Do Hedge Funds Manipulate Stock Prices?

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Abstract

We provide evidence suggesting that some hedge funds manipulate stock prices on critical reporting dates. Stocks in the top quartile of hedge fund holdings exhibit abnormal returns of 0.30% on the last day of the quarter and a reversal of 0.25% on the following day. A significant part of the return is earned during the last minutes of trading. Analysis of intraday volume and order imbalance provides further evidence consistent with manipulation. These patterns are stronger for funds that have higher incentives to improve their ranking relative to their peers.

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> "If I were long and I would like to make things a little bit more rosy, I'd go in and take a bunch of stocks and make sure that they are higher…. A hedge fund needs to do a lot to save itself."
>
> Jim Cramer, ex-hedge fund manager, in an interview to TheStreet.com, December 2006

1. Introduction

In a conventional description of financial markets, arbitrageurs are considered a stabilizing force that absorbs non-fundamental shocks and keeps prices close to the fundamental value. Recent research, however, challenges this view by pointing out that institutional investors can be constrained by agency frictions. These institutional frictions can be the very source of non-fundamental demand shocks (Shleifer and Vishny 1997, and Gromb and Vayanos 2010 for a survey). One dimension of institutional constraints on arbitrageurs' activity arises from their incentives to attract funds and the competition with other financial intermediaries for investors' assets. Consistent with this view, Carhart, Kaniel, Musto, and Reed (2002) find that mutual funds pump the prices of the stocks they hold prior to quarterly reporting dates. Blocher, Engelberg, and Reed (2010) show that short-sellers exercise selling pressure in the last minutes of the year to inflate their returns.

Here, we focus on the prototypical arbitrageurs, hedge funds, and ask whether their incentive to attract and retain capital can lead them to distort stock prices. We present a collection of facts that suggest that some hedge funds pump up the end-of-month prices of the stocks in their portfolios in order to improve their reported returns. The literature provides mounting evidence that some institutions in the hedge fund sector manipulate their reported performance (e.g., Bollen and Pool 2009 and Agarwal, Daniel, and Naik 2011). The incremental contribution of this paper is to argue that these activities can have a significant impact on market prices.

The first goal of the paper is to study whether the distortions of asset managers' trading behavior originating from agency conflicts can systematically affect asset prices. In this sense, our work identifies the source of some of the anomalous behavior in stock prices in the institutional frictions that constrain arbitrageurs' actions. Secondly, from a more practical perspective, we wish to contribute to the recent regulatory debate concerning hedge funds. For example, the Dodd-Frank Act requires hedge fund registration and more extensive disclosure about assets and leverage. The practice of portfolio pumping that we explore in this paper does not involve misreporting or misvaluation of the portfolio holdings. As such, it is not likely to be detected by the regulator or an external auditor, unless it is systematically searched for using the appropriate statistical methodology. This paper, along with prior work on hedge fund manipulation (e.g., Bollen and Pool 2009 and Agarwal, Daniel, and Naik 2011), contributes to developing the machinery of manipulation detection.

The study has two parts. First, based on 2000-2010 quarterly 13F holdings data of hedge fund management companies that we match to daily and intraday stock prices, we document that stocks held by hedge funds experience on average large abnormal returns on the last trading day of the month. This effect is statistically and economically significant: stocks at the top quartile of hedge fund ownership earn, on average, an abnormal return of 0.30% on the last day of the quarter, most of which reverts the next day. This effect is similar in magnitude to the 0.25% end-of-quarter manipulation by mutual funds documented by Carhart, Kaniel, Musto, and Reed (2002). Moreover, about half of the average increase in the prices of stocks that are owned by hedge funds takes place in the last twenty minutes of trading, and reverts in the first ten minutes of trading on the following day. The effect exists at the monthly level, although our precision is lower at this frequency due to the quarterly measurement of hedge fund ownership. In the cross-section, we find evidence that this price pattern is concentrated in illiquid stocks, consistent with the idea that manipulators would focus on stocks on which they can have larger price impact.[1]

We move beyond prices and study trading volume. Specifically, we focus on trading activity patterns around the turn of the quarter for stocks owned by hedge funds. We show that high-hedge-fund-ownership stocks experience a surge in buying pressure in the last two hours of the quarter, and a strong selling pressure during the first day of following quarter. Also, we find that these stocks exhibit an abnormally high turnover during the last hours of the last day of the quarter and during the first hours of the first day of the following quarter. Drawing on prior research that identifies institutional trades by their large size (e.g., Campbell, Ramadorai, and

[1] We wish to clarify from the start that the observational unit in our data set is a hedge-fund management company. 13F filings provide asset holdings at the management-company level or at the adviser-entity level. Each company/adviser reports consolidated holdings for all the funds that it has under management. When we use the wording ‘hedge funds’, we broadly refer to the firms that belong to this asset class rather than to the specific funds within a management company.

Schwartz 2009), we show that high-hedge-fund-ownership stocks display a stronger intensity of institutional buy trades in the last ten minutes of the last day of the quarter than they do on the neighboring days in the same time interval. Consistent with the manipulation hypothesis, we do not find a symmetric result for institutional sales of these stocks.

In the second part of the paper, we present evidence linking stock-price patterns that are consistent with manipulation to hedge funds' incentives to improve their reported returns. To this end, we match the 13F data to TASS, by aggregating the fund-level variables in TASS at the management-company level. As a proxy for this pattern of manipulation activity, we use the return difference between the last day of the quarter and the following day on the management company's long-equity portfolio. We label this quantity the "blip." This blip is more pronounced for management companies with concentrated portfolios, which is consistent with a greater "bang for the buck" from manipulation when there are only a few stocks in the portfolio. In addition, we find that high-blip companies rank at the top in terms of year-to-date performance. This result resonates with the evidence in Carhart, Kaniel, Musto, and Reed (2002) that mutual funds that appear to manipulate stock prices are those with the best past performance. The authors argue that, given a convex flow-performance relation for mutual funds (Ippolito 1992, Sirri and Tufano 1998), the best performers have the strongest incentive to manipulate. Further, hedge fund management companies that had a poor month in terms of total returns are also more likely to have a high blip, which is probably related to their incentive to avoid reporting very low returns to their investors. Somewhat related to this incentive, we show that the discontinuity of hedge fund returns around zero, first pointed out by Bollen and Pool (2009), is significantly stronger for management companies with a high blip. This suggests that the evidence that we present partly explains the evidence in Bollen and Pool's (2009) paper. A complementary interpretation is that management companies that misbehave on one front are likely to do it on other fronts as well, possibly as a result of poor internal control systems. Also consistent with a 'genetic' tendency to misbehave, we detect persistence in hedge fund companies' blips, i.e., companies that had a high blip in past quarters are more likely to have another in the future.

The hedge fund companies' blips vary with market conditions. While the blips' existence is consistent throughout the sample period, they are stronger in quarters in which market returns are low. This fact is consistent with the idea that a period of low market returns presents an opportunity for hedge funds to demonstrate their skill to investors and to separate from the competition.

We run a battery of robustness checks to rule out alternative explanations for our findings. First, we test whether our effect is not generated mechanically by portfolio reallocation, resulting either from asset inflows or rebalancing. When we lag our stock-level hedge-fund-ownership measure by one month or control for current and future inflows, the relation remains strong. Second, there is no overlap with price reversals around the turn of the quarter in mutual fund portfolios, such as those documented by Carhart, Kaniel, Musto, and Reed (2002). We conclude that these two alternative explanations are not likely to be responsible for the observed price regularities. Also, we perform a feasibility test, in which we show that for stocks in the bottom half of the liquidity spectrum, a price change of one percent is associated with a volume of less than $500,000. This means that manipulation is potentially plausible, even for small hedge funds, if it takes place in illiquid stocks.

Hedge funds typically report performance figures to their investors on a monthly basis. Several studies have raised doubts about the reliability of these reports, as managers have an incentive to modify their numbers in order to boost performance fees and attract capital. A recent study by Agarwal, Daniel, and Naik (2011) presents strong evidence of performance manipulation. They mostly focus on the funds' incentive to generate performance fees, which is strongest at the end of the year. Consequently, they show that hedge fund returns display a December spike. They argue that the manipulation mainly comes from postponing the recognition of the positive returns of illiquid assets to the last month of the year. However, their evidence of price pumping is only marginal. The focus of our paper is different from, and complementary to, theirs. We look at the impact of likely return manipulation in the stock market and show evidence suggesting that manipulation can generate significant distortions in monthly stock prices. We are able to find significant evidence consistent with price pumping thanks to the stock holdings of a larger sample of hedge funds and to the power derived from the daily frequency of our tests. Furthermore, our analysis extends to the entire year, as the ability to attract and retain capital does not solely depend on end-of-year returns.

Additional studies have provided evidence consistent with performance manipulation. Jylhä (2010) elaborates on the evidence in Bollen and Pool (2009) by showing that the discontinuity of hedge fund returns at zero is stronger in bad states, for funds with stronger managerial incentives, and to preempt future redemptions. Bollen and Pool (2008) also present evidence that hedge fund total returns are more strongly autocorrelated when they are conditioned on past performance, potentially suggesting that returns are manipulated. Liang (2003) shows that audited hedge funds report more accurate returns. Cici, Kempt, and Puetz (2010) compare the equity prices that hedge funds report on their 13F filings to prices on CRSP, and find that the prices on the 13F forms are higher on average. A complementary explanation for some of these results is that many of the assets held by hedge funds are illiquid, and their valuations could therefore be imprecise, with the autocorrelation due to the smoothing of imputed returns (Getmansky, Lo, and Makarov 2004). Also, Patton, Ramadorai, and Streatfield (2011) find that historical returns are routinely revised by the worst-performing funds. Aragon and Nanda (2011) show that hedge funds delay their return reporting when their performance is poor. Patton and Ramadorai (2011) find that hedge funds' risk exposure tends to increase following reporting dates, suggesting that hedge funds manipulate their reported risk exposure.

More broadly, our paper joins the prior literature that documents end-of-day security price manipulation in other contexts. Hillion and Suominen (2004) find that the probability of a large trade in the last minute of trading is very high, consistent with the idea that market participants attempt to influence closing prices. Ni, Pearson, and Poteshman (2005) report that stock prices tend to cluster around option strike prices on expiration dates. Blocher, Engelberg, and Reed (2010) show that short-sellers put downward pressure on prices in the last moments of trading before the end of the year. [2]

The paper proceeds as follows. Section 2 describes the data sources used, while Section 3 develops the hypotheses about the incentive to manipulate security prices, and the methods that may enable such practices. Section 4 presents the daily and intraday empirical evidence of end-of-month returns and volume that is consistent with manipulations and relates it to stock-level characteristics. Section 5 studies the determinants of hedge fund behavior and investigates cross-

[2] Other studies examine stock market manipulation from a different perspective. Aggarwal and Wu (2006) discuss spreading rumors and analyze SEC enforcement actions to show that manipulations are associated with increased stock volatility, liquidity, and returns. Allen, Litov, and Mei (2006) present evidence that large investors manipulate the prices of stocks and commodities by putting pressure on prices in the desired direction; as a result, prices are distorted and have higher volatility.

sectional heterogeneity in the exposure to these determinants. Section 6 assesses the feasibility of manipulation using price impact regressions, and Section 7 concludes.

2. Data Sources and Sample Construction

2.1. Hedge Fund Holding Data

The main dataset used in the study combines a list of hedge fund management companies (by Thomson-Reuters), mandatory institutional quarterly portfolio holdings reports (13F), and information about hedge fund characteristics and performance (TASS) for the period from 2000Q1 to 2010Q3. A similarly constructed dataset, albeit for a shorter period, is used by Ben-David, Franzoni, and Moussawi (2012).

The 13F mandatory institutional reports are filed with the SEC on a calendar quarter basis and are compiled by Thomson-Reuters (formerly known as the 13F CDA Spectrum 34 database).[3] Form 13F requires that all institutions with investment discretion of over \$100 million in qualified securities (mainly publicly traded equity, convertible bonds, and options) report, at the end of the year, their long holdings in the following year.[4] Therefore, all hedge funds with assets in qualified securities that exceed a total of \$100 million are required to report their holdings in 13F filings. 13F reporting is done at the consolidated management-company level.[5]

We match the list of 13F institutions in Thomson-Reuters with a proprietary list of 13F hedge fund management companies and other institutional filers provided by Thomson-Reuters. Relative to the self-reported industry lists commonly used to identify hedge funds, the Thomson

[3] According to Lemke and Lins (1987), Congress justified the adoption of Section 13F of the Securities Exchange Act in 1975 because, among other reasons, it facilitates consideration of the influence and impact of institutional managers on market liquidity: "Among the uses for this information that were suggested for the SEC were to analyze the effects of institutional holdings and trading in equity securities upon the securities markets, the potential consequences of these activities on a national market system, block trading and market liquidity…"

[4] With specific regard to equity, this provision concerns all long positions greater than 10,000 shares or \$200,000 over which the manager exercises sole or shared investment discretion. The official list of Section 13F securities can be found at: http://www.sec.gov/divisions/investment/13flists.htm. More general information about the requirements of Form 13F pursuant to Section 13F of the Securities Exchange Act of 1934 can be found at: http://www.sec.gov/divisions/investment/13ffaq.htm.

[5] 13F filings have been used intensely in research into the role of institutional investors in financial markets. Brunnermeier and Nagel (2004) explore the behavior of hedge funds during the Internet bubble. Campbell, Ramadorai, and Schwartz (2009) combine 13F filings with intraday data to explore the behavior of institutional investors around earnings announcements.

list is certainly more comprehensive, as it classifies all 13F filers.[6] Moreover, the Thomson-Reuters hedge fund list identifies hedge funds at the disaggregated adviser level, not at the 13F report consolidated level. For example, for Blackstone Group holdings in 13F data, Thomson-Reuters provided us with a classification of each of the advisers within Blackstone that reported their holdings under the same filing.[7] Overall, our access to Thomson-Reuters' proprietary list of hedge funds puts us in a privileged position.

The 13F data available to us range from 1989Q3 to 2010Q3. Before applying the filters described below, the number of hedge funds in the Thomson-Reuters list varies from a few dozen in the early years to over 1,000 at the 2007 peak. We cross-check our list of hedge funds with the FactSet database and we find it congruent with the FactSet LionShares identification of hedge fund companies. With some caveats that we mention below, an additional advantage of the 13F filings is that they are not affected by the selection and survivorship biases that occur when relying on TASS and other self-reported databases for hedge fund identification (Agarwal, Fos, and Jiang 2010).

The data in the 13F filings have a number of known limitations. First, small institutions that fall below the reporting threshold ($100 million in U.S. equity) at the end of the year are not in the sample in the following year. Second, we do not observe positions that do not reach the threshold of $200,000 or 10,000 shares. Third, short equity positions are not reported. Fourth, the filings are aggregated at the management-company level, but as mentioned above, the Thompson classification allows us to separately identify the advisers within a management company. Fifth,

[6] This comprehensiveness depends on Thomson's long-lasting and deep involvement with institutional filings. The SEC has long contracted the collection of various institutional data out to Thomson-Reuters, even when those reports were paper filings or microfiche in a public reference room. They also have directories of the different types of institutions, with extensive information about their businesses and staff. The list of hedge funds to which we have access is normally used by Thomson-Reuters for their consulting business and, to the best of our knowledge, has not been provided to other academic clients. References to Thomson-Reuters (or the companies that it acquired, such as CDA/Spectrum, formerly known as Disclosure Inc. and Bechtel) can be found at:

1. http://www.sec.gov/rules/final/33-8224.htm (search for Thomson);
2. SEC Annual Reports, 1982, http://www.sec.gov/about/annual_report/1982.pdf (page 37, or 59 of the pdf file);
3. http://www.sec.gov/rules/final/33-7432.txt (search for contractor);
4. http://www.sec.gov/about/annual_report/1989.pdf (search for contractor).

[7] There are three adviser entities within Blackstone Group LP that report their holdings in the same consolidated Blackstone Group report. Among the three advisers included, GSO Capital Partners and Blackstone Kailix Advisers are classified by Thomson-Reuters as Hedge Funds (which an ADV form confirms), while Blackstone Capital Partners V LP is classified as an Investment Adviser. See the "List of Other Included Managers" section in the September 30, 2009, Blackstone 13F reports filed on November 16, 2009: http://www.sec.gov/Archives/edgar/data/1393818/000119312509235951/0001193125-09-235951.txt.

we only observe end-of-quarter snapshots on hedge fund holdings. In spite of these limitations, it must be stressed that our data is not plagued by survivorship bias, as it also contains the filings of defunct hedge fund firms.

