LnSizeM (t-27_t-6)						-1.135
						3.99
LnBM						-0.049
						0.32
AveHBAS (t-5_t-1)						-3.857
						0.08
LnAvePRC (t-27_t-6)						-0.182
						0.72
AdjRSQ	11.75%	0.19%	0.29%	11.75%	11.84%	11.93%

Table 7 – *MF*, *SS* and Long-Term Future Stock Returns

The table reports results of daily Fama-Macbeth (1973) cross-sectional regressions of stock returns on selected explanatory variables from January 3, 2005 to July 6, 2007, a total of 626 trading days. All coefficients are multiplied by 100 for ease of presentation. *RET* is the daily CRSP stock return (in %). *DGTW* is the stock return (*RET)* minus the *DGTW* (1997)-matched daily benchmark portfolio return. *SS* is the daily ratio of the stock's shorting volume to total trading volume multiplied by negative one (in %). *MF* is the daily ratio of net purchases by mutual funds to total trading volume (in %). In the table, *(t-j)* refers to the j_{th} lag of the explanatory variable, For example, *SS (t-1)* is the first lag of *SS*. As in Tables 4 and 5, the prefix "Ave" refers to the average from *(t-1)* to *(t-5)*. For example, "Ave SS (*t*-5_*t*-1)" is the average of *SS* from day *(t-5)* to *(t-1)*. *DGTW_10* (*DGTW_21*) is the 10-day (21-day) cumulative *DGTW* return starting from day *t+1*. Ave*SS**Ave*MF* (*t-5_t-1*) is the interaction between *AveSS(t-5_t-1)* and *AveMF(t-5_t-1)*. To permit a natural interpretation of the interaction variables we cross-sectionally demean all explanatory variables. All specifications include stock controls, which are the control variables reported in tables 2 and 3 (not reported for brevity). *t*-statistics below the coefficients are adjusted for serial correlation using Newey-West (1987) correction, where the number of lags is set to the number of the dependent variable's overlapping days.

	DGTW_10				*DGTW_21*			
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ave SS (t-5_t-1)	2.409		2.186	2.208	4.412		4.062	4.100
	8.90		7.59	7.55	8.03		6.86	6.79
Ave MF (t-5_t-1)		-1.011	-0.730	-0.667		-1.641	-1.123	-1.065
		6.66	5.47	4.11		6.93	5.18	3.99
Ave RET (t-5_t-1)	10.349	8.925	11.699	11.590	21.640	18.897	23.705	23.689
	2.41	2.13	2.72	2.70	2.46	2.26	2.74	2.73
*Ave SS*MF (t-5_t-1)*				-0.050				-0.067
				2.64				2.11
Stock Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AdjRSQ	3.00%	2.90%	3.05%	3.08%	3.09%	2.95%	3.13%	3.16%

Table 8 – Cumulative Abnormal Return of Double-Sorted Portfolios based on *AveSS* and *AveMF*

The table reports the average cumulative abnormal return to double-sorted portfolios in the 21, 42, and 63 trading days after portfolio formation. To construct this table, firms are sorted independently into quintiles each day based on *AveMF(t-5_t-1)* and *AveSS(t-5_t-1)*, where *MF1* and *SS1* (*MF5* and *SS5*) denote the firms with the lowest (highest) values. *SS* is the daily ratio of the stock's shorting volume to total trading volume multiplied by negative one. *MF* is the daily ratio of net purchases by mutual funds to total trading volume. *AveSS* (*AveMF*) is the average of *SS* (*MF*) over days *t*-5 to *t*-1. *RET* is the stock's CRSP's daily return. *DGTW* abnormal return is *RET* minus the stock's *DGTW* (1997)-matched daily benchmark portfolio return.

Panel A reports results for independent double-sorted portfolio. For each portfolio, we report the time series average *DGTW* abnormal return, *t*-statistic, and average number of stocks. In both panels the headers, 21, 42, and 63 refer to the 21, 42, and 63-day cumulative *DGTW* abnormal returns, starting from day *t*+1. Specifically, we use *AveMF* and *AveSS* quintiles to construct 25 equally-weighted portfolios. We keep the top and bottom *AveMF* and *AveSS* intersection quintile portfolios. For example, the intersection between *MF1* and *SS1* (denoted as *MF1_SS1*) is the portfolio of firms in the lowest *AveMF* (*MF1*) and the lowest *AveSS* (*SS1*) quintiles.