Because many financial advisers manage hedge-fund-like operations alongside other investment management services, we need to apply a number of filters to the data to ensure that, for the institutions captured in our sample, their main line of operation is a hedge fund business. To this end, we drop institutions that have advisers who have a majority of non-hedge-fund business, even though they have hedge funds that are managed in-house and included with their holdings in the parent management company's 13F report. Thomson-Reuters' hedge fund list also provides the classification of non-hedge-fund entities that file under the same 13F entity. We use this list to screen out all companies with other reported non-hedge-fund advisers that file their 13F holdings with their hedge funds. Additionally, we manually verify that large investment banks and prime brokers that might have an internal hedge fund business are excluded from our list (e.g., Goldman Sachs Group, JP Morgan Chase & Co., American International Group Inc.) As a further filter, we double-check the hedge fund classification by Thomson-Reuters against a list of ADV filings by investment advisers since 2006, when available.[8] We match those filings by adviser name to our 13F data. Then, following Brunnermeier and Nagel (2004) and Griffin and Xu (2009), we keep only the institutions that have more than half their clientele classified as "High Net Worth Individuals" or "Other Pooled Investment Vehicles (e.g., Hedge Funds)" in Item 5.D (Information About Your Advisery Business) of Form ADV. Therefore, we believe that our final list of hedge funds contains only institutions with the majority of their assets and reported holdings in the hedge fund business, which we label "pure-play" hedge fund management companies.

We augment our data with hedge fund characteristics and monthly returns from the Thomson-Reuters' Lipper-TASS database (drawn in July 2010).[9] We use both the "Graveyard"

[8] ADV forms are filed by investment advisers. In these forms, advisers provide information about the investment adviser's business, ownership, clients, employees, business practices, affiliations, and any disciplinary events for the adviser or its employees. The ADV filings were only mandatory for all hedge funds for a short time in 2006. In the later period, they were filed on a voluntary basis. All current adviser ADV filings are available on the SEC's investment adviser public disclosure website:
http://www.adviserinfo.sec.gov/IAPD/Content/Search/iapd_OrgSearch.aspx.

[9] While we use the most recent TASS data feed for hedge fund information (July 2010), we use an older version (August 2007) to identify firms (as it includes management companies' names).

and "Live" databases. We use hedge fund company names in TASS and map them to the adviser company name that appears in the 13F filings. The Lipper-TASS database provides hedge fund characteristics (such as investment style and average leverage) and monthly return information at the fund level. We aggregate the TASS fund-level data at the management-company level, on a quarterly frequency, and match it to the 13F dataset using the consolidated management company name. We use fund-level assets under management as weights in aggregating fund characteristics and the reported returns. We exclude management companies with total assets under management of less than $1 million, in order to ensure that our results are not driven by hedge funds with insignificant holdings or errors in the matching process. We let the sample start in the first quarter of the year 2000, as we want to focus on the impact of hedge funds on the stock market in recent years, when the explosion in the hedge fund industry took place (See Table 1, Panel A). The sample end coincides with the end of 13F data availability (2010Q3).

In Panel A of Table 1, we provide annual statistics for our sample of hedge fund management companies that result from the match between 13F and TASS. In 2000, we have 309 such management companies; this figure peaks in 2006, when our match results in 552 management companies. Following the financial crisis, the number of managers declines to 288 in 2010. In terms of representativeness, in the year 2000, our matched sample covers 63.4% of the total AUM in TASS and 94.7% of the AUM of the TASS funds following equity-based styles. In 2010, these figures are 37.6% and 63.7%, respectively.

Notice that the median number of funds per management company is two throughout the sample (while the mean is slightly larger than two). Also important, for most of the most sample period close to 70% of the management companies in our sample, and never fewer than 62% of them, have no more than two funds under management. Separate analysis shows that, for 50% of the companies with two funds under management, the correlation of the returns of these two funds is at least 96%, and for 39% of them the return correlation between their two funds is larger than 99%. Further, 23% of the companies with two funds display the label "offshore" in the name of one of the two funds. These facts suggest that a large fraction of management companies offer twin funds to cater to on-shore and off-shore investors, possibly in a master-feeder structure. Given this evidence, although our observational unit is the hedge fund management company, we are inclined to believe that our results would not change with fund level observations.

Finally, from Panel A, we infer that on average, the companies in our sample hold portfolios with slightly more than 100 stocks. However, about half of them hold portfolios of less than 50 stocks.

2.2. Daily Stock Returns and Stock Characteristics

For daily stock returns and stock characteristics, we use standard databases: CRSP and Compustat. In order to adjust the daily total return for common risk factors, we construct benchmark portfolio returns following the procedure detailed in Daniel, Grinblatt, Titman, and Wermers (1997, DGTW). At the end of each year, a stock is assigned to one of 125 portfolios that are constructed based on market capitalization, the industry-adjusted book-to-market ratio, and the prior 12-month return, until the end of next year. Following DGTW, we construct size portfolios using NYSE size breakpoints measured in June of each year. Within each size group, we construct the industry-adjusted book-to-market ratio using the Fama-French forty-eight industries. For each day during the following year, the benchmark portfolio returns are computed as the value-weighted return for each of the 125 portfolios. The benchmark-adjusted return for each stock is thus the difference between the stock's total return and the return of the benchmark portfolio to which it belongs.

2.3. NYSE TAQ Data for Intraday Trades

We use the TAQ intraday trades dataset to calculate the intraday return and volume information during several intervals within each trading day. We have 30 minute intervals between 9:30 and 15:00, and 10 minute intervals between 15:00 and 16:00. To do that, we first drop the corrected trades and all trades with conditions O, B, Z, T, L, G, W, J or K (e.g., bunched trades, trades outside trading hours). Then, we keep only the trades with no missing size and price information, as long as they are made before 16:00 or before a closing price (trade condition of 6, @6, or M), is generated. Interval returns are computed as the logged difference between the price of the last trade during the interval, and the last trade price before the start of the interval. If there is no trade during the interval, then the return is set to zero. Interval volume is computed as the sum of all dollar volume for all trades during the interval, zero if there were no trades.

In the analysis of the price impact of trading (Section 6), we use TAQ trading data for January 2000 until December 2009. We keep only data for the last ten seconds of trading on the last day of each month during the period. Over each stock-second, we consolidate the dollar amount of trades and compute the return.

2.4. Summary Statistics

In Panels B and C of Table 1, we present summary statistics for the sample used in our analysis. Panel B shows information about the universe of stock-days in which we detect price patterns that are consistent with end-of-quarter price manipulation. In this sample, hedge fund ownership is 2.6% on average; mutual fund ownership is, on average, 13.6%. The average returns on the last day of the quarter is 0.02%, while returns are slightly negative on the second-to-last day (-0.02%), as well as on the first and second days of the following quarter (-0.13% and -0.06%, respectively).

Panel C describes the hedge-fund-management-company sample used for studying the characteristics related to stock manipulation patterns at the quarterly frequency. The information in this panel is based on the TASS data aggregate at the management-company level. The average of the logarithm of assets under management (AUM) is 5.44, which corresponds to $230.4 million. The average age of the companies in our sample is 7.8 years. Panel D contains the variables constructed from TAQ that are used in the trade-size analysis in Section 4.3.

3. Development of the Hypotheses

Contract theory predicts that agents try to strategically manipulate to their advantage the signals that principals use to evaluate their skill level or their effort (Holmström 1999, Holmström and Milgrom 1991). Hedge funds report monthly returns to their current investors; the track record they use to attract new capital is also based on monthly returns. It follows then that hedge funds have incentives to manipulate their short-term performance as long as the expected costs do not exceed the expected benefits. Manipulating stock prices at month-end in order to boost monthly performance could be beneficial for some hedge funds because it allows them to avoid a negative return that would tarnish their track record or because, by being ranked higher, they could attract more capital and thus collect more fees. The primary costs of manipulation would presumably include the transaction costs and the risk of detection and legal indictment.[10]

Since the signal that some of the hedge funds try to manipulate to their advantage is their monthly return, manipulation could be expected to happen at the very end of the month. This timing is drawn from two considerations. First, to be effective, the manipulation needs to last until month-end; beginning a manipulation earlier could be unnecessarily costly. Second, funds know only toward the month-end whether manipulation in a given month is advantageous (e.g., depending on their monthly performance), and whether they should thus exercise the option to manipulate.

There is some anecdotal evidence for portfolio pumping in the hedge fund industry. In an interview with TheStreet.com (cited as the epigraph),[11] ex-hedge fund manager Jim Cramer describes how his hedge fund used to manipulate security prices in order to improve performance towards paydays. Importantly, Cramer suggests that $5 or $10 million dollars are sufficient to move stock prices enough to achieve profit goals and present the impression that the fund is successful.

Our first hypothesis, therefore, is that the stock prices held in hedge funds' portfolios exhibit returns that are abnormally higher towards the end of the month. Since these returns are a result of price pressure, we conjecture that prices revert following the turn of the month:

H1: Stocks held by hedge funds exhibit:

a. *Abnormal <u>positive</u> returns <u>towards the end</u> of the month;*

b. *Abnormal <u>negative</u> returns <u>following the turn</u> of the month.*

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[10] There are several reported cases where hedge fund managers have been indicted by the SEC for inflating their performance by buying stocks at month-end. For instance, The Securities and Exchange Commission charged San Francisco investment adviser MedCap Management & Research LLC (MMR) and its principal, Charles Frederick Toney, Jr., with reporting misleading results to hedge fund investors by engaging in "portfolio pumping". The SEC alleges that Toney made extensive quarter-end purchases of a thinly traded penny stock in which his fund was heavily invested, more than quadrupling the stock price and allowing him to report artificially inflated quarterly results to fund investors (http://www.sec.gov/news/press/2008/2008-251.htm).

[11] http://www.liveleak.com/view?i=b1b_1237128864.

According to our conjecture, some hedge funds manipulate the stocks in their portfolios by increasing their positions in them up at the end of the month. They possibly, but not necessarily, dump the same stocks the next day, if they wish to revert back to their optimal portfolio allocation as soon as possible. If this pattern holds, we would observe abnormal volume and buying pressure in stocks with large hedge fund ownership on the last day of the month and abnormal volume and selling pressure on the first day of the next month. Also, we would like to tie this trading activity as much as possible to hedge fund trades. To this purpose, we draw on the results in Campbell, Ramadorai, and Schwartz (2009), who argue that the probability of an institutional trade is largest for trades above $50,000. So, for stocks largely held by hedge funds at the end of the month, we expect to find significantly more buy trades in sizes that are typical of institutions. We summarize these conjectures as:

H2: Stocks held by hedge funds exhibit:

a. *Abnormal volume during the two days around the turn of the month;*
b. *Abnormal buying pressure towards the end of the last day of the month and abnormal selling pressure at the beginning of the first day of the month;*
c. *Significantly more <u>institutional buy trades</u> on the last day of the month.*

We propose that stocks that are more likely to be manipulated are those that are relatively illiquid. For these stocks, the bang for the buck is higher, and they therefore can be manipulated at a lower cost. This prediction is consistent with Comerton-Forde and Putnins (2011), who suggest that illiquid stocks with a high degree of information asymmetry are the most prone to manipulation. Therefore:

H3: Illiquid stocks are more likely to be manipulated.

We next move to the hedge-fund-management-company level and characterize those companies that engage in manipulation activity. We conjecture that manipulation is more likely for hedge fund management companies with less diversified portfolios. For these managers, performance results are easier to boost, as the manipulation of a small number of stocks can translate into a large performance impact. In contrast, it is more costly to manipulate the performance of a highly diversified portfolio.

H4: Manipulation is more likely for hedge fund management companies with less diversified portfolios.

We also analyze the incentives that lead hedge funds to manipulate stock prices. For hedge funds, the month-, quarter-, and year-ends are important dates for two reasons. First, performance fees are paid based on past performance, typically measured at the end of these periods. Second, hedge funds, like mutual funds, care deeply about their performance ranking, as investors often select funds based on past performance. Empirically, it is difficult to separate the two incentives in the data because fees are increasing in performance for all firms.

Nevertheless, some hedge fund managers value improved rankings more than others: top performing managers may have more of an incentive to manipulate stock returns than others do, potentially because they are competing for the highest positions on the list. This prediction follows Carhart, Kaniel, Musto, and Reed (2002), who find similar results for mutual funds. In a further distinction within the top performers, management companies that were bad performers in a previous quarter but that have caught up to their peers might have an even stronger incentive to attract investors' attention. Managers that had a low Year-to-Date (YTD) ranking in the *past* quarter but a high YTD ranking in the current quarter might be especially eager to boost earnings in order to get noticed by investors and potentially be reassessed as a winner rather than a loser. Certain circumstances are likely to make investors' impressions of a manager more elastic. For example, investors' belief regarding young companies might be more sensitive to performance due to these managers' shorter track records. Thus, young companies should be more prone to manipulate when they are doing well, so as to maximize investors' reaction to a good performance. In addition, earlier in the year, relative year-to-date performance rankings are more dependent on monthly performance (because YTD performance is, on average, smaller earlier in the year). To summarize, we conjecture that:

H5: The incentive for manipulation aimed at boosting performance rankings is stronger for top-performing hedge fund management companies. This incentive is magnified:

a. *For companies with a currently good but a poor past relative performance;*
b. *For young companies;*
c. *Earlier in the calendar year.*

Hedge funds may gain more exposure if they exhibit an atypical performance when the market performs poorly. This is consistent with Asness, Krail, and Liew (2001), who suggest that hedge funds attempt to perform well in a down market to signal their skill. We explore the hypothesis that the magnitude of the high blip (i.e., potential manipulation) is related to the stock market's recent performance, as investors may benchmark hedge fund performance to the performance of the market. Specifically, a major reason for institutional investors to invest in hedge funds is to diversify away from systematic risk. Hence, to attract and keep capital, hedge funds need to prove that they can offer strong protection against market downturns. Thus, it is valuable to them to display relatively stronger returns when the market does poorly.[12] For this reason, we expect that hedge funds will, on average, be more prone to manipulate in months when the market performs badly. Then:

H6: Manipulation is stronger when market returns are low.

We expect to observe persistence in the pattern consistent with manipulation over time. This persistence may arise for several reasons. The first is purely statistical: it is likely that only some (rather than all) funds engage in this practice. For instance, some funds might have internal risk management standards that ban this type of activity. Thus, conditional on observing evidence of manipulation for a particular company at quarter-end *t*, the company is statistically more likely to exhibit such evidence again in the next period. A second reason for persistence is that if a manager has pumped up returns in the prior month, current-month returns are going to be lower due to the reversal, unless the manager also manipulates the performance this month.

H7: Manipulation activity is persistent over time at the hedge-fund-management-company level.

Finally, we conduct a feasibility study. In keeping with the intuition expressed in the Cramer interview, we propose that the manipulation must be feasible even for smaller management companies, i.e., moving stock prices before the closing does not require much capital.

H8: Traders can move prices at the end of the month by investing relatively small amounts of capital.

[12] The same logic (i.e., reducing the market beta of their returns) suggests that hedge funds may have lower incentives to pump up their portfolios when the market is doing well.

In the next sections, we analyze the data and seek confirmation for these hypotheses.

4. Evidence of End-of-Quarter Manipulation

4.1. Evidence from Daily Returns

Our goal is to test whether some hedge funds manipulate the price of the stocks in their portfolios at the end of the quarter. Using 13F information, for each stock and quarter we compute the fraction of market capitalization held by hedge fund management companies. Panel B of Table 1 has the unconditional distribution of the hedge-fund-ownership variable. For each stock quarter, we construct indicator variables based on the quartiles of hedge fund ownership. In other parts of the analysis, we use an indicator variable for above-median hedge fund ownership. The median ownership by hedge funds across quarters is 1.3%.

Our initial approach focuses on the four months that correspond to quarter-ends (March, June, September, and December) so that the 13F information, which is also filed at quarter-ends, is mostly up to date in terms of hedge funds' end-of-month ownership. In Table 2, we regress the risk-adjusted daily stock return for the four days around the quarter-end (the second-to-last and last days of the quarter and the first and second days of the following quarter) onto the hedge-fund-ownership indicators. Returns are risk-adjusted using the DGTW approach. Standard errors are clustered at the date level in these regressions and in the other stock-level regressions in this section.