Panel B reports results of portfolios which capture the wealth transfers between *MF* and *SS*. Specifically, "*Disagree*" is the return difference between *MF1_SS5* and *MF5_SS1* portfolios, i.e. it represents the future *DGTW* return for a cash-neutral portfolio of firms where *MF* and *SS* are trade in opposite directions. "*Agree*" is the return difference between the *MF5_SS5* and *MF1_SS1* portfolios, i.e. where *MF* and *SS* trade in the same direction. "*DMA*" is the Disagree-minus-Agree portfolio, which is the return difference between the "*Disagree*" and "*Agree*" portfolios.

For completeness, Panel C reports results for alternative strategies based on the information in Panel A. "*Pure MF portfolios*" presents results for top-minus-bottom *MF* strategies (i.e., *MF5*-minus-*MF1*) conditioning on *SS1* and *SS5* quintiles. "*Pure SS portfolios*" provides results for top-minus-bottom *SS* strategies (*SS5*-minus-*SS1*) conditioning on *MF1* and *MF5* quintiles.

To isolate the effect of the August 2007 'quant meltdown', we report results for three separate time periods: The pre-meltdown period, from January 3, 2005 to April 30, 2007, a total of 579 trading days (Specifications (1) – (3)); the meltdown period, May 1, 2007 to July 6, 2007 a total of 47 trading days (Specification (4)); and the total sample period, from January 3, 2005 to July 6, 2007, a total of 626 trading days (Specification (5)). *t*-statistics below the portfolio averages are adjusted for serial correlation using Newey-West (1987) correction, where the number of lags is set to equal the overlap in the dependent variable.

Panel 8.A – *MF* and *SS* Independent Sort Quintile Portfolios

	(1)		(2)		(3)		(4)		(5)	
	21		*42*		*63*		*63 - Aug 2007*			
	AveMF		***AveMF***		***AveMF***		***AveMF***		***AveMF***	
	MF1	*MF5*	*MF1*	*MF5*	*MF1*	*MF5*	*MF1*	*MF5*	*MF1*	*MF5*
AveSS										
SS1 (Heavily shorted)	-0.20	-0.33	-0.17	-0.57	-0.18	-0.84	-1.70	1.23	-0.29	-0.68
t-stat	1.21	3.55	0.57	3.89	1.24	4.32	3.39	4.32	2.10	3.23
Num Stocks	18	48	18	48	18	48	23	60	19	49
SS5 (Lightly shorted)	0.64	0.30	0.89	0.34	1.15	0.39	-0.63	-1.45	1.01	0.26
t-stat	4.02	3.01	4.23	1.96	4.15	1.99	4.15	2.38	3.64	2.79
Num Stocks	56	25	56	25	56	25	60	25	56	25
N		579		579		579		47		626

Panel 8.B – *Disagree*, *Agree* and the *DMA* (Disagree-minus-Agree) Portfolios

	(1)	(2)	(3)	(4)	(5)
	21	*42*	*63*	*63 - Aug 2007*	
Disagreement portfoio:	0.97	1.46	1.98	-1.86	1.69
MF1_SS5 minus MF5_SS1	4.13	3.98	4.32	4.13	3.71
Agreement portfolio:	0.50	0.51	0.57	0.25	0.55
MF5_SS5 minus MF1_SS1	1.99	2.55	1.96	0.38	2.00
***DMA* - Disagree-minus-Agree**	0.47	0.95	1.41	-2.11	1.15
	2.13	3.20	3.46	2.01	2.71
N	579	579	579	47	626

Panel 8.C – Returns to Alternative Strategies

	(1)	(2)	(3)	(4)	(5)
	21	*42*	*63*	*63 - Aug 2007*	
Pure MF portfolio (controlling for SS):					
MF5 minus MF1 within SS1	-0.13	-0.40	-0.66	2.94	-0.39
t-stat	0.83	1.82	1.98	3.21	1.06
MF5 minus MF1 within SS5	-0.34	-0.55	-0.75	-0.83	-0.76
t-stat	2.68	2.99	3.28	1.78	4.67
Pure SS portfolio (controlling for MF):					
SS5 minus SS1 within MF1	0.84	1.06	1.32	1.08	1.30
t-stat	3.70	3.54	3.76	2.34	5.00
SS5 minus SS1 within MF5	0.63	0.91	1.23	-2.69	0.94
t-stat	3.41	3.74	4.39	4.99	3.37
N	579	579	579	47	626

Table 9 – *DMA* Portfolio Returns based on *MF* Holdings, Variance of Change in Holdings and other Selected Variables

The Table examines the effect of various firm characteristics on the returns to the Disagree-minus-Agree portfolio (the *DMA* portfolio as defined in Table 8). In Panels A and B we evaluate the effect of *MF* holdings (hereafter, "*MFH*") and *MF* volatility of quarterly change in holding (hereafter, "*MFSD*") on the magnitude of *DMA* returns. *MFH* (Panel A) is the aggregate *MF* holdings of a given stock at the end of quarter *t-1*, scaled by shares outstanding. *MFSD* (Panel B) is the standard deviation of aggregate *MF* quarterly changes in holdings of a given stock based on quarters *t-5* to *t-1*. Aggregate quarterly change in MF holdings is calculated following Sias, Stark and Titman (2006) as the difference between total shares held by mutual funds at the beginning of the quarter and total shares held by mutual funds at the end of the quarter divided by shares outstanding (in %). Since size and institutional ownership are positively correlated, in Panels A and B, we first sort stocks into tertiles based on their average daily market capitalization from day *t-27* to *t-6* (*Size*). Then, within each *Size* tertile, we further sort stocks into tertiles by either *MFH* or MFSD. We then evaluate the effect of directional concordance (or discordance) in MFs and SSs trades by focusing on the size of the *DMA* returns. To construct Panels' A and B *DMA* portfolios, within of each of the nine portfolios (i.e., *Size*-*MFH* and *Size*-*MFSD*) we further sort the stocks based on *AveSS* and *AveMF* tertiles. We then keep the intersection of the top and bottom tertiles

Panel C presents *DMA* portfolios results for tertile sub-samples based on four selected variables: *MFH* (Specification 1), *MFSD* (Specification 2), *Size* (Specification 3) and *Relative Spread* (Specification 4). *Relative Spread* is the average relative half bid-ask spread from day *t*-27 to *t*-6, calculated as [(Ask-Bid)/Midpoint]/2 using *CRSP* end of day quotes. Specifically, each day stocks are sorted by the four variables into tertiles. Then, within each tertile portfolio, stocks are further sorted into quintiles based on *AveSS* and *AveMF*. "*Diff- in-DMA*" is the difference between the top ("3") and the bottom ("1") tertiles. *t*-statistics below the portfolio averages are adjusted for serial correlation using Newey-West (1987) correction, where the number of lags is set to equal the overlap in the dependent variable. The sample period covers January 3, 2005 to April 30, 2007, a total of 579 trading days.

Panel 9.A – *DMA* Portfolio Returns based on *MFH*, after controlling for *Size*

	(1) *Size 1*	(2) *Size 2*	(3) *Size 3*
MFH 1	2.13%	0.82%	-1.12%
	2.65	1.88	1.41
MFH 3	2.21%	1.83%	1.04%
	2.04	1.93	2.61

Panel 9.B – *DMA* Portfolio Returns based on *MFSD*, after controlling for *Size*

	(1) *Size 1*	(2) *Size 2*	(3) *Size 3*
MFSD 1	0.70%	0.12%	0.21%
	1.02	0.51	0.75
MFSD 3	2.33%	1.90%	0.57%
	2.54	2.43	0.92

Panel 9.C – Diff in *DMA* Returns across Tertiles of Various Firm Characteristics

	(1) *MFH*		(2) *MFSD*		(3) *Size*		(4) *Relative Spread*	
	1	*3*	*1*	*3*	*1*	*3*	*1*	*3*
DMA	1.19%	2.81%	0.80%	1.79%	2.58%	-0.47%	-0.74%	1.97%
	1.69	3.96	1.71	3.61	2.91	0.89	1.31	2.89
Diff-in-DMA		1.62%		0.99%		-3.05%		2.71%
		1.77		1.64		2.88		2.87