Panel A of Table 2 shows a strong pattern for the last day of the quarter as well as a reversal on the following day (the first day of the following quarter). The returns of stocks in the top ownership quartile increase on average by 30 bps (basis points) on the last day of the quarter, and decrease by 25 bps on the following day. The panel shows that there is no effect on the second-to-last day of the quarter or the second day of the next quarter. This is the first piece of evidence consistent with Hypothesis H1a, indicating the possibility that some hedge funds are pumping up the price of the stocks they own. Consistent with the reversion of a pure price pressure effect, the return is significantly more negative for the same stocks on the following day (consistent with Hypothesis H1b). Panel B performs a similar analysis, where the stock universe is split by half according to ownership by hedge funds. Stocks with above-median hedge fund ownership experience an average increase of 18 bps on the last day of the quarter and an average reversal of 14 bps on the following day.

In Table 3, we break down the previous results by quarter. The end-of-month price surge for high-hedge-fund-ownership stocks seems to increase over the course of the year. However, the fund-level evidence that we present below indicates that the impact on fund returns remains stable throughout the year (see Table 8).

The relation between end-of-month returns and hedge fund ownership raises a few concerns about omitted variables. Table 4 presents robustness tests for some of these possibilities. One potential interpretation of our results is that the observed price spikes for stocks that are owned by hedge funds are due to portfolio reallocation at the end of the month rather than to intentional price manipulation. Hence, it could be that high hedge fund ownership (recorded on the last day of the quarter) depends on purchases that occurred on that very day for reasons unrelated to price manipulation, and that these stock purchases consequently push the price temporarily up.

To rule this possibility out, we decouple the measurement of ownership and returns. Specifically, we relate end-of-quarter ownership to returns at the end of the next month. For example, in Table 4, Panel A, we associate end-of-April returns with ownership measured at the end of March. Following a similar logic, Panel B presents regressions in which two-month future returns are regressed on current hedge fund ownership (e.g., we relate end-of-May returns to end-of-March ownership). The panels show that the end-of-month price jumps and the next-day reversals are still significant for stocks with high hedge fund ownership, although the magnitude of the price swings is smaller than it was in Table 2. This change is easily explained by the fact that, in Table 4, the ownership variable reflects stale information relative to the returns. In the time between the measurement of ownership and the measurement of returns, hedge fund portfolios may have changed considerably. It is therefore reassuring that we still find a significant end-of-month effect for stocks with high ownership, which tends to rule out the alternative explanation based on a mechanical link between portfolio reallocation and price impact.

Importantly, this finding lends support to the claim that manipulation occurs on a monthly basis, although we observe holdings at a lower frequency. In other words, since a management company's current holdings are correlated with its future holdings (for stocks that were not sold by hedge funds), and because the current holdings are correlated with one- and two-month future end-of-month returns, as in the results from Table 4, Panels A and B, one can arguably infer if manipulation is present, it occurs on a monthly basis.

Another concern is that the end-of-month price surge originates from the impact caused by hedge funds' attempts to scale up existing positions after positive flows of money. To rule out this possibility, we first identify the management companies that are in the top tercile of flows (in percentage of assets under management) for that quarter. Then we create an indicator variable for stocks with above-median ownership by high-flow companies. We include this dummy in the original specification, which also has above-median ownership dummy by all hedge funds. Finally, we add an interaction between the two ownership dummies. If the price impact is especially strong for stocks owned by high-flow funds, the interaction should be positive and significant. Table 4, Panel C shows that on the last day of the quarter, the interaction is negative and statistically insignificant, while the coefficient on the above-median ownership by all hedge funds retains its significance. We conclude that high-flow funds are not behind the observed price surge. Further evidence ruling out a role for inflows is shown in Section 5 using a hedge-fund-management-company-level analysis.

Another possibility is that hedge fund holdings are correlated with mutual fund holdings and therefore our result simply reflects Carhart, Kaniel, Musto, and Reed's (2002) prior evidence of mutual funds' manipulation of stock prices at the end of the quarter. To rule out this possibility, we add a control for stocks with above-median ownership by mutual funds (Table 4, Panel D). We also present specifications that only include mutual fund ownership, which is computed at the management-company level using 13F data. The results show that hedge fund ownership retains its significance and magnitude when controlling for mutual fund ownership. We interpret this evidence as suggesting that hedge funds add an independent layer of manipulation relative to what has already been found for mutual funds.[13]

[13] Incidentally, it is worth noting that the mutual-fund-ownership variable is associated with a negative end-of-month effect and a reversion on the first day of the month, although these effects are not statistically significant. This evidence would seem to suggest that the Carhart, Kaniel, Musto, and Reed (2002) effect is not present in our sample period. The lack of a significant coefficient on the mutual-fund-ownership dummy is in line with Duong and Meschke (2008), who document a disappearance of significant portfolio pumping by mutual funds after 2001, potentially due to the increased regulatory attention of the Securities and Exchange Commission.

Finally, there is a concern about the economic importance of the effect in terms of the noise added to monthly prices. In particular, while the increase in prices on the last day of the quarter is sizeable, it reverts the next day. Thus there is a possibility that the aggregate effect of hedge fund trades on monthly returns is zero on average, because the same stock might have low returns on the first day of the month and higher returns on the last day of the month. In other words, inflated returns at the last day of the month may come at the expense of a previous return decline at the beginning of the month due to downward price pressure following stock manipulation in the previous month. To test this idea, we re-run the Table 2, Panel B regressions while controlling for the stock's return on the first day of the last month of the quarter (Table 4, Panel E). The regression shows that the correlation between the returns on the first and last days of the month is practically zero. Further, the correlation between the returns around the turn of the month and hedge fund ownership remains unaffected. This evidence is consistent with the conjecture that there is some rotation in the sets of stocks that are subject to manipulation over time.

4.2. Intraday Returns

To minimize the cost of inflating the stock price, hedge funds that manipulate have an incentive to purchase stocks towards the end of the last trading day of the month. Inflating the price earlier in the day can be more expensive because the market has time to absorb the demand pressure, which may make further purchases necessary. The likelihood of this occurrence is minimized when price pumping occurs at the end of the day. To verify this conjecture, we compute the stock returns for each thirty-minute interval between 9:30 and 15:00 and for each ten-minute interval between 15:00 and 16:00. We then regress the intra-day returns onto the above-median ownership dummy. Ownership is measured in the same month in order to maximize power. We expect to see the strongest effect of ownership on returns at the end of the day.

In Table 5, the columns are labeled by the start time of the interval; the results confirm the validity of our conjecture. The price impact of hedge fund ownership becomes significantly different from zero in the interval that begins at 14:00. Consistent with our prediction, the price impact is the strongest in the last ten minutes of the trading day. The magnitude is large. Stocks with high hedge fund ownership have higher returns in the last twenty minutes of the day by roughly 10 basis points, which constitute about half of the daily increase (compare this to the 18 bps in Table 2, Panel B).

We illustrate the intraday patterns graphically. Figure 1a shows four event studies corresponding to the four days around the turn of the quarter. The days considered are the second-to-last of the quarter, the last day of the quarter, the first day of the following quarter, and the second day of the following quarter. The charts show the spread in average cumulative returns between stocks with above-median hedge fund ownership and those with below-median ownership. The horizontal axis is scaled as follows: until 15:00 returns are measured every 30 minutes, every 10 minutes from 15:00 onwards. We also report two standard error bands to gauge significance. The standard errors are computed using the time-series variation of the cumulative return for a given time interval in the same day of the quarter.

The results show that there is no significant trend in the spread on the second-to-last day of the quarter. Conversely, on the last day of the quarter the spread in returns increases to become significantly different from zero in the last two hours, reaching about 25bps. On the first day of the following quarter, the trend reverses: the spread in returns is significantly negative throughout the entire day and reaches about –25bps at the end of the day. There is also some minor decline in cumulative returns of high hedge fund ownership on the second day of the following quarter, but it is not statistically significant. Overall, our results show that stocks owned by hedge funds exhibit abnormally high returns in the last hours of trading on the last day of the quarter and abnormally low returns in the first hours of the following day.

4.3. Intraday Turnover, Order Imbalance, and Trade Size

Our second hypothesis argues that manipulation should leave a trace in volume, both in terms of turnover and in terms of order imbalance. Figure 1b shows evidence regarding stock turnover. This analysis is akin to Blocher, Engelberg, and Reed (2010), which analyzes abnormal short-selling volume. Turnover is calculated as shares traded scaled by total shares outstanding. Since volume follows a standard pattern during the day, which dominates the effect of manipulation that we want to capture, we use the second-to-last day of the quarter as a benchmark for the last day of the quarter and for the first day of the following quarter. This approach amounts to a difference-in-difference analysis. The charts show that share turnover surges in the last twenty minutes of the last day for high-hedge-fund-ownership stocks. On the following morning, the share turnover of stocks owned by hedge funds is high as well, and significantly different from zero; it dies out during the day. So, the graphs points to abnormally high trading activity around the turn of the quarter, consistent with hypothesis H2a.

Figure 1c explores the patterns in the order imbalance around the turn of the quarter for high- versus low-hedge-fund-ownership stocks. A buy-sell order imbalance is computed as the difference in the relevant time period between buyer-initiated trades and seller-initiated trades, classified using the Lee and Ready (1991) algorithm. Buyer-initiated trades are transactions that are executed at prices above the mid-quote; seller-initiated trades are transactions that are executed at prices below the mid-quote. The difference between buyer- and seller-initiated transactions is scaled by the number of transactions in the specific time frame. Hence, this variable takes values between -1 and +1. We present the difference between the order imbalance for the high-hedge-fund-ownership stocks minus the order imbalance for the low-hedge-fund-ownership stocks. The standard errors are computed using the time-series variation of this variable. The charts show a statistically significant buying pressure in the last half hour of the last day of the quarter. The other three days that we consider show a negative order imbalance for the stocks in the hedge fund portfolio. This finding suggests that hedge funds are likely liquidity providers on average. While this evidence prevents us from stating that the significantly negative order imbalance on the first day of the quarter is evidence that manipulating hedge funds are undoing their manipulation from the previous day, it underscores the importance of the positive order imbalance on the last half hour of the quarter. We take the evidence in this chart as broadly consistent with hypothesis H2b.

We wish to relate the abnormal trading patterns around the turn of the quarter that we have just identified to hedge fund trading. While we do not have data on hedge fund trades, the literature has developed a procedure to identify institutional trades in intraday data. In particular, Campbell, Ramadorai, and Schwartz (2009) show that, above a threshold of $2,000, the likelihood that a given trade can be ascribed to institutional traders is increasing in trade size and reaches a plateau around $50,000 (see Fig 2, p.77, in Campbell, Ramadorai, and Schwartz (2009)). They note that for medium or small firms, institutions appear to often split their trades into small dollar amounts (less than $2,000). They argue that such small institutional trades are a result of using algorithms such as VWAP to minimize the price impact. Our assumption, however, is that using an algorithm to split trades would defeat the purpose of a manipulative trade. This consideration motivates our approach of focusing on large trades only to detect institutional actions aiming at price manipulation.

So, we test whether the proportion of large buy trades on the last day of the quarter is abnormally high for stocks owned by hedge funds. To detect an abnormal volume of large buying trades, we benchmark the last day of the quarter against the surrounding days. Hence, for each of the four days around the quarter-end (second-to-last, last, first, and second), we construct a stock-day-level variable "*Large Buy*" equal to the fraction of dollar-measured buying trades observed in the last ten minutes of trading that exceed the $50,000 threshold, out of all dollar-measured buying trades.[14] As a further benchmark, we construct "*Large Sell*" (the fraction of dollar-measured selling trades observed in the last 10 minutes that exceed $50,000).

We then run the following regressions at the end of each quarter q in our sample for each day j out of the four days around the turn of the quarter, and for stock i in our sample:

$$Large\ Buy_{i,j,q} = a + b^{*}I(Top\ HF\ ownership\ quartile)_{i,j,q} + controls + u_{i,j,q},$$

where *I(Top HF ownership quartile)* is an indicator as to whether the stock is in the top quartile of hedge fund ownership for the quarter (using quarter-end 13F reports). The controls include the Amihud (2002) ratio computed over the prior sixty days ending two days prior to quarter-end, the logarithm of the quarter-end market capitalization, and date fixed effects. The purpose of having stock characteristics in the regressions is to account for the fact that stocks of different liquidities may trade in different sizes. Standard errors are clustered at the date level.

The results are reported in Table 6, Panel A. Confirming our conjecture, we find that the effect of high hedge fund ownership on the presence of large buys, measured by the coefficient b, is significantly stronger on the last day of the quarter than it is on the other three days that we consider. Stocks held by hedge funds are thus more likely to experience large buy trades at the very end of the quarter. To test for statistical significance, we pool all the four days in one regression and interact all coefficients with an indicator for the last day of the quarter (Column

[14] The likelihood of a trade being institutional remains constant for the threshold of $50,000 for all firm sizes in Campbell, Ramadorai, and Schwartz's (2009) estimation.

(5)). The interaction between *I(Top HF ownership quartile)* and the indicator for the last day is statistically significant, which validates our conjecture.

The results are economically significant. Our estimates imply that stocks in the top hedge-fund-ownership quartile have a higher fraction of large trades by about 0.7% (the coefficient on the interaction in Column (5)). This is a significant figure, as the average fraction of large trades in the last ten minutes of the days that we examine is about 15%.

As an additional check of our interpretation, we run the same regression with large sells instead of large buys (Columns (6) to (10)) and find no significant presence of end-of-day large sells at quarter-end for stocks held by hedge funds (Column (10)). We see this as a sort of placebo test for our main specification. As a further statistical check, we use the difference between large sells and large buys as a dependent variable (Column (11)). Also this analysis suggests that stocks with high hedge fund ownership experience significantly larger buy trades (than sell trades) on the last day of the quarter, relative to the surrounding days.

One potential concern with these specifications is that the 13F holdings data are mechanically more representative of holdings on the last day of the quarter than on adjacent days. This is particularly valid for high frequency trading companies that might turn a large fraction of their portfolios over on a daily basis. For such managers, our high-hedge-fund-ownership dummy may be a weak signal of ownership for days other than the last day of the quarter, which could explain the lower explanatory power and a lower estimate for these days. To address this issue, we run the same set of regressions using prior-quarter-end holdings as a proxy for the current-quarter-end holdings (reported in the bottom part Table 6, Panel A). The results in Column (5) show that the magnitude of the increase in large buy trades for high-hedge-fund-ownership stocks on the last day of the quarter remains similar: 0.8%. The other results are also robust to using lagged hedge fund ownership.

In addition, we re-run the whole set of regressions using $100,000 as the threshold for large trades and find similar results in both size and statistical significance. The results are provided in Table 6, Panel B. The economic significance of these results is even stronger. The likelihood of a large trade on the last day of the month, relative to the other days, is 0.8%, where the base likelihood for all days is about 9%.

In the Internet Appendix to this paper, we carry out a related analysis which makes a different use of the methodology in Campbell, Ramadorai, and Schwartz (2009). The intuition behind the test is as follows. If hedge funds manipulate the closing price of some stocks, these stocks should experience large buying pressure and a price reversal at the turn of the quarter. Therefore, our test focuses on a significant positive relation between the increases in management company holdings over the quarter and the interaction between buying pressure and a high price reversal at the turn of the quarter. In a similar fashion, we expect that in the following quarter hedge funds unload the stocks they have pumped up. Therefore, we should observe a negative relation between decreases in management companies' holdings and selling pressure for stocks that experienced a high price reversal at the turn of the quarter. The results of the analysis in the Internet Appendix (Appendix Table 4) are consistent with this intuition and provide support for the conjecture of manipulation.

Overall, the evidence above supports hypothesis H2c that stocks held by hedge funds display an abnormal amount of institutional buy trades at the very end of the quarter, which is consistent with manipulative activity by some hedge funds.