Table 10 – Profitability of *AveMF, AveSS* and DMA Trading Strategies within Subperiods of Retail Investor Sentiment ("*NEIO")*

This table examines the sensitivity of future returns to *AveMF*, *AveSS* and DMA trading strategies to retail investor sentiment. Following Ben-Rephael, Kandel and Wohl (2012), we measure retail investor sentiment as the net flows from bond funds to equity funds (*NEIO*) within the same MF family. Fund flows and net asset values are obtained from the Investment Company Institute (ICI) and include the following fund categories: domestic equity, international equity, and mixed funds. ICI data include four flow categories: new sales, redemptions, ''exchanges in,'' and ''exchanges out.'' We construct *NEIO* as ''exchanges in'' minus ''exchanges out'' normalized each month by the previous month's fund asset value (in %). Specifically, in each panel, days are classified according to *NEIO* (or "*Sentiment*") into quartiles from smallest-to-largest, where "*Low", "Mid" and "High"* refer to periods of low (quartile 1), medium (quartiles 2 and 3) and high (quartile 4) sentiment. Panel A reports cross-sectional averages of differences in mutual fund trading activity between the *High* and *Low* sentiment sub-periods. Trading activity is measured by *MFVOL*, *AbsMF* and *MF* (as defined in Table 1). To account for cross-sectional heterogeneity in trading activity, the reported statistics are calculated at the stock level. Specifically, for each stock in our sample, the percentage change (difference) is defined as $[X_{High}-X_{Low}]/X_{Low}$ ($[X_{High}-X_{Low}]$), where X is the selected variable and *High* and *Low* are the sentiment sub-periods. We report cross-sectional averages of the percentage change in *MFVOL* and *AbsMF* and cross-sectional averages of the difference in *MF* between high and low sentiment periods. ***t***-statistics are reported below the averages. "*ALL*" refer to all stocks in our sample, "*Size1*" (Small Firms) to "*Size 5*" (Large Firms) refer to subsamples based on market cap quintiles.

Panel B analyzes the profitability of *MF* and *SS* strategies within sentiment sub-periods. Specifically, within each sentiment sub-period, stocks are further sorted into deciles by *AveSS* (Specification (1)) and *AveMF* (Specification (2)), where D1 (D10) denotes the bottom (top) decile. *TmB* is the return difference between the top and bottom deciles. "*Sub Sample N*" is the number of days within each subperiod. Panel C examines the effect of investor sentiment on Disagree-Minus-Agree (*DMA)* portfolio returns (as defined in Table 8). In all panels "*High-Low*" refers to the difference between the high and low sentiment periods. ***t***-statistics below the portfolio averages are adjusted for serial correlation using Newey-West (1987) correction, where the number of lags is set by the number of the dependent variable's overlapping days. The sample period ranges from January 3, 2005 to April 30, 2007, a total of 579 trading days.

Panel 10.A – Changes in Mutual Fund Trading Activity across Sentiment Sub-periods

High vs. Low Sentiment Periods Differences in Trading Activity	*ALL* (1)	*Size1* (2)	*Size3* (3)	*Size5* (4)
Stock Level Percentage Change:				
MF VOL (MF volume)	15.9%	28.1%	13.4%	8.8%
	10.02	4.99	2.94	3.72
AbsMF (Absolute MF)	14.2%	24.4%	11.9%	5.8%
	8.95	4.39	2.45	2.9
Stock Level Difference:				
MF	-0.17%	-0.54%	0.42%	-0.26%
	0.91	0.94	1.03	1.08

Panel 10.B - Profitability of *AveSS* and *AveMF* Top-minus-Bottom Strategies across Sentiment Sub-periods

	Sentiment			*Sentiment*		
	Low	*Mid*	*High*	*Low*	*Mid*	*High*
	AveSS			*AveMF*		
	(1)			(2)		
TmB	1.27%	1.42%	2.22%	-1.13%	-1.39%	-1.60%
	2.44	3.72	5.01	4.84	4.76	3.70
High - Low			0.95%			-0.48%
			1.87			1.17
Sub Sample N	145	289	145	145	289	145