4.4. Which Stocks Are Prone to Manipulation?

To understand the extent of manipulation in the stock market we explore the characteristics of stocks that exhibit manipulation-consistent patterns. According to Hypothesis H3, stocks are more likely to be manipulated by hedge funds if they are relatively illiquid. To test this hypothesis, we regress the daily returns around the turn of the quarter on an interaction of the high-hedge-fund-ownership indicator and the high Amihud (2002) illiquidity indicator, as well as on the main effects.[15] We also control for the size indicator and its interaction with the hedge-fund-ownership indicator. The results in Table 7 are strongly consistent with the prediction of Hypothesis H3. Above-median illiquid stocks with above-median hedge fund ownership exhibit an abnormal return of 17 basis points, relative to the abnormal return of all stocks. After controlling for liquidity, we find no significant effect of market capitalization and

[15] Following Amihud (2002), stock illiquidity is measured by the average ratio of the absolute value of the daily returns to the daily volume in the quarter.

its interaction with hedge fund ownership. It appears that the illiquidity of the stock is a catalyst for manipulation.

4.5. Hedge-Fund-Management-Company-Level Evidence of Quarter-End Manipulation

Having provided evidence consistent with manipulation at the stock level, we now turn to the hedge-fund-management-company-level evidence by looking at the behavior of the equity portfolios held by management companies at quarter-ends. We have a twofold objective. First, we seek to confirm that the price pattern that we document at the stock level does indeed translate into higher hedge-fund-management-company returns. Second, we wish to explore which managers tend to have portfolio returns that display patterns consistent with end-of-month manipulation and to analyze the circumstances in which these patterns are more pronounced.

We calculate a management-company-level proxy of manipulation at the quarterly frequency based on the last-day-of-the-month run-up and the following day's reversal. For each management company in the intersected dataset of 13F and TASS, we calculate *ret(last day)*, the return of the management company's long-equity portfolio, weighted by dollar holdings as reported in the company's 13F for that quarter-end. Similarly, we define the return of that *same* portfolio on the *next* day (*ret(last day* + 1*)*) and the *previous* day (*ret(last day* – 1*)*), relative to the last trading day of the quarter.

A useful measure to proxy for the manipulation-consistent pattern is the "blip" of each fund's equity portfolio at the end of the quarter:

$$Blip_{i,t} = ret(last\ day)_{i,t} - ret(last\ day + 1)_{i,t}.$$

Indeed, if a firm pushes its returns upward at the end of a quarter, we expect a high *ret(last day)* followed by quick reversal, i.e., a low next-day returns and thus a high blip. The blip can then be used to identify potential manipulations. For the purpose of describing the variable, we adjust returns by the value-weighted market portfolio. Using self-explanatory notations, we call the market-adjusted variables: *Adj ret(last day)*, *Adj ret(last day* + 1*), Adj ret(last day* – 1*)*, and *Adj Blip*.

As a starting point, we wish to confirm at the management-company level the anomaly that we reported earlier at the stock level. In Table 8, we report the descriptive statistics of these last four variables, calculated at the company level and averaged across quarters. In line with what one would expect if a fraction of the managers were engaging in monthly return pumping of their long-equity holdings, we find significantly positive adjusted returns at the end of the quarter, followed by negative adjusted returns on the next quarter's first day. This abnormal adjusted blip is 52 bps on average and is not specific to December (the level is highly stable among the calendar months). The market-adjusted blips are significant for all of the four quarter-end months at the 2% level, where the standard errors are clustered by date. In addition, we can reject the hypothesis that the returns on 'last day – 1' are equal to the returns on the last day. That is to say, they are significantly smaller.[16]

Thus, we confirm at the hedge-fund-management-company level the anomaly documented at the stock level: that the portfolio of long-equity holdings of hedge funds experience abnormal positive returns, on average, at the end of the quarter, followed by a reversal on the next trading day. This is consistent with some hedge funds pumping up stock prices at month-end. As we have done for the stock-level evidence, we will address other possible explanations, such as end-of-month rebalancing, in the section below.

5. The Determinants of Manipulation

5.1. Link with Incentives to Improve Returns

In order to better understand the economics of stock price manipulation, we try to identify the hedge fund management companies that exhibit return patterns consistent with manipulation activity. Having described the blip measure for each company, we now examine the company-level characteristics that relate to high levels of blip. Since, for purely statistical reasons, more volatile hedge fund portfolios are more likely to exhibit a blip, a more accurate company-level signal of manipulation is the volatility-adjusted blip ($AdjBlip_{i,t} = Blip/volatility_{i,t}$), where we divide $Blip_{i,t}$ by the volatility of the daily returns of company i's

[16] Table 3 suggests that, at the stock level, the evidence of manipulation increases over the year, whereas the fund-level blip in Table 8 does not display this pattern. The two results are not in contradiction. The stock-level results are equally weighted across stocks. In contrast, to compute the fund-level returns in Table 8, the stocks are given the weight that they have in each hedge fund's portfolio. Further, the returns in Table 8 are equally weighted across funds. In conclusion, the difference in weighting schemes does not allow a direct comparison between the two tables.

portfolio, estimated using the daily returns during the quarter finishing at time *t* (and using the quarter-end weights from the 13F portfolio). This volatility-adjusted variable, which will be used to detect signs of manipulation in the data, is distributed independent of volatility and, absent manipulations or other end-of-month anomalies, would be centered around zero. Note that at the individual level, a high level of the variable $AdjBlip_{i,t}$ gives a statistical indicator of the likelihood that a fund company is engaging in portfolio pumping. But this is not evidence per se that manipulation has occurred. A high level of $AdjBlip_{i,t}$ might be the result of statistical randomness; it could also occur if another fund with overlapping portfolio holdings is doing the manipulation.

In Table 9, Columns (1) to (4), we regress the company-level volatility-adjusted blip on a set of company characteristics. Our regressions include calendar quarter fixed effects; standard errors are clustered at the fund level. We examine a number of explanatory variables: $log(AUM)_t$ is the log of the company's assets under management at the end of quarter *t*; *log(# Stocks in equity portfolio)*$_t$ is the log of the number of stocks held by the company as a measure of diversification at the end of quarter *t*. Both variables are constructed using funds' 13F filings. Aggregating the TASS data at the company level, we compute the percentage of flows out of lagged assets under management *Fund flows/lag(AUM)(%)*.

The results in Table 9 show that management companies with less diversified portfolios (i.e., a smaller number of stocks in the portfolio) have higher blips, in line with the view that it is easier (less costly) for such managers to move their portfolio performance. In contrast, a highly diversified manager cannot generate a high impact on its returns by pushing a small number of stocks (Hypothesis H4).[17]

To test Hypothesis H5, which links the incentives to manipulate to the pattern of manipulation-consistent activity, we consider relative and absolute performance measures constructed aggregating the TASS data at the company level. We call *I(Bad month)*$_t$ a dummy equal to one if the company's performance at month *t* is below -2% (a threshold that corresponds to the bottom 15% of the distribution of monthly returns). To assess relative performance, we sort companies according to their year-to-date performance: *YTD performance quintile* X_t is an

[17] We note that since we use the *volatility-adjusted blip* in our regressions (*blip* scaled by volatility), the result is not likely to be a mechanical effect resulting from the high volatility of the *blip* measure for undiversified firms.

ordinal discrete variable that distributes companies into five quintiles of year-to-date (YTD) performance as of the end of month *t*. We focus on YTD performance because it is a variable frequently used by investors to compare managers within the year. For instance, HSBC's "Hedge Weekly" report provides a "Top list" and "Bottom list" of managers according to their YTD performance.

The results in Table 9, Panel A confirm that hedge fund management companies in the highest year-to-date performance quintile exhibit higher blips (Hypothesis H5). This evidence is consistent with the cross-sectional analysis of Carhart, Kaniel, Musto, and Reed (2002), which shows that mutual funds that engage in end-of-quarter price manipulations are past winners, potentially attempting to take advantage of the convexity of the flow-performance relation. It is also in line with several papers documenting the behavior of mutual funds: Chevalier and Ellison (1997) find that mutual fund managers who are performing well relative to the market gamble in order to make year-end lists of "top performers." Jain and Wu (2000) demonstrate that the marketing expenditures of mutual funds are higher for top performers and Sirri and Tufano (1998) show that flows into mutual funds are correlated with the level of media attention.

We also find that companies having a bad month (less than -2%) are more likely to experience a blip. This correlation can be explained by the concern that an overly negative return might tarnish the manager's track record (e.g., by increasing historical volatility), providing an inducement to manipulate. These results are economically sizable. Moving from the first to the fifth YTD performance quintile increases the expected volatility-adjusted blip by about 10 percentage points, which is 6.7% of the standard deviation of the volatility-adjusted blip (Columns (3) and (4)). A similar magnitude is observed for the effect of having a bad month (Columns (3) and (4)). The magnitude of the effects can also be assessed in Table 9, Columns (5) to (8), where the dependent variable is *ret(last day)*—the quarter's last-day return of the portfolio. These regressions show that companies that are experiencing a bad month or that are in the highest quintile of YTD performance have last-day returns that are around 20 or 15 bps, respectively, higher than others.

To further investigate the link between incentives to manipulate and observed blips, we perform a more detailed analysis of the characteristics of management companies that exhibit portfolio return patterns that are consistent with manipulation activity (i.e., a high blip). To validate Hypotheses H5a-c, we propose that manipulation that appears to be aimed at boosting YTD performance is stronger for: (i) companies with a currently good relative performance but a poor past relative performance, (ii) young companies, and (iii) the early months of the calendar year.

In Table 9, Panel B, we find supportive evidence for all three hypotheses: hedge fund management companies are more likely to experience a high blip when their YTD performance is high and they possess one of the characteristics that we explore. For the first case (Column (1)), *Low reputation* is a dummy equal to one if the YTD performance as of the previous quarter (i.e., at month t – 3) was in the bottom two quintiles (similar results hold in magnitude and significance by using the first quintile only in the definition of Low reputation). Companies where *Low reputation* = 1 were thus perceived, as of the previous quarter, to be underperformers. Then, if one of these managers has an already high current YTD return, it might benefit relatively more by climbing further in the rankings, to make it, for example, into the top ten. As for the second part of the hypothesis (Column (2)), *Young* is a dummy equal to one if the company's age (measured from the first date of its inclusion in TASS) at month t is below the sample's median, i.e., 7 years. In the third part of the hypothesis (Column (3)), which proposes that there is stronger manipulation early in the year, *March* is a dummy equal to one if the current calendar month is March. Note, finally, that the finding that the *March* dummy positively interacts with the relative performance incentive does not imply that blips are higher in the first quarter, as it appears from Table 8. Rather, it means that the incentive to manipulate that originates from the YTD performance rankings is stronger at the beginning of the year.

It is interesting to consider the relation between manipulation and hedge funds' reported returns. In particular, we conjecture that management companies that manipulate stocks are expected to have higher monthly returns on average. In Table 1 of the Internet Appendix, we regress hedge fund management companies' total returns on the high-blip indicator (the top 10% of hedge funds' blip distribution each month). The regressions show that companies with the high-blip measure earn monthly total returns higher by 0.3% to 0.4%. The magnitude of this result is consistent across specifications, which include different controls for company-level incentives from Table 9.

5.2. Link with the Discontinuity of Total Returns at Zero

Previous studies documented other types of manipulation arising in the hedge fund sector. We examine whether our findings relate to previous evidence of hedge fund return manipulation. Since Getmansky, Lo, and Makarov (2004) and Bollen and Pool (2008, 2009), it has been known that hedge fund returns are particularly smooth over time, which is consistent with their incentive to avoid reporting negative and excessively volatile returns to their investors. Agarwal et al. (2011) and Bollen and Pool (2009) both find that investors respond with flows to funds that have a paucity of losses even after controlling for average performance. This is why it can be rational for funds that have marginally negative returns to find ways to make their monthly performance positive. It is thus natural to ask whether the kind of "portfolio pumping" behavior documented in our paper is one of the tools used by hedge funds to maintain such results. Indeed, the small end-of-month abnormal returns that we document are most likely driven by a concern for embellishing a fund's track record rather than immediate profit through performance fees. We test this by looking at whether the discontinuity at zero in the distribution of monthly returns is stronger for management companies with a high return blip at the end of the month. As above, we use the company-level variable *High Blip* as a proxy for manipulation. High Blip is an indicator as to whether the company-level volatility-adjusted blip (Blip/Volatility) is in the top decile of the distribution of that quarter. Companies with "*High Blip*=1" are then interpreted as the most likely "portfolio pumpers" at the end of that quarter. Notice that *High Blip* is constructed using the long-equity part of the management company's portfolio. We wish to test whether the distribution of returns reported by the company in a month in which it experiences a high blip has a particularly strong discontinuity at zero, reflecting the fact that portfolio pumping aims to transform slightly negative returns into positive ones.[18]

To perform this test, we merge TASS monthly returns, aggregated at the management company level, with the quarterly data from 13F. We keep only the observations corresponding to quarter-ends. In Figure 2, we plot two histograms of company returns for *High Blip* and *Non High Blip* companies, using bins of 20 basis points (bps). Bin "-1" contains the density (the frequency divided by the total number of observations) of observed returns between -20 bps and

[18] In Table 4 of the Internet Appendix we present results from an alternative method, akin to the one used in Bollen and Pool (2009). The results from that analysis suggest the same conclusion.

zero, Bin "0" between zero and 20 bps, etc. A visual inspection of the two histograms reveals that the discontinuity at zero is indeed larger for *High Blip* than *Non High Blip* firms.

To establish this more formally, we conduct a regression that tests for discontinuity between Bins -1 and 0. Specifically, we estimate separate polynomials for the positive and negative sides of the histogram. Then we test whether these polynomials have different constants. This analysis tells us whether the distribution is smooth and gives an estimate of the jump at zero (i.e., between Bin -1 and Bin 0) and its significance. Specifically, we use polynomials of order three and run the following regression on the forty bins [-20, 19]:

$$Density\ in\ Bin\ i = a + b * I(i \geq 0\ ) + \sum_{k=1}^{3} \mu_k * I(i \geq 0\ ) * |i|^k + \sum_{k=1}^{3} \pi_k * I(i < 0) * |i|^k + \varepsilon_{i,}$$

where i= -20,…, 19.

The regression, therefore, fits two 3rd degree polynomials onto the histogram: one for the positive part of the histogram, and the other for the histogram's negative part. The coefficient of interest is b, which tests whether there is a discontinuity at zero.[19]

The results are reported in Table 10, Panel A. We find that the jump in the distribution at zero is significant (at 5%) for both categories of managers. We use robust *t*-statistics in these regressions to account for the mechanical heteroskedasticity of observations arising from the fact that the frequency observed in the less populated bins is a noisier estimate of the true underlying distribution than it is of the frequency estimated in the more populated bins.

Our main interest, however, is whether the discontinuity at zero differs between *High Blip* and *Non High Blip* companies as a result of portfolio pumping. Hence, we also run a regression pooling the two groups of managers. To be specific, we create a data set with two observations per bin of returns, namely the frequency of observations in that bin for *High Blip* and *Non High Blip* companies. Then, we interact each variable in the above specification with a *High Blip* dummy. The *t*-statistic for the coefficient on the interaction between the *High Blip* dummy and the $I(i \geq 0)$ dummy provides a test for whether the discontinuity at zero differs between the two groups of managers. The results in Table 10, Panel A, Column (3) confirm that

[19] A similar technique was used in Ben-David and Hirshleifer (2012).

High Blip companies have significantly larger discontinuity of returns at zero, consistent with portfolio pumping having a significant effect on these management companies' total returns.

These results are robust to various modifications such as using Bins [-15, 14] or [-10, 9] instead of Bins [-20, 19] or using polynomials of order 2 on Bins [-10, 9]. See Table 2 of the Internet Appendix.

Finally, we conjecture that the discontinuity at zero is stronger for long/short managers than it is for other styles. The reason is that non-long/short hedge funds can trade illiquid non-publicly traded assets and can thus more easily smooth/manipulate the prices at which they mark their assets. But, for long/short equity companies—which trade public equities—portfolio pumping is one of the likeliest options for manipulating returns (if one rules out plain misreporting, which is not feasible for the majority of funds that use an independent administrator and a custodian for the valuation and reporting of their assets.) Therefore, within long/short management companies, one would expect jumps at zero to exist primarily for the *High Blip* managers. The empirical evidence in Table 10, Panel B, confirms this conjecture.[20]

5.3. Time-Series Evidence

Manipulation activity could be stronger in certain periods more than in others. We explore the time-series dimension of price patterns that are consistent with manipulation. First, we would like to verify that the manipulation-consistent pattern takes place consistently over time and is not limited to a single episode in the decade being examined. Figure 3 presents a time-series of the DGTW adjusted, equally weighted, average last-day-of-the-quarter returns over the sample period, where the stock sample is split for above- and below-median hedge fund holdings. The figure shows that in most quarters the end-of-month returns are higher for stocks with high hedge fund holdings.

To test the hypothesis that manipulation is stronger when stock market returns are low (Hypothesis H6), we compute for each quarter-end the average market-adjusted blips and test whether these aggregate blips are stronger when the market performs poorly. In Table 11, we report evidence that this is indeed the case: the aggregate adjusted blips are significantly

[20] The data used in Panel B include only 293 High Blip fund-month observations when we restrict the sample to long/short managers, which obliges us to reduce the number of bins to 30 so as to get less noisy estimates.

negatively correlated with market performance in the corresponding quarter. When the market is below its median, the average market-adjusted blip is higher by 44 bps, about two-thirds of a standard deviation move for this variable (the standard deviation is 67 bps). We present a scatter plot of the Blip/Volatility, as a function of market returns in Figure 4. The figure shows that the result is not driven by outliers; rather, it reflects a strong pattern in the data. This suggests that performing relatively well when the market tanks is rewarding for hedge funds, possibly because they advertise themselves as a hedge against negative market moves.

5.4. Robustness and Alternative Explanations

We now address a few potential concerns regarding the interpretation of the management-company-level results. First, the link between YTD performance and blips might come from a reverse causality, whereby the high blips are themselves the determinant of the high YTD performance. Note that the endogeneity of the YTD performance only occurs if the current-month manipulation-consistent pattern affects the current-month relative performance. Hence, the endogeneity concern can be addressed by including in the regression the fund's relative performance for the current month. We report this robustness check in Table 3 of the Internet Appendix: *Current performance quintile* X_t is an ordered discrete variable that breaks funds into five quintiles according to month-*t* performance. The baseline results of Table 9 are unaffected by such a control. (They are also unchanged when the continuous relative performance variable is included.)

Another concern is that the results we report might be related to the price impact of trades that specifically occur at the end of the month rather than to intentional price manipulations. For instance, some companies with a high YTD performance might experience high inflows, leading to a large flow of stocks being bought at the quarter-end. To alleviate this concern, we control for the percentage net flows in assets received by the company at quarter-end, *Flows/lag(AUM) (%)*. Following the literature standard (Chevalier and Ellison 1997, Sirri and Tufano 1998, Agarwal, Daniel, and Naik 2011, among others), we compute company flows as the quarterly difference in AUM at quarter-end minus the dollar return on the previous quarter AUM. Flows are then scaled by the lagged AUM. Columns (4) and (8) of Table 9 show that the results are unaffected by the inclusion of this control. The blip and last-day returns are actually uncorrelated with fund net flows, relaxing the concern that the price impact at month-end is a driving force in these regressions.

5.5. Persistence of Manipulation

In the final part of the hedge-fund-management-company-level analysis, we investigate whether high blips, which we take as a proxy for manipulation, are persistent for a given company (Hypothesis H7). To this end, we regress the current quarterly blip on the lagged blip of the management company. Table 12 documents that blips are indeed significantly persistent from one quarter to the next: volatility-adjusted blips have an autocorrelation coefficient of around 0.11. This persistence remains significant even when controlling for all the variables that have been found to be predictors of manipulation, as Column (3) indicates. This suggests that manipulating returns is a "habit" that tends to persist over time at the company level.

The issue of persistence raises a related question: how many hedge fund management companies are actually engaged in manipulation? This is a hard question to answer since there is nothing that prevents hedge funds from manipulating stock prices sporadically, in a way that is difficult to distinguish from a random pattern in the data. In the Internet Appendix, Section 6, we investigate this issue. For each hedge fund management company, we calculate the fraction of quarters in which our manipulation proxy, *AdjBlip* is positive. Under the null, the average fraction of positive *AdjBlip* quarters should be 50%. Our results show that this average in the data is 61.3%. In addition, it appears that the distribution has two centers of mass: at 50% and around 60%.

However, this analysis is subject to an important caveat. Hedge funds in particular tend to hold portfolios that partly overlap. Thus, it is possible that some hedge funds appear to have statistical characteristics that are consistent with manipulation, but they are not intentional manipulators. Hence, our analysis cannot provide an accurate estimation of the number of manipulating hedge fund management companies.

6. Feasibility Analysis

For stock manipulation on the part of some hedge funds to drive end-of-month returns, it must be the case that manipulation of stock prices is feasible with a reasonable amount of capital. That is, the amount of money necessary to move prices by the observed magnitude should be accessible even to smaller hedge funds. Therefore, the more immediate question is: how much capital does it take to move the price of a stock by 1%?

To this end, we examine the association between stock returns and signed volume. We focus on the last seconds of trading on the last day of the month. An estimate of the sensitivity of stock prices to volume around this time is likely to provide an upper estimate for the amount of money needed for such trades, as stocks have a generally high level of volume towards the end of the trading day.

We begin by splitting the universe of stocks into five groups according to their Amihud (2002) illiquidity measure. We then extract the last nine seconds of trading (15:59:51 to 15:59:59), in addition to the closing trades at 16:00:00 of the last day of the month for all the months from January 2000 to December 2009.

For each stock-second, we compute returns and aggregate the dollar volume. To guard against the influence of erroneous data, we drop extreme observations beyond the 2nd and 98th percentiles. In each Amihud illiquidity group, for each second, we run the following regression for all stock-seconds with non-zero dollar volume:

$$ret_{i,t} = a + b * sign(ret_{i,t}) * \$vol_{i,t} + e_{i,t.}$$

As $ret_{i,t}$ is expressed in percentage points, the inverse of the coefficient b represents the dollar amount associated with a 1% movement in the price. We compute the inverse of the coefficient b and present it in Figure 5 (using a logarithmic scale).

The figure shows that during trading hours, changes of 1% in the prices of stocks with low liquidity (groups 3 to 5) are associated with dollar volumes well below $0.5m. Changes in price at the closing trade are associated with much larger amounts of money. At the closing (16:00:00), one needs $1m to $10m to move the price of low liquidity stocks by 1%.

Consistent with Hypothesis H8 and with Cramer's aforementioned admission, we find that with a few millions a trader can move the price of illiquid stocks by a percentage point or more. Thus, the manipulation of prices appears to be feasible with moderate resources.

7. Conclusion

In this paper, we use hedge-fund-management-company-holdings data to test the conjecture that some hedge funds manipulate stock prices at the end of the month by buying some of their stock holdings before market close. We find evidence to support this claim. Stocks with high hedge fund ownership exhibit high end-of-month returns, and a subsequent reversal on the following day. In intraday data, we find that these stocks' returns are especially high in the last minutes of trading. Turnover and order imbalance are abnormally high in these periods as well. We show that these effects are more likely to take place in cases where the incentives to manipulate are stronger, both at the stock and at the hedge-fund-management-company level.

The results show that the limits of arbitrage arising from agency conflicts (Shleifer and Vishny 1997, and Gromb and Vayanos 2010 for a survey) can have a significant impact on market prices. In doing that, our paper joins previous literature showing that price manipulation by different groups of investors creates predictable patterns in asset prices. Carhart, Kaniel, Musto, and Reed (2002) present evidence of end-of-quarter manipulations by mutual funds. Ni, Pearson, and Poteshman (2005) do the same for option traders, as do Blocher, Engelberg, and Reed (2010) for short-sellers. In a sense, our paper complements the latter study, since a large fraction of short-selling volume is attributed to hedge funds (as argued by Boehmer, Ekkehart, and Jones 2008 and Goldman Sachs 2010).

The likely distortion of end-of-month prices by some hedge funds, to which the evidence in this paper appears to testify, is likely to have wider welfare consequences beyond jamming the hedge fund performance signal. Specifically, many players in the economy use end-of-month stock prices in contracting. For example, some executive compensation contracts are based on stock price performance. Also, asset manager compensation fees and asset manager rankings (e.g., mutual funds) are based on monthly performance. Thus, the potential noise added to stock returns distorts other contract signals and consequently imposes a negative externality in aggregate. It is important to note that, although the evidence in support of manipulation to stock prices is shown to revert quickly, we also show that it does not cancel itself out within the same month. That is, a stock whose price decreased due to a reversal on the first day of the month is not likely to be manipulated again at the end of the month.

We also contribute to the recent debate on regulatory reforms concerning hedge funds. The paper uncovers a mechanism by which hedge fund returns can be manipulated without misvaluation or misreporting. In this sense, we expand on prior evidence by Agarwal, Daniel, and Naik (2011) and Bollen and Pool (2009). These results, taken together, seem to suggest that it is possible for returns to be influenced by a manager even when hedge funds fully comply with the legal requirements, such as SEC registration, or best practices, such as third-party custody. One alternative to regulation that can prove more powerful in enforcing the correct behavior is for investors and regulators to develop more sophisticated techniques to detect manipulation in reported returns. Recent academic research in this field, including this paper, provides a number of tools that can be easily implemented using reported returns and public data on stock holdings.

References

Agarwal, Vikas, Naveen D. Daniel, and Narayan Y. Naik, 2011, Do Hedge Funds Manage Their Reported Returns? *Review of Financial Studies* 24(10), 3281-3320.

Agarwal, Vikas, Vyacheslav Fos, and Wei Jiang, 2010, Inferring Reporting Biases in Hedge Fund Databases from Hedge Fund Equity Holdings, Working Paper, Columbia University.

Aggarwal, Rajesh K., and Guojun Wu, 2006, Stock Market Manipulations, *Journal of Business* 79(4), 1915-1953.

Allen, Franklin, Lubomir Litov, and Jianping Mei, 2006, Large Investors, Price Manipulation, and Limits to Arbitrage: An Anatomy of Market Corners, *Review of Finance* 10(4), 645-693.

Amihud, Yakov, 2002, Illiquidity and Stock Returns: Cross-Section and Time-Series Effects, *Journal of Financial Markets* 5, 31-56.

Aragon, George O., and Vikram Nanda, 2011, Strategic Delays and Clustering in Hedge Fund Reported Returns, Working Paper, Arizona State University.

Asness, Cliff, Robert Krail, and John Liew, 2001, Do Hedge Funds Hedge? Working Paper, AQR Capital.

Ben-David, Itzhak, Francesco Franzoni, and Rabih Moussawi, 2011, Hedge Fund Stock Trading during the Financial Crisis of 2007-2009, *Review of Financial Studies* 25(1), 1-54.

Ben-David, Itzhak, and David Hirshleifer, 2012, Are Investors Really Reluctant to Realize their Losses? Trading Responses to Past Returns and the Disposition Effect, *Review of Financial Studies* 25(8), 2485-2532.

Blocher, Jesse, Joseph Engelberg, and Adam V. Reed, 2010, The Long-Short Wars: Evidence of End-of-Year Manipulation by Short Sellers, Working Paper, University of North Carolina.

Boehmer, Ekkehart, and Charles M. Jones, 2008, Which Shorts Are Informed? *Journal of Finance* 63(2), 491-527.

Bollen, Nicolas P. B., and Veronika K. Pool, 2008, Conditional Return Smoothing in the Hedge Fund Industry, *Journal of Financial and Quantitative Analysis* 43(2), 267-298.

Bollen, Nicolas P. B., and Veronika K. Pool, 2009, Do Hedge Funds Misreport Returns? Evidence from Pooled Distributions, *Journal of Finance* 64(5), 2257-2288.

Brunnermeier, Markus K., and Stefan Nagel, 2004, Hedge Funds and the Technology Bubble, *Journal of Finance* 59(5), 2013-2040.

Campbell, John Y., Tarun Ramadorai, and Allie Schwartz, 2009, Caught on Tape: Institutional Trading, Stock Returns, and Earnings Announcements, *Journal of Financial Economics* 92(1), 66-91.

Carhart, Mark, Ron Kaniel, David Musto, and Adam Reed, 2002, Leaning for the Tape: Evidence of Gaming Behavior in Equity Mutual Funds, *Journal of Finance* 57(2), 661-693.

Chevalier, Judith, and Ellison, Glenn, 1997, Risk Taking by Mutual Funds as a Response to Incentives, *Journal of Political Economy* 105(6), 1167-1200.

Cici, Gjergji, Alexander Kempt, and Alexander Puetz, 2010, Caught in the Act: How Hedge Funds Manipulate their Equity Positions, Working Paper, William and Mary College.

Comerton-Forde, Carole, and Talis J. Putnins, 2011, The Prevalence and Underpinnings of Closing Price Manipulation, Working Paper, University of Sydney and Stockholm School of Economics.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Ross Wermers, 1997, Measuring Mutual Fund Performance with Characteristic Based Benchmarks, *Journal of Finance* 52, 1035-1058.

Duong, Truong X., and Felix Meschke, 2008, The Rise and Fall of Portfolio Pumping among U.S. Mutual Funds, Working Paper, National University of Singapore.

Getmansky, Mila, Andy W. Lo, and Igor Makarov, 2004, An Econometric Model of Serial Correlation and Illiquidity in Hedge Fund Returns, *Journal of Financial Economics* 74(3), 529-610.

Goldman Sachs, 2010, Hedge Fund Monitor, 2010Q2 Portfolio Strategy Report.

Griffin, John, and Jin Xu, 2009, How Smart Are the Smart Guys? Unique View from Hedge Fund Stock Holdings, Review of Financial Studies 22(7), 2531-2570.

Gromb, Denis, and Dimitri Vayanos, 2010, Limits of Arbitrage, Working Paper, London School of Economics.

Hillion, Pierre, and Matti Suominen, 2004, The Manipulation of Closing Prices, *Journal of Financial Markets* 7, 351-375.

Holmström, Bengt, 1999, Managerial Incentive Problems: A Dynamic Perspective, *Review of Economic Studies* 66, 169-182.

Holmström, Bengt, and Paul Milgrom, 1991, Multitask Principal-Agent Analyses: Incentive Contracts, Asset Ownership, and Job Design, *Journal of Law, Economics, & Organization* 7, 24-52.

Ippolito, Roger A., 1992, Consumer Reaction to Measures of Poor Quality: Evidence from the Mutual Fund Industry, *Journal of Law and Economics* 35, 45-70.

Jain, P.C., and J.S. Wu, 2000, Truth in Mutual Fund Advertising: Evidence on Future Performance and Fund Flows, *Journal of Finance* 55, 937-958.

Jylhä, Petri, 2010, When Do Hedge Fund Managers Misreport Returns? Working Paper, Aalto University.

Lee, Charles M. C. and Ready, Mark J., Inferring Trade Direction from Intraday Data, *Journal of Finance* 46(2), 733-746.

Lemke, Thomas P., and Gerald T. Lins, 1987, Disclosure of Equity Holdings by Institutional Investment Managers: An Analysis of Section 13(f) of the Securities Exchange Act of 1934, *Business Lawyer (ABA)* 43, 93-119.

Liang, Bing, 2003, The Accuracy of Hedge Fund Returns, *Journal of Portfolio Management* 29(3), 111-122.

Ni, Sophie, Neil Pearson, and Allen M. Poteshman, 2005, Stock Price Clustering on Option Expiration Dates, *Journal of Financial Economics* 78, 49-87.

Patton, Andrew J., and Tarun Ramadorai, 2011, On the High-Frequency Dynamics of Hedge Fund Risk Exposures, Working Paper, University of Oxford.

Patton, Andrew J., Tarun Ramadorai, and Michael Streatfield, 2011, The Reliability of Voluntary Disclosures: Evidence from Hedge Funds, Working Paper, Duke University and University of Oxford.

Shleifer, Andrei, and Robert W. Vishny 1997, The Limits of Arbitrage, *Journal of Finance* 52(1), 35-55.

Sirri, Erik R., and Peter Tufano, 1998, Costly Search and Mutual Fund Flows, *Journal of Finance* 53, 1589-1622.

Table 1. Summary Statistics

The table reports summary statistics. Panel A presents the aggregate summary statistics for the universe of hedge fund management companies available in the 13F filings as well as for the subset that could be matched with TASS. Panel B presents the summary statistics of stock-day observations for the last day of the month. Panel C presents summary statistics at the hedge-fund-quarter level. Panel D shows statistics on buy and sell trades that exceed a given threshold, as a fraction of total buys and sells, in the last ten minutes of trading in the four days around the turn of the quarter. The sample period is 2000Q1 to 2010Q3.