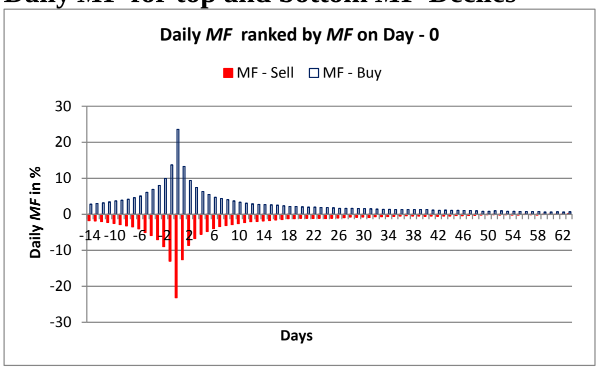
Panel 10.C - Profitability of 63-day *DMA* Portfolios across Sentiment Sub-periods

	Sentiment		
	Low	*Mid*	*High*
DMA	0.17%	1.62%	2.27%
	0.26	2.46	4.62
High-Low			2.10%
			2.59
Sub Sample N	145	289	145

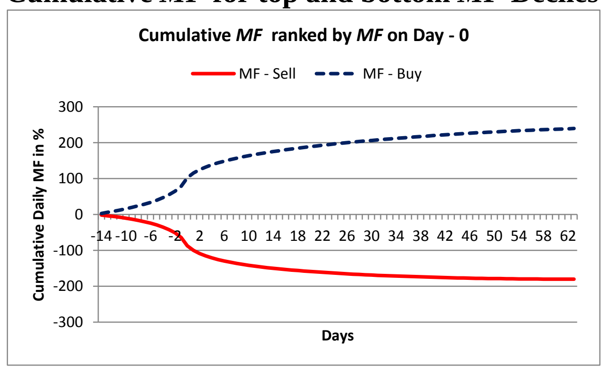
Figure 1 – Daily Trading Patterns for *MF* and *SS* sorted on Top and Bottom *MF* flow deciles on Day *t*

These figures depict daily trading patterns by mutual funds and short sellers, based on *MF* top and bottom decile portfolios. *MF* is the daily ratio of net purchases by mutual funds to total trading volume (in %). *SS* is the daily ratio of the stock's shorting volume to total trading volume multiplied by negative one (in %). Sample period is January 3, 2005 to July 6, 2007, a total of 626 trading days. Specifically, in all four graphs, stocks are sorted into deciles based on *MF* on day *t*. Graphs 1.A and 1.B plot *MF* trades. Specifically, Graph 1.A reports the cross-sectional mean of *MF* each day from *t*-14 to *t*+63 and Graph 1.B reports the cumulative cross-sectional averages of *MF* from Day *t*-14 to Day *t*+63. MF-Buy refers to the decile of stocks with the most positive net MF trading on Day *t* (i.e. those with the largest net MF purchases). MF-Sell refers to the decile of stocks with the most negative net MF trading on Day *t* (i.e. those stocks with the largest net MF sales). Graphs 1.C and 1.D plot *SS* trades. Since *SS* is in terms of volume, both graphs present *SS* in terms of deviations from the long-run mean. Graph 1.C reports the cross-sectional mean of *SS* deviations each day from *t*-14 to *t*+63. Similarly, Graph 1.D reports the cumulative cross-sectional *SS* deviations from Day *t*-14 to Day *t*+63.

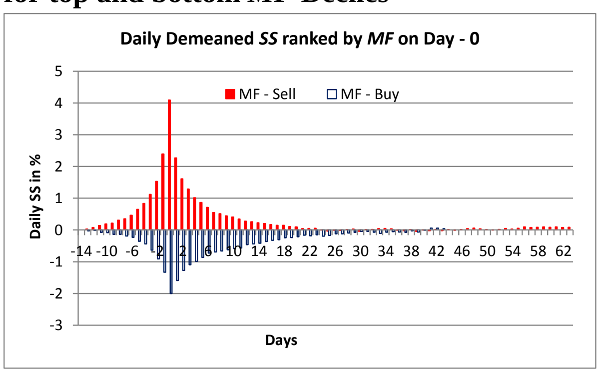
Graph 1.A
Daily *MF* for top and bottom *MF* Deciles



Graph 1.B
Cumulative *MF* for top and bottom *MF* Deciles



Graph 1.C
Daily Demeaned *SS*
for top and bottom *MF* Deciles



Graph 1.D
Cumulative Demeaned *SS*
for top and bottom *MF* Deciles

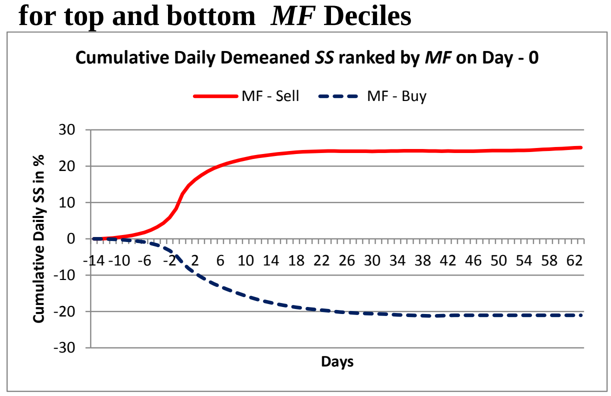


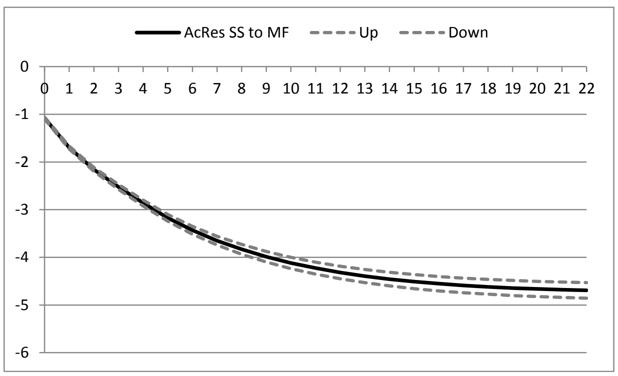
Figure 2 – Accumulated Impulse Response Functions of *SS* and *MF*

These figures depict the accumulated impulse response functions for *SS* and *MF*. Specifically, we estimate a three-equation *VAR* system of *RET*, *MF* and *SS* with five lags of *RET*, *MF* and *SS* as follows:

$$RET_t = \alpha_1 + \sum_{t=1}^{5}\gamma_{1i}RET_{t-i} + \sum_{t=1}^{5}\gamma_{1i}MF_{t-i} + \sum_{t=1}^{5}\delta_{1i}SS_{t-i} + \varepsilon_{1t}$$
$$MF_t = \alpha_2 + \sum_{t=1}^{5}\gamma_{2i}RET_{t-i} + \sum_{t=1}^{5}\gamma_{2i}MF_{t-i} + \sum_{t=1}^{5}\delta_{2i}SS_{t-i} + \varepsilon_{2t}$$
$$SS_t = \alpha_3 + \sum_{t=1}^{5}\gamma_{3i}RET_{t-i} + \sum_{t=1}^{5}\gamma_{3i}MF_{t-i} + \sum_{t=1}^{5}\delta_{3i}SS_{t-i} + \varepsilon_{3t}$$

In the following figures, the Cholesky order is set to be *RET*, *MF*, and *SS*. Responses for alternative order selection assumptions appear in Appendix A. Graph 2.A depicts the accumulated response of *SS* to a positive one standard deviation shock in *MF* (i.e., the response of SS when *MF*s are net buyers). Graph B plots the accumulated response of *MF* to a negative one standard deviation shock in *SS* (i.e., the response of MF when SSs increase their short activity). In each graph the solid black line represents the impulse response and the dashed gray lines represents the 5% confidence intervals.