Panel A: Summary Statistics on the Hedge Fund Management Companies

Year	Number of Fund Companies Matched with TASS	AUM of Matched Hedge Fund Sample ($bn)	Total AUM of TASS ($bn)	AUM of Equity Hedge Funds in TASS ($bn)	Number of Funds per Hedge Fund Company		% of Companies with 1 or 2 Hedge Funds	Number of Stocks per Hedge Fund Company	
					Average	Median		Average	Median
2000	309	$125	$197	$132	2.5	2	70%	111.9	59
2001	328	$156	$290	$191	2.6	2	69%	114.3	56
2002	387	$211	$366	$233	2.7	2	68%	103.6	55
2003	419	$253	$460	$277	2.8	2	68%	112.7	52
2004	470	$370	$695	$435	3.1	2	63%	110.4	52
2005	530	$425	$1'051	$732	3.1	2	62%	108.9	49
2006	552	$543	$1'108	$721	3.1	2	62%	105.6	46
2007	531	$658	$1'428	$944	3.3	2	64%	110.7	46
2008	415	$697	$1'842	$901	3.1	2	69%	100.8	35
2009	317	$445	$1'245	$659	2.6	2	69%	108.3	41
2010	288	$391	$1'040	$614	2.4	2	70%	109.9	48

Panel B: Stock-Day Level Summary Statistics

	N	Mean	Std Dev	Min	p25	p50	p75	Max
Return last day (%, DGTW adjusted)	128,841	0.021	3.772	-74.251	-1.361	-0.067	1.260	14.469
Return first day (%, DGTW adjusted)	128,868	-0.126	3.728	-81.250	-1.539	-0.072	1.398	14.469
Return second day (%, DGTW adjusted)	128,800	-0.059	3.612	-94.788	-1.451	-0.070	1.358	14.469
Return second-to-last day (%, DGTW adjusted)	128,844	-0.019	3.484	-71.286	-1.288	-0.060	1.224	14.469
HF ownership (%)	128,910	2.615	3.803	0.000	0.440	1.258	3.246	100.000
Mutual Fund ownership (%)	128,910	13.637	9.481	0.000	6.095	12.303	19.656	100.000
Ownership by high-inflow funds (%)	128,910	0.640	1.829	0.000	0.000	0.043	0.456	100.000
Amihud illiquidity measure	128,910	0.310	0.974	0.000	0.001	0.008	0.072	5.000
Market capitalization	125,861	4.08E+09	1.77E+10	-1.03E+09	1.60E+08	5.40E+08	1.89E+09	5.71E+11

Table 1. Summary Statistics (Cont.)

Panel C: Management-Company-Quarter-Level Summary Statistics

	N	Mean	Std Dev	Min	p25	p50	p75	Max
Adj ret(last day)	6,649	0.368	1.558	-8.527	-0.400	0.063	0.725	14.743
Adj ret(last day + 1)	6,649	0.002	0.020	-0.138	-0.007	0.003	0.012	0.118
Adj ret(last day - 1)	6,649	0.001	0.020	-0.167	-0.002	0.002	0.010	0.091
Adj Blip = Adj ret(last day + 1) - Adj ret(last day)	6,649	0.008	0.044	-0.553	-0.006	0.008	0.022	0.746
log(AUM)	6,649	5.439	1.742	-5.163	4.498	5.490	6.512	10.915
log(# Stocks in equity portfolio)	6,649	3.885	1.281	0.000	3.219	3.892	4.575	7.839
Fund flows / lag(AUM) (%)	5,741	0.010	0.041	-0.311	-0.003	0.003	0.019	0.237
Hedge fund age	6,649	7.803	4.484	0.000	4.343	7.124	10.567	25.421
Blip/vol	6,649	0.012	1.484	-1.006	-0.186	0.904	-3.982	8.637

Panel D: Summary Statistics on Buy and Sell Trades above a Given Threshold

Threshold: $50K

	N	Mean	Std Dev	Min	p25	p50	p75	Max
% of $ buy trades > $50k out of total $ buy trades	532,432	0.15	0.27	0.00	0.00	0.00	0.20	1.00
% of $ sell trades > $50k out of total $ sell trades	532,432	0.13	0.25	0.00	0.00	0.00	0.14	1.00
Conditioning on Variable>0:								
% of $ buy trades > $50k out of total $ buy trades	171,528	0.46	0.27	0.00	0.22	0.44	0.69	1.00
% of $ sell trades > $50k out of total $ sell trades	157,891	0.45	0.28	0.01	0.21	0.42	0.68	1.00

Threshold: $100K

	N	Mean	Std Dev	Min	p25	p50	p75	Max
% of $ buy trades > $100k out of total $ buy trades	532,432	0.09	0.21	0.00	0.00	0.00	0.00	1.00
% of $ sell trades > $100k out of total $ sell trades	532,432	0.08	0.20	0.00	0.00	0.00	0.00	1.00
Conditioning on Variable>0:								
% of $ buy trades > $100k out of total $ buy trades	113,582	0.43	0.26	0.01	0.20	0.40	0.64	1.00
% of $ sell trades > $100k out of total $ sell trades	101,151	0.42	0.27	0.01	0.19	0.39	0.63	1.00

Table 2. End-of-Quarter Returns for High-Hedge-Fund-Ownership Stocks

The table reports results from OLS regressions in which the dependent variable is the daily percentage return adjusted using the DGTW approach. Four specifications are reported for which the dependent variables are the stock return on the second-to-last and last days of the quarter, and the first and second days of the following quarter, respectively. In Panel A, the explanatory variable is an indicator for stocks' hedge fund ownership (by quartile) for that same quarter. In Panel B, the explanatory variable is an indicator as to whether stocks' hedge fund ownership is above the median for that same quarter. *t*-statistics are reported in parentheses. Standard errors are clustered by date. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2000Q1 to 2010Q3.

Panel A: Regression on Hedge-Fund-Ownership Quartiles

	Dependent variable: DGTW adjusted return			
Day of the month:	last day - 1	last day	last day + 1	last day + 2
	(1)	(2)	(3)	(4)
HF ownership Q2 (low)	-0.012	0.044	-0.018	-0.019
	(-0.425)	(1.350)	(-0.626)	(-0.749)
HF ownership Q3	0.043	0.119**	-0.088*	-0.018
	(1.506)	(2.687)	(-1.984)	(-0.321)
HF ownership Q4 (high)	0.003	0.299***	-0.245***	-0.097
	(0.069)	(6.802)	(-4.175)	(-1.606)
Constant	-0.028	-0.092***	-0.033	-0.016
	(-1.379)	(-2.989)	(-1.218)	(-0.617)
Observations	128844	128841	122804	122802
Adjusted R^2	0.000	0.001	0.001	0.000

Panel B: Regression on Hedge-Fund-Ownership Halves

	Dependent variable: DGTW adjusted return			
Day of the month:	last day - 1	last day	last day + 1	last day + 2
	(1)	(2)	(3)	(4)
HF ownership (top half)	0.034	0.184***	-0.140***	-0.046
	(1.185)	(6.398)	(-3.440)	(-0.993)
Constant	-0.039**	-0.065**	-0.051**	-0.036
	(-2.684)	(-2.237)	(-2.059)	(-1.491)
Observations	126630	126627	122326	122324
Adjusted R^2	0.000	0.001	0.000	0.000

Table 3. End-of-Quarter Returns for High-Hedge-Fund-Ownership Stocks, by Quarter

The table reports results from OLS regressions in which the dependent variable is the daily percentage return adjusted using the DGTW approach. For each quarter, the dependent variable is the stock return on the last day of the quarter and the first day of the next quarter. The explanatory variable is an indicator for those stocks for which hedge fund ownership is above the median for that quarter. *t*-statistics are reported in parentheses. Standard errors are clustered by date. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2000Q1 to 2010Q3.

	Dependent variable: DGTW adjusted return							
Calendar quarter:	Q1		Q2		Q3		Q4	
Day of the quarter:	last day	last day + 1	last day	last day + 1	last day	last day + 1	last day	last day + 1
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HF ownership (top half)	0.141	-0.155*	0.185**	-0.280**	0.348***	-0.133	0.407***	-0.207**
	(1.808)	(-1.871)	(3.004)	(-2.395)	(4.673)	(-1.513)	(5.468)	(-2.766)
Constant	0.017	-0.141*	0.019	-0.067	-0.068	-0.125**	-0.076	0.015
	(0.498)	(-2.148)	(0.414)	(-1.705)	(-0.768)	(-2.415)	(-1.030)	(0.318)
Observations	32366	32172	31838	31657	31289	31062	31134	27435
Adjusted R^2	0.000	0.000	0.000	0.001	0.001	0.000	0.002	0.000

Table 4. Robustness of the Daily Return Analysis

The table reports results from OLS regressions in which the dependent variable is the daily percentage return adjusted using the DGTW approach. Four specifications are reported in which the dependent variables are the stock return on the second-to-last and last days of the quarter, and the first and second days of the following quarter. In Panels A and B, the dependent variable is the one- and two-month future returns relative to end-of-quarter ownership, respectively. The explanatory variable in Panels A and B is an indicator for stocks for which hedge fund ownership is above the median at the end of the quarter. In Panels C, D, and E, the dependent variable is the adjusted daily return at the turn of the quarter in which ownership is measured. In Panel C, the explanatory variables include: an indicator for stocks for which hedge fund ownership is above the median for that same quarter, an indicator for stocks with above-median ownership by high-flow hedge funds (which are in the top tercile of the flow distribution in the quarter), and the interaction between these two variables. In Panel D, the explanatory variables are two indicators for stocks for which mutual and hedge fund ownership are above the median for that same quarter, respectively. The explanatory variables in Panel E is an indicator for stocks for which hedge fund ownership is above the median at the end of the quarter, and the DGTW adjusted return of the first day of the month in which ownership is measured. *t*-statistics are reported in parentheses. Standard errors are clustered by date. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2000Q1 to 2010Q3.

Panel A: Regressions of One-Month Future Returns Around the Turn of the Quarter on Hedge Fund Ownership

	Dependent variable: DGTW adjusted return (t + 1)			
Day of the quarter:	last day - 1	last day	last day + 1	last day + 2
	(1)	(2)	(3)	(4)
HF ownership (top half)	-0.014	0.065**	-0.077**	-0.042
	(-0.318)	(2.113)	(-2.441)	(-1.392)
Constant	0.006	0.031	-0.000	0.009
	(0.363)	(1.668)	(-0.019)	(0.499)
Observations	130664	130108	130005	129975
Adjusted R^2	-0.000	0.000	0.000	0.000

Panel B: Regressions of Returns Around the Turn of the Month on Two-Month-Lagged Hedge Fund Ownership

	Dependent variable: DGTW adjusted return (t + 2)			
Day of the quarter:	last day - 1	last day	last day + 1	last day + 2
	(1)	(2)	(3)	(4)
HF ownership (top half)	-0.010	0.116***	0.036	-0.031
	(-0.338)	(3.793)	(0.853)	(-0.766)
Constant	0.015	0.024	0.012	0.006
	(0.721)	(1.622)	(0.580)	(0.352)
Observations	129970	129341	129249	129209
Adjusted R^2	-0.000	0.000	0.000	0.000

Table 4. Robustness of Daily Return Analysis (Cont.)

Panel C: Controlling for Stocks Owned by Companies with High Flows

	Dependent variable: DGTW adjusted return			
Day of the quarter:	last day - 1	last day	last day + 1	last day + 2
	(1)	(2)	(3)	(4)
HF ownership (top half)	0.083	0.244***	-0.207***	-0.110
	(1.289)	(4.715)	(-3.411)	(-1.151)
Ownership by high-inflow funds (top half)	0.072*	0.058	0.056	-0.017
	(1.814)	(1.386)	(1.305)	(-0.450)
HF ownership × ownership by high-inflow funds	-0.095	-0.102*	0.101*	0.109
	(-1.364)	(-1.796)	(1.708)	(1.145)
Constant	-0.073**	-0.101**	-0.088**	-0.028
	(-2.230)	(-2.116)	(-2.125)	(-0.756)
Observations	128871	128868	128349	128347
Adjusted R^2	0.000	0.001	0.001	0.000

Panel D: Controlling for Mutual Fund Ownership

	Dependent variable: DGTW adjusted return							
Day of the quarter:	last day - 1	last day	last day + 1	last day + 2	last day - 1	last day	last day + 1	last day + 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HF ownership (top half)					0.034	0.185***	-0.146***	-0.046
					(1.156)	(6.401)	(-3.390)	(-1.012)
MF ownership (top half)	0.106	-0.103	0.101	-0.016	0.106	-0.104	0.102	-0.016
	(1.620)	(-1.583)	(1.255)	(-0.172)	(1.615)	(-1.601)	(1.271)	(-0.167)
Constant	-0.091	0.095	-0.192**	-0.050	-0.108*	0.005	-0.122*	-0.027
	(-1.490)	(1.614)	(-2.524)	(-0.568)	(-1.980)	(0.085)	(-1.793)	(-0.360)
Observations	126630	126627	124066	124064	126630	126627	124066	124064
Adjusted R^2	0.000	0.000	0.000	-0.000	0.000	0.001	0.001	0.000

Panel E: Regressions of Returns Around the Turn of the Quarter on Hedge Fund Ownership, Controlling for Returns of the First Day of the Month

	Dependent variable: DGTW adjusted return			
Day of the quarter:	last day - 1	last day	last day + 1	last day + 2
	(1)	(2)	(3)	(4)
HF ownership (top half)	0.033	0.185***	-0.140***	-0.048
	(1.164)	(6.432)	(-3.436)	(-1.050)
First-day-of-the-month DGTW return	0.010	-0.011	0.013	-0.012
	(0.738)	(-1.055)	(1.125)	(-0.685)
Constant	-0.039**	-0.065**	-0.052**	-0.036
	(-2.642)	(-2.236)	(-2.080)	(-1.489)
Observations	126626	126623	122276	122324
Adjusted R^2	0.000	0.001	0.001	0.000

Table 5. Intraday Returns

The table reports results from OLS regressions in which the dependent variable is the percentage return in the relevant time interval for which we report the beginning time. We consider both thirty minute and ten minute intervals. We report results for four different days: the second-to-last and last days of the quarter, and the firs tand second days of the following quarter, respectively. The explanatory variable is an indicator for stocks for which hedge fund ownership is above the median for that same quarter. *t*-statistics are reported in parentheses. Standard errors are clustered by date. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2000Q1 to 2010Q3.

	Stock return (half an hour intervals)					Stock return (10 minute intervals)					
	9:30	11:30	13:30	14:00	14:30	15:00	15:10	15:20	15:30	15:40	15:50
Sample: Last day -1 (N = 139291)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
HF ownership (top half)	0.020	-0.001	0.018	-0.003	0.001	0.002	0.004	-0.001	0.002	0.008	0.016*
	(0.970)	(-0.138)	(1.394)	(-0.341)	(0.171)	(0.436)	(0.589)	(-0.116)	(0.279)	(0.945)	(1.919)
Constant	-0.160	-0.001	-0.080	0.013	0.010	-0.007	-0.036*	-0.013	0.018	0.039*	0.082**
	(-1.106)	(-0.041)	(-1.515)	(0.346)	(0.305)	(-0.375)	(-1.756)	(-0.506)	(1.052)	(1.955)	(2.639)
Sample: Last day (N = 139536)											
HF ownership (top half)	0.031*	0.009	0.009	0.014*	0.010	0.013***	0.010*	0.008	0.004	0.024**	0.073***
	(1.699)	(1.123)	(1.315)	(1.866)	(1.321)	(2.950)	(1.824)	(1.502)	(0.537)	(2.703)	(8.172)
Constant	-0.072	0.030	0.055**	0.030	0.044	-0.044*	-0.017	-0.017	-0.037	-0.020	-0.020
	(-0.802)	(1.198)	(2.125)	(1.045)	(1.469)	(-1.975)	(-0.736)	(-0.774)	(-1.248)	(-0.739)	(-0.804)
Sample: First day (N = 135010)											
HF ownership (top half)	-0.076***	0.001	-0.011*	-0.018***	-0.011	0.003	-0.006	-0.011**	-0.009	-0.003	0.014*
	(-2.896)	(0.146)	(-1.732)	(-2.897)	(-1.276)	(0.395)	(-0.915)	(-2.134)	(-1.573)	(-0.548)	(1.997)
Constant	-0.102	0.005	0.002	0.019	-0.030	-0.024	-0.007	0.008	0.011	0.006	0.060**
	(-1.027)	(0.190)	(0.069)	(0.527)	(-0.809)	(-0.854)	(-0.523)	(0.496)	(0.464)	(0.362)	(2.464)
Sample: Second day (N = 134942)											
HF ownership (top half)	-0.022	-0.013	0.022	0.009	-0.010	0.005	0.004	0.001	0.007	0.001	0.017**
	(-0.690)	(-0.899)	(1.241)	(0.775)	(-0.834)	(0.967)	(1.028)	(0.084)	(1.171)	(0.229)	(2.265)
Constant	-0.167	-0.040	0.069*	-0.035	-0.047	-0.018	-0.021	-0.023	-0.007	-0.013	0.036
	(-1.178)	(-0.675)	(1.962)	(-0.768)	(-1.623)	(-0.945)	(-0.982)	(-0.857)	(-0.299)	(-0.665)	(1.602)

Table 6. Large Transactions at the End of the Quarter

The table reports results from OLS regressions in which the dependent variable is the percentage of shares traded in large transactions in the last 10 minutes of the days around the turn of the quarter (last day -1, last day, last day +1, last day +2). In Panel A, large transactions are defined as transactions greater than \$50,000. In Panel B, large transactions are defined as transactions greater than \$100,000. *I(Top HF ownership quartile)* is an indicator as to whether the stock was at the top hedge-fund-ownership quartile at the end of the quarter. *I(lag(Top HF ownership quartile))* is an indicator as to whether the stock was at the top hedge-fund-ownership quartile at the previous end of the quarter. *Last day* is an indicator as to whether the day is the last day of the quarter. *t*-statistics are reported in parentheses. All regressions include stock fixed effects and date fixed effects. Standard errors are clustered by date. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2000Q1 to 2010Q3.

Panel A: Transactions >\$50,000

	% of \$ buy trades > \$50k out of total \$ buy trades					% of \$ sell trades > \$50k out of total \$ sell trades					
	last day - 1	last day	last day + 1	last day + 2	All	last day - 1	last day	last day + 1	last day + 2	All	Buys-Sales
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
I(Top HF ownership quartile)	0.022***	0.030***	0.022***	0.023***	0.022***	0.026***	0.025***	0.022***	0.026***	0.025***	-0.002**
	(8.149)	(9.342)	(8.363)	(10.047)	(15.280)	(7.910)	(9.742)	(9.187)	(9.040)	(14.899)	(-2.364)
× Last day					0.007**					0.001	0.007***
					(2.165)					(0.264)	(2.960)
Stock characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	135,775	137,516	128,749	128,656	530,696	135,775	137,516	128,749	128,656	530,696	530,696
Adjusted R^2	0.263	0.282	0.271	0.267	0.272	0.224	0.263	0.238	0.240	0.242	0.005
I(lag(Top HF ownership quartile))	0.018***	0.026***	0.017***	0.018***	0.018***	0.021***	0.022***	0.018***	0.019***	0.020***	-0.002*
	(8.233)	(8.699)	(7.506)	(9.968)	(14.674)	(6.896)	(8.451)	(7.658)	(8.512)	(13.056)	(-1.850)
× Last day					0.008**					0.002	0.006**
					(2.524)					(0.717)	(2.510)
Stock characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124,984	126,374	118,347	118,235	487,940	124,984	126,374	118,347	118,235	487,940	487,940
Adjusted R^2	0.353	0.364	0.356	0.348	0.357	0.309	0.350	0.325	0.324	0.328	0.006

Table 6. Large Transactions at the End of the Quarter (Cont.)

Panel B: Transactions >$100,000

	% of $ buy trades > $100k out of total $ buy trades					% of $ sell trades > $100k out of total $ sell trades					
	last day - 1	last day	last day + 1	last day + 2	All	last day - 1	last day	last day + 1	last day + 2	All	Buys-Sales
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
I(Top HF ownership quartile)	0.015***	0.023***	0.015***	0.016***	0.015***	0.018***	0.019***	0.016***	0.018***	0.017***	-0.002**
	(7.874)	(8.338)	(7.025)	(8.960)	(13.775)	(8.263)	(8.159)	(8.301)	(7.841)	(14.087)	(-2.303)
× Last day					0.008***					0.002	0.006***
					(2.615)					(0.683)	(2.791)
Stock characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	135,775	137,516	128,749	128,656	530,696	135,775	137,516	128,749	128,656	530,696	530,696
Adjusted R^2	0.263	0.282	0.271	0.267	0.272	0.224	0.263	0.238	0.240	0.242	0.006
I(lag(Top HF ownership quartile))	0.013***	0.021***	0.012***	0.014***	0.013***	0.016***	0.017***	0.013***	0.013***	0.014***	-0.001*
	(7.254)	(7.734)	(5.893)	(8.216)	(12.282)	(6.427)	(8.105)	(6.783)	(8.147)	(11.880)	(-1.685)
× Last day					0.008***					0.003	0.005**
					(2.740)					(1.134)	(2.589)
Stock characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124,984	126,374	118,347	118,235	487,940	124,984	126,374	118,347	118,235	487,940	487,940
Adjusted R^2	0.265	0.282	0.269	0.268	0.273	0.225	0.264	0.237	0.240	0.243	0.006

Table 7. Stock-Level Incentives to Manipulate

The table reports results from OLS regressions in which the dependent variable is the daily percentage return adjusted using the DGTW approach. The stock returns are measured on the second-to-last and last days of the quarter, and the first and second days of the following quarter, respectively. The explanatory variables are indicators for above-median hedge fund ownership, above-median market capitalization, above-median Amihud (2002) price impact measure, and interactions. *t*-statistics are reported in parentheses. Standard errors are clustered by date. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2000Q1 to 2010Q3.

	Dependent variable: DGTW adjusted return			
Day of the month:	last day - 1	last day	last day + 1	last day + 2
	(1)	(2)	(3)	(4)
High HF ownership (top half)	0.096	0.089	-0.122	0.016
	(1.289)	(1.311)	(-1.528)	(0.263)
× High mkt cap	-0.100	0.004	0.055	-0.052
	(-1.267)	(0.055)	(0.669)	(-0.712)
× High Amihud	-0.007	0.174**	-0.077	-0.073
	(-0.089)	(2.319)	(-0.926)	(-1.054)
High mkt cap (top half)	0.162**	-0.082	0.225**	0.077
	(2.249)	(-0.909)	(2.292)	(1.016)
High Amihud (top half)	0.025	-0.064	0.144*	0.095
	(0.366)	(-0.727)	(1.817)	(1.352)
Constant	-0.137**	0.005	-0.237***	-0.111*
	(-2.027)	(0.052)	(-2.777)	(-1.715)
Observations	125857	125854	122799	122797
Adjusted R^2	0.000	0.001	0.001	0.000

Table 8. Company-Level Evidence of Abnormal Month-End Returns

The table reports the average market-adjusted daily returns for long-equity portfolios held at quarter-ends by hedge fund management companies. *Adj ret (last day)* is the market-adjusted return of this portfolio on the last trading day of the quarter; *Adj ret (last day - 1)* and (*Adj ret (last day* + 1*)*) are the returns of the same portfolio on the next (previous) trading day. *Adj Blip* is defined at the fund level as the difference between *Adj ret (last day)* and *Adj ret (last day* + 1*)*. The universe is all management companies in TASS for 2000Q1 to 2010Q3 with a match to 13F filings. *t*-statistics are reported in parentheses and are based on date-clustered standard errors.

	Average market-adjusted returns				
	All	March	June	September	December
	(1)	(2)	(3)	(4)	(5)
Adj ret(last day - 1)	0.13%	0.11%	0.15%	0.15%	0.11%
	(3.85)	(2.09)	(2.21)	(2.64)	(1.21)
Adj ret(last day)	0.31%	0.31%	0.33%	0.31%	0.30%
	(6.07)	(4.46)	(2.32)	(3.38)	(2.71)
Adj ret(last day + 1)	-0.20%	-0.19%	-0.26%	-0.26%	-0.12%
	(-3.28)	(-1.24)	(-2.20)	(-1.77)	(-1.21)
Adj Blip = Adj ret(last day) - Adj ret(last day + 1)	0.52%	0.50%	0.59%	0.55%	0.44%
	(5.38)	(2.58)	(2.43)	(2.80)	(2.83)

Table 9. Company-Level Incentives to Manipulate

The table explores the link between hedge fund manipulation and incentives with OLS regressions. The universe is all management companies in TASS for 2000Q1 to 2010Q3 with a match to 13F filings. The dependent variable in Columns (1) to (4) of Panel A and in Panel B is *Blip/volatility*, which is defined for each company quarter as the difference between *ret(last day)* and *ret(last day* + 1*)* divided by the daily volatility of the portfolio over the quarter. The dependent variable in Columns (5) to (8) of Panel A is *ret(last day of quarter)*, which is the quarter-end daily returns of the company's long-equity portfolio (based on holdings reported in 13F). *ret(last day)* is the return of this portfolio on the last trading day of the quarter and *ret(last day* + 1*)* is the return of the same portfolio on the next trading day. The explanatory variables are: the log of assets under management reported to TASS by the management company (*log(AUM)*), the log of the number of stocks reported in the 13F (*log(# Stocks in equity portfolio)*), asset net flows as a percentage of lagged AUM (*Fund flows / lag(AUM) (%)*), a dummy variable (*I(Bad month)*) as to whether the current month's performance is below -2%, and the YTD performance (as of quarter-end) by quintiles (*YTD performance quintile X*). In Panel B, year-to-date performance is interacted with three characteristics: whether the company's age is below the median (dummy *Young*), whether the YTD performance of the company as of the last quarter was in the lower two quintiles (dummy *Low reputation*) and whether the current quarter ends in March (dummy *March*). *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the company level and time fixed effects are included.

Panel A: Incentives to Manipulate

Dependent Variable:	Blip/volatility				ret(last day of quarter)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(AUM)	-0.001	0.000	-0.001	-0.003	-0.024*	-0.023*	-0.025**	-0.026*
	(-0.083)	(0.043)	(-0.146)	(-0.231)	(-1.929)	(-1.826)	(-2.038)	(-1.766)
log(# Stocks in equity portfolio)	-0.030**	-0.031**	-0.028**	-0.030**	-0.041**	-0.042**	-0.038**	-0.040**
	(-2.126)	(-2.239)	(-2.026)	(-1.975)	(-2.334)	(-2.372)	(-2.133)	(-2.146)
Flows / lag(AUM) (%)				0.281				-0.002
				(0.841)				(-0.007)
I(Bad month)		0.062	0.082**	0.086**		0.161***	0.189***	0.211***
		(1.594)	(2.173)	(2.123)		(3.076)	(3.653)	(3.663)
YTD performance Q2 (low)	0.017		0.033	0.020	-0.032		0.004	0.017
	(0.485)		(0.976)	(0.563)	(-0.790)		(0.110)	(0.394)
YTD performance Q3	-0.015		0.005	0.003	-0.041		0.005	0.025
	(-0.433)		(0.157)	(0.078)	(-0.984)		(0.125)	(0.576)
YTD performance Q4	0.017		0.038	0.015	0.014		0.063	0.071
	(0.475)		(1.097)	(0.399)	(0.320)		(1.544)	(1.593)
YTD performance Q5 (High)	0.083**		0.104***	0.095**	0.090**		0.139***	0.162***
	(2.060)		(2.638)	(2.198)	(2.030)		(3.212)	(3.403)
Calendar quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,598	6,598	6,598	5,710	6,598	6,598	6,598	5,710
Adjusted R^2	0.702	0.702	0.702	0.700	0.549	0.549	0.550	0.542

Table 9. Company-Level Incentives to Manipulate (Cont.)

Panel B: Magnifying Factors for Performance Incentive

	Dependent Variable: Blip/volatility		
Interaction characteristic:	*Low reputation*	*Young*	*March*
	(1)	(2)	(3)
log(AUM)	-0.001	-0.003	-0.001
	(-0.109)	(-0.261)	(-0.116)
log(# Stocks in equity portfolio)	-0.030*	-0.030*	-0.031**
	(-1.898)	(-1.965)	(-2.056)
Flows / lag(AUM) (%)	0.193	0.302	0.293
	(0.571)	(0.911)	(0.876)
I(Bad month)	0.093**	0.088**	0.095**
	(2.219)	(2.160)	(2.350)
Characteristic	-0.047	-0.074	
	(-0.749)	(-1.375)	
YTD performance Q2 (low)	0.004	-0.024	0.028
	(0.063)	(-0.461)	(0.644)
YTD performance Q3	-0.028	-0.007	-0.024
	(-0.461)	(-0.133)	(-0.579)
YTD performance Q4	-0.006	0.024	-0.011
	(-0.099)	(0.469)	(-0.250)
YTD performance Q5 (High)	0.043	0.009	0.038
	(0.687)	(0.162)	(0.823)
Characteristic × YTD performance Q2 (low)	0.005	0.090	-0.021
	(0.064)	(1.290)	(-0.268)
Characteristic × YTD performance Q3	0.049	0.019	0.106
	(0.680)	(0.273)	(1.459)
Characteristic × YTD performance Q4	0.075	-0.018	0.106
	(0.859)	(-0.260)	(1.357)
Characteristic × YTD performance Q5 (High)	0.251**	0.177**	0.222***
	(2.339)	(2.390)	(3.126)
Calendar quarter FE	Yes	Yes	Yes
Observations	5,354	5,710	5,710
Adjusted R^2	0.708	0.700	0.700

Table 10. Discontinuity at Zero in the Distribution of Companies' Total Returns

The table presents a discontinuity analysis of monthly hedge fund management company returns around zero. The dependent variable is the density in a return bin. Bins are defined over a 20 bps range: e.g., Bin 0 is the number of management companies that reported aggregate monthly returns between 0.00% and 0.20%, Bin 1 is the number of companies that reported aggregate monthly returns between 0.21% and 0.40%, etc. The number of bins is given in the panels. The return distributions are for *High Blip* companies and for *Non High Blip* companies. *High Blip* is an indicator as to whether the company-level volatility-adjusted blip (Blip/Volatility) of the company's long-equity portfolio is in the top decile for that quarter. Panel A includes all mangers. Panel B focuses on long/short equity managers. The independent variables include an indicator as to whether the bins contain positive returns and whether the companies in the bin are of the *High Blip* type, and an interaction between the two. All regressions include two sets of 3rd degree polynomials: one set for positive bins and one set for negative bins. *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. We use robust standard errors.

Panel A: All Management Companies

Dependent variable:	Density in bins		
Sample:	High blip	Non-high blip	All companies
	(1)	(2)	(3)
Positive returns ($I(i \geq 0)$)	0.022***	0.008**	0.008**
	(4.544)	(2.549)	(2.549)
High blip company			-0.016***
			(-4.085)
High blip company × Positive returns ($I(i \geq 0)$)			0.014**
			(2.473)
Bin range	[-20, 19]	[-20, 19]	[-20, 19]
Polynomial degree	3rd	3rd	3rd
Observations	40	40	80
Adjusted R^2	0.752	0.962	0.870

Panel B: Long-Short Equity Management Companies

Dependent variable:	Density in bins		
Sample:	High blip	Non-high blip	All companies
	(1)	(2)	(3)
Positive returns (I(i ≥ 0))	0.019**	-0.003	-0.003
	(2.737)	(-0.968)	(-0.968)
High blip company			-0.008
			(-1.127)
High blip company × Positive returns (I(i ≥ 0))			0.022***
			(2.903)
Bin range	[-15, 14]	[-15, 14]	[-15, 14]
Polynomial degree	3rd	3rd	3rd
Observations	30	30	60
Adjusted R^2	0.316	0.838	0.537

Table 11. Stock Price Manipulation and Market Direction

The table reports OLS regressions of the cross-sectional average of quarter-end "blips" of hedge fund management companies' long-equity portfolios. Specifically, the dependent variable is the average across companies at a given quarter-end of *AdjBlip* and *AdjBlip/volatility*. These variables are constructed for all management companies in TASS for 2000Q1 to 2010Q3 with a match to 13F filings in the following manner: *Adj ret (last day)* is the market-adjusted return of the company's long-equity portfolio on the last trading day of the quarter and *Adj ret (last day* – 1*)* (*Adj ret (last day* + 1*)*) is the return of the same portfolio on the previous (next) trading day. *Adj Blip* is defined at the company level as the difference between *Adj ret (last day)* and *Adj ret (last day* + 1*)*. The variable on the right hand side, *Quarterly market return*, is the value-weighted market portfolio over the last quarter and *I(Market return below median)* is a dummy equal to one if the market portfolio's performance is below its median in the sample period (1.06%). *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Adj. Blip		Adj. Blip/volatility	
	(1)	(2)	(3)	(4)
Quarterly market return	-0.063***		-2.665**	
	(-2.786)		(-2.419)	
I(Market return below median)		0.004**		0.226**
		(2.103)		(2.305)
Constant	0.006***	0.004**	0.305***	0.200***
	(5.678)	(2.536)	(6.241)	(2.916)
Observations	39	39	39	39
Adjusted R^2	0.151	0.083	0.113	0.102

Table 12. Autocorrelation of Quarter-End Blips

The table reports company-level OLS regressions. The dependent variable, *Blip/Volatility*, is defined for each company quarter as the difference between *ret(last day)* and *ret(last day* + 1*)* divided by the daily volatility of the portfolio over the quarter. *ret(last day)* is the return of the management company's long-equity portfolio on the last trading day of the quarter; *ret(last day* + 1*)* is the return of the same portfolio on the next trading day. *Lag(Blip/volatility)* is defined for each company as last quarter's measure of *Blip/volatility*. The universe is all management companies in TASS for 2000Q1 to 2010Q3 for which the 13F filing is available. *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the date level and time fixed effects are included.

	Dependent Variable: Blip/volatility		
	(1)	(2)	(3)
lag(Blip/volatility)	0.123***	0.120***	0.113***
	(11.925)	(11.509)	(6.753)
log(AUM)		-0.005	-0.005
		(-0.976)	(-0.557)
log(# Stocks in equity portfolio)		-0.030***	-0.026**
		(-4.101)	(-2.129)
I(Bad month)			0.092**
			(2.512)
YTD performance Q2 (low)			0.029
			(0.871)
YTD performance Q3			0.013
			(0.412)
YTD performance Q4			0.050
			(1.460)
YTD performance Q5 (High)			0.085**
			(2.272)
Calendar quarter FE	Yes	Yes	Yes
Observations	19,799	19,799	6,130
Adjusted R^2	0.704	0.704	0.713

Figure 1. Intraday Trading Statistics around the Turn of the Quarter

The figure reports trading statistics for the difference between two groups of stocks: stocks that have above-median hedge fund ownership and those with below-median hedge fund ownership. Figure 1a shows intraday cumulative returns over the second-to-last day of the quarter, the last day of the quarter, the first day of the following quarter, and the second day of the following quarter. Figure 1b shows the spread in intraday turnover (as the fraction of shares outstanding in %) between high and low hedge fund ownership relative to the spread in a benchmark day. The benchmark day for the last day is the second-to-last day of the quarter. The benchmark for the first day of the following quarter is the second day of the following quarter. Figure 1c shows the intraday buy-sell order imbalance over the same four days. Note that the scale of the horizontal axis is defined as follows: thirty-minute intervals up to 15:00; ten-minute intervals afterwards. The mean is presented in solid line, two-standard error bands are presented in dashed lines. The sample period is 2000Q1 to 2010Q3.

Figure 1a: High – Low-Hedge-Fund-Ownership Cumulative Returns

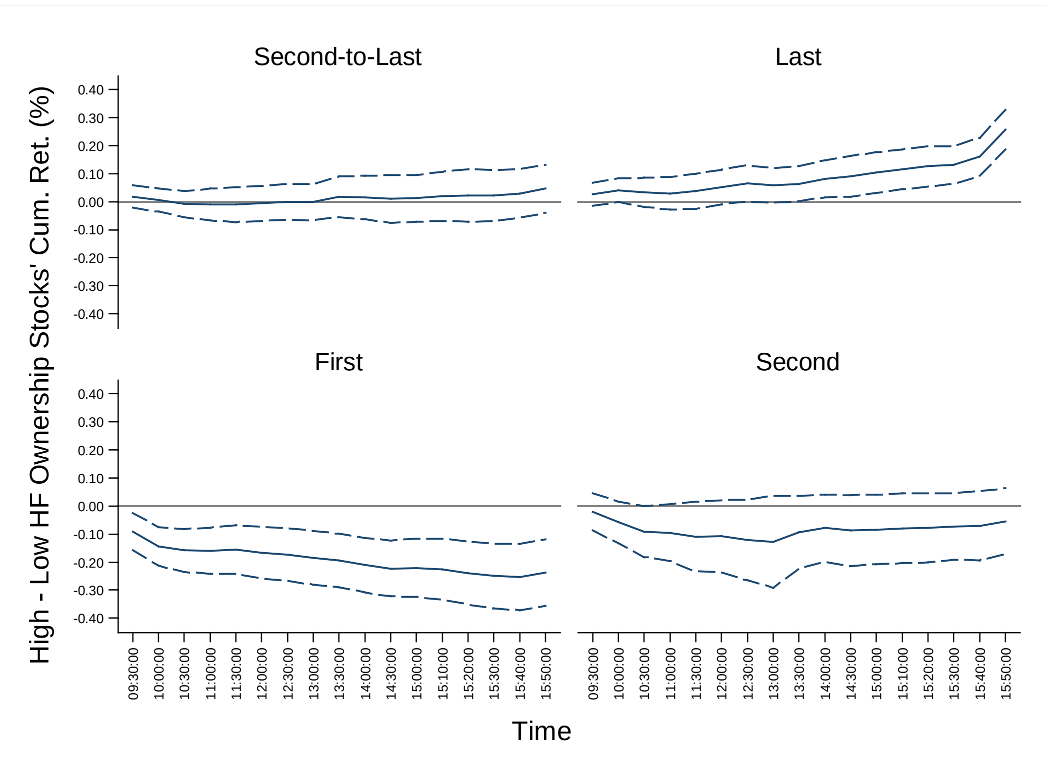


Figure 1. Intraday Trading Statistics around the Turn of Quarter (Cont.)

Figure 1b: High – Low Hedge-Fund-Ownership Turnover

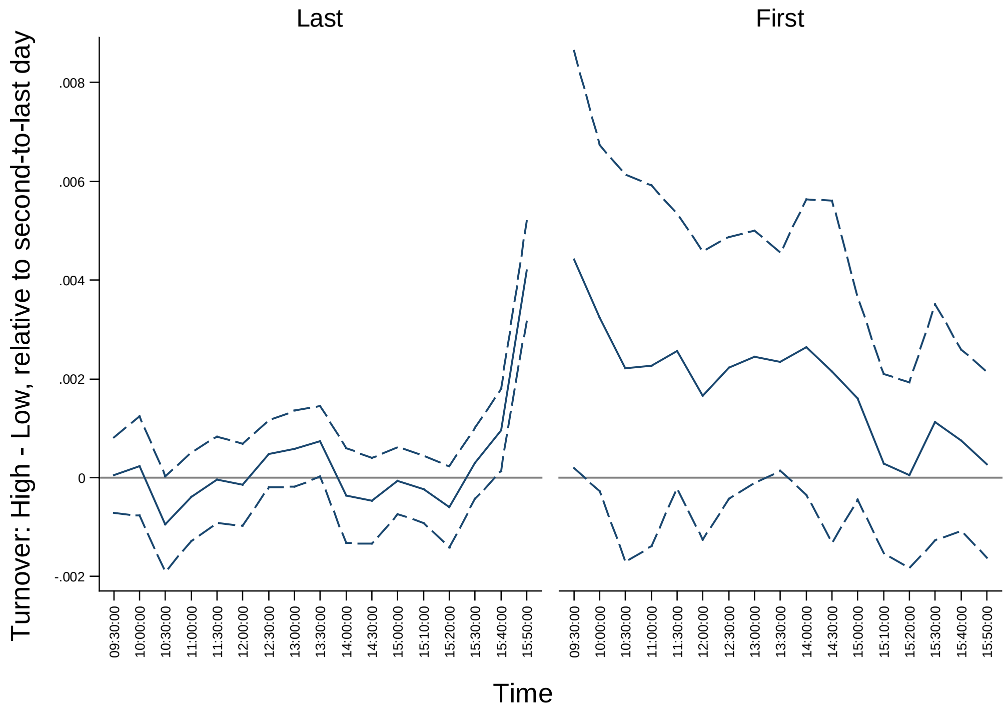


Figure 1c: High – Low Hedge-Fund-Ownership Buy-Sell Order Imbalance

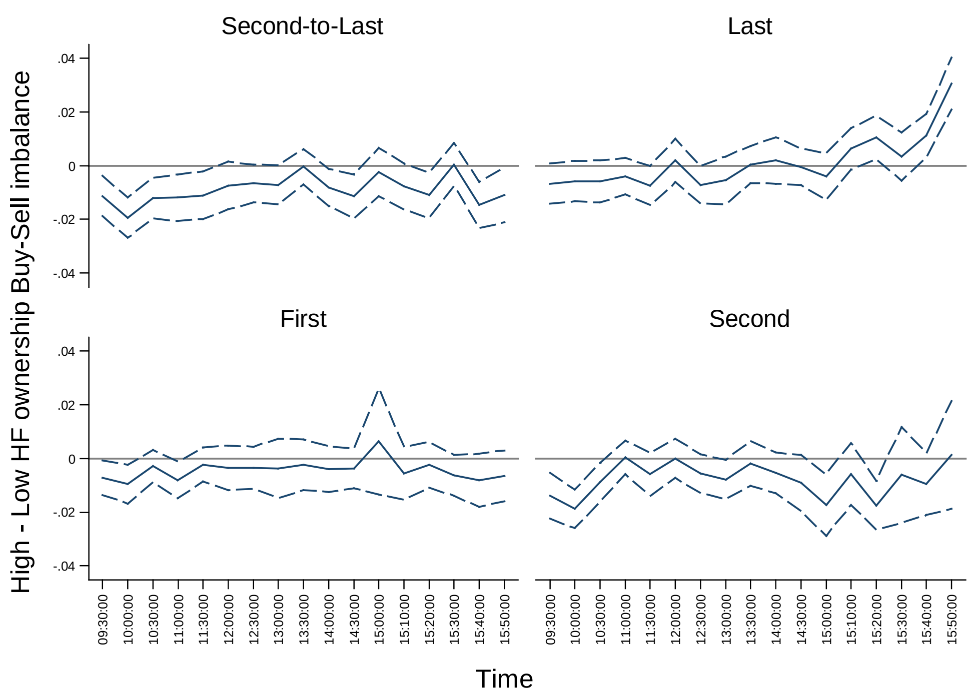


Figure 2. Monthly Return Distributions for High-Blip and Non-High-Blip Managers

The figure presents the distribution of monthly total returns observed at quarter-end months for hedge fund management companies that are classified as high blip vs. non-high blip. *High Blip* is an indicator as to whether the company-level volatility-adjusted blip (Blip/Volatility) of the company's long-equity portfolio is in the top decile for that quarter. The curve represents an estimated polynomial interpolation such as the one estimated in Table 10; the bars correspond to a realized histogram of monthly returns. The sample period is 2000Q1 to 2010Q3.

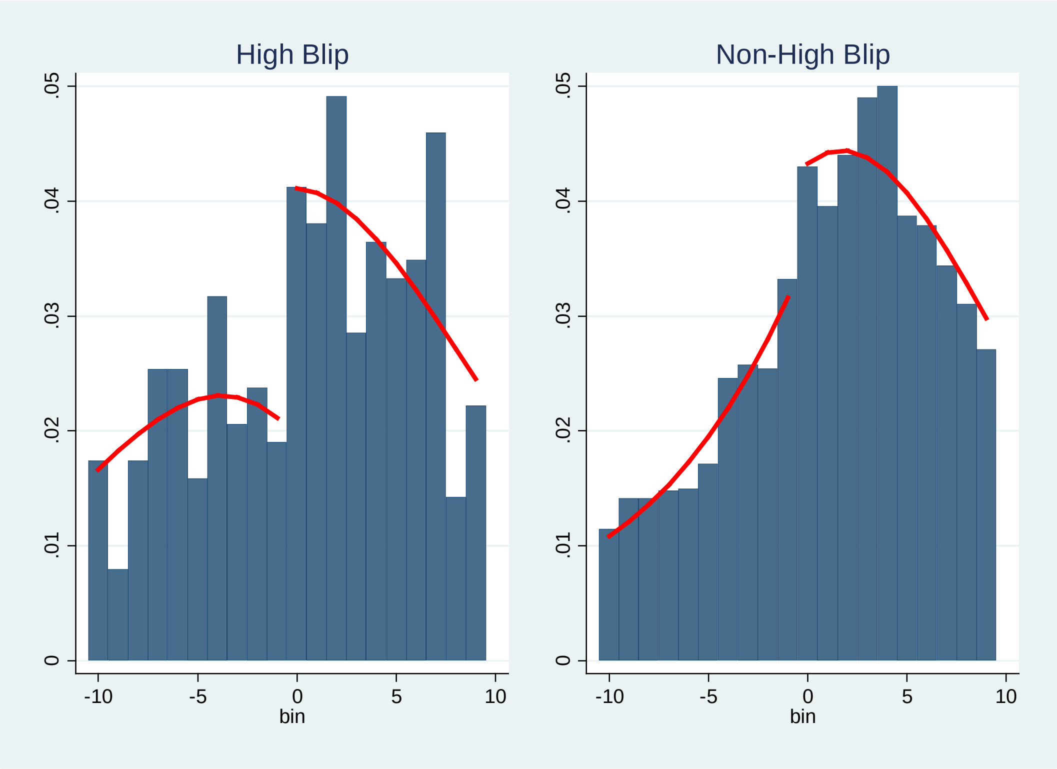


Figure 3. Time-Series of the Returns on the Last Day of the Quarter

The chart presents the time-series average adjusted returns for stocks with high and low ownership by hedge funds. Adjustment is made using the DGTW approach. The sample period is 2000Q1 to 2010Q3.

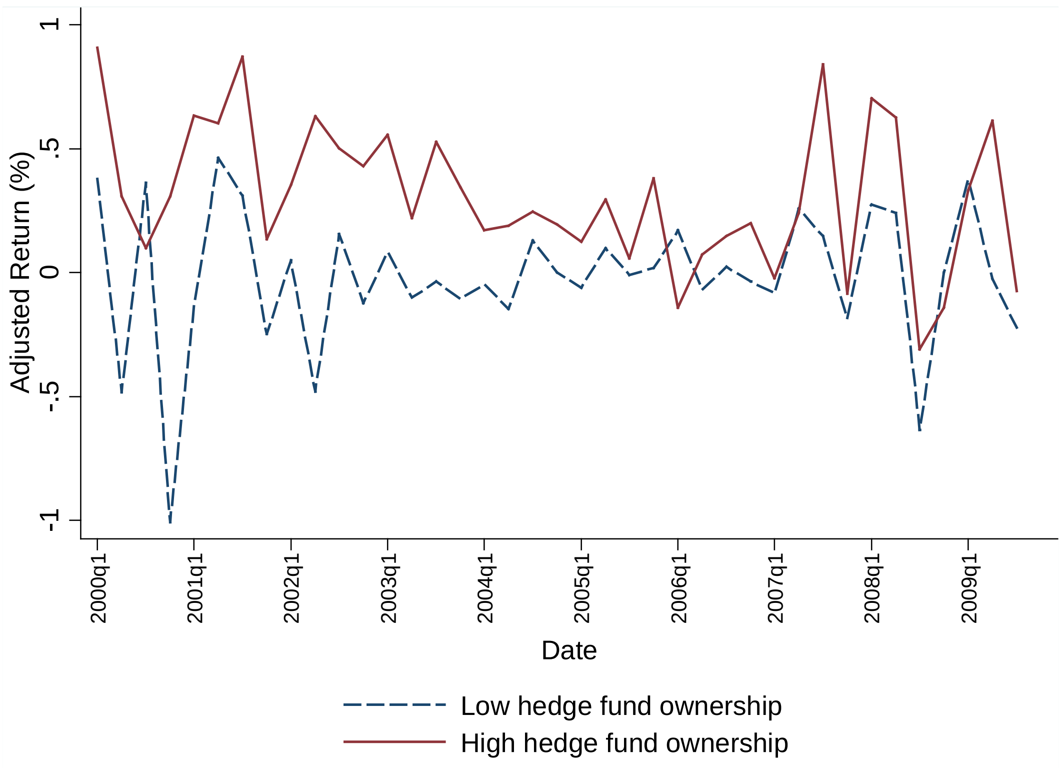