Graph 2.A – Accumulated Response of *SS* to a Positive One Standard Deviation Shock in *MF*



Graph 2.B – Accumulated Response of *MF* to a Negative One Standard Deviation Shock in *SS*

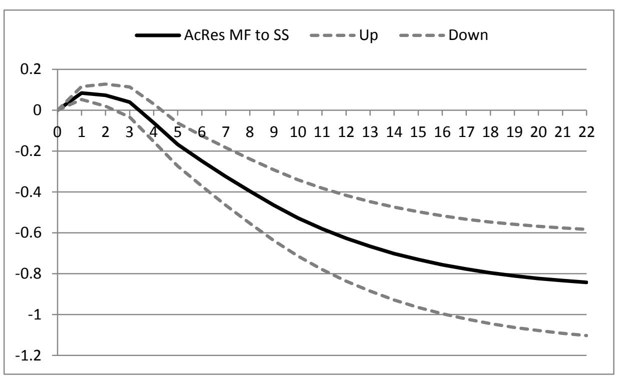
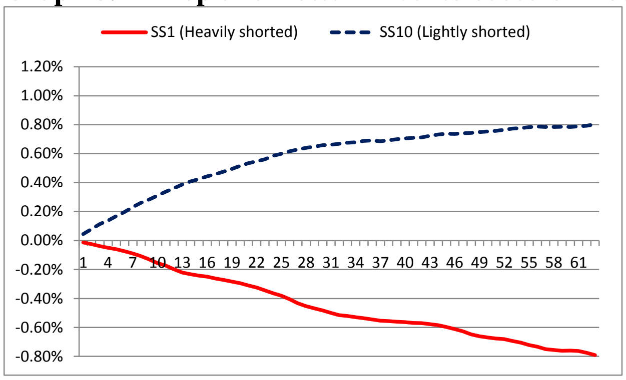


Figure 3 – Cumulative Abnormal Return of *AveSS* and *AveMF* Single Sorted Portfolios

The figure depicts the *DGTW* (1997)-adjusted cumulative abnormal returns for single sorted equally-weighted portfolios up to 63 days following daily portfolio formation. *SS* is the daily ratio of the stock's shorting volume to total trading volume multiplied by negative one (in %). *MF* is the daily ratio of net purchases by mutual funds to total trading volume (in %). *AveSS* (*AveMF*) is the average of *SS* (*MF*) from *t-5* to *t*-1. Specifically, Graph 3.A (3.B) presents the portfolio returns of top and bottom *AveSS* (*AveMF*) decile portfolios presented in Table 6 panel A (B). The sample period is January 3, 2005 to April 30, 2007, a total of 579 trading days.

Graph 3.A - Top and Bottom Deciles based on *AveSS* (t-5_t-1)



Graph 3.B - Top and Bottom Deciles based on *AveMF* (t-5_t-1)

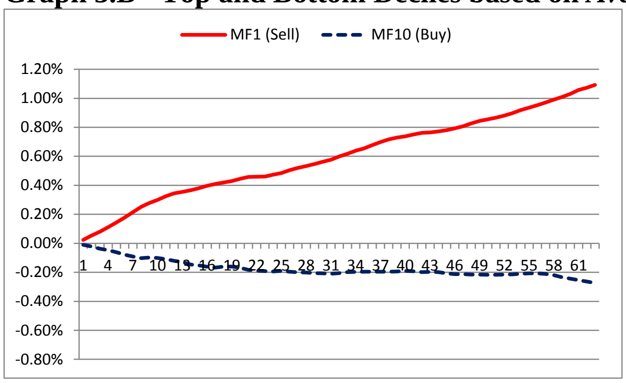


Figure 4 – Cumulative Abnormal Return of Double Sorted Portfolios based on *AveSS* and *AveMF*

The figure depicts the average *DGTW* (1997)-adjusted cumulative returns for 63 trading days following daily portfolio formation for double sorted equally-weighted portfolios. The graphed returns correspond to the average returns of the portfolios reported in Specification 3 of Table 8. The portfolios are constructed based on the intersection between *AveSS* and *AveMF* top and bottom quintiles. For example, the intersection between *MF1* and *SS1* (denoted as *MF1_SS1*) is a portfolio of firms in the lowest *AveMF* (*MF1*) and the lowest *AveSS* (*SS1*) quintiles. The sample period is January 3, 2005 to April 30, 2007, a total of 579 trading days.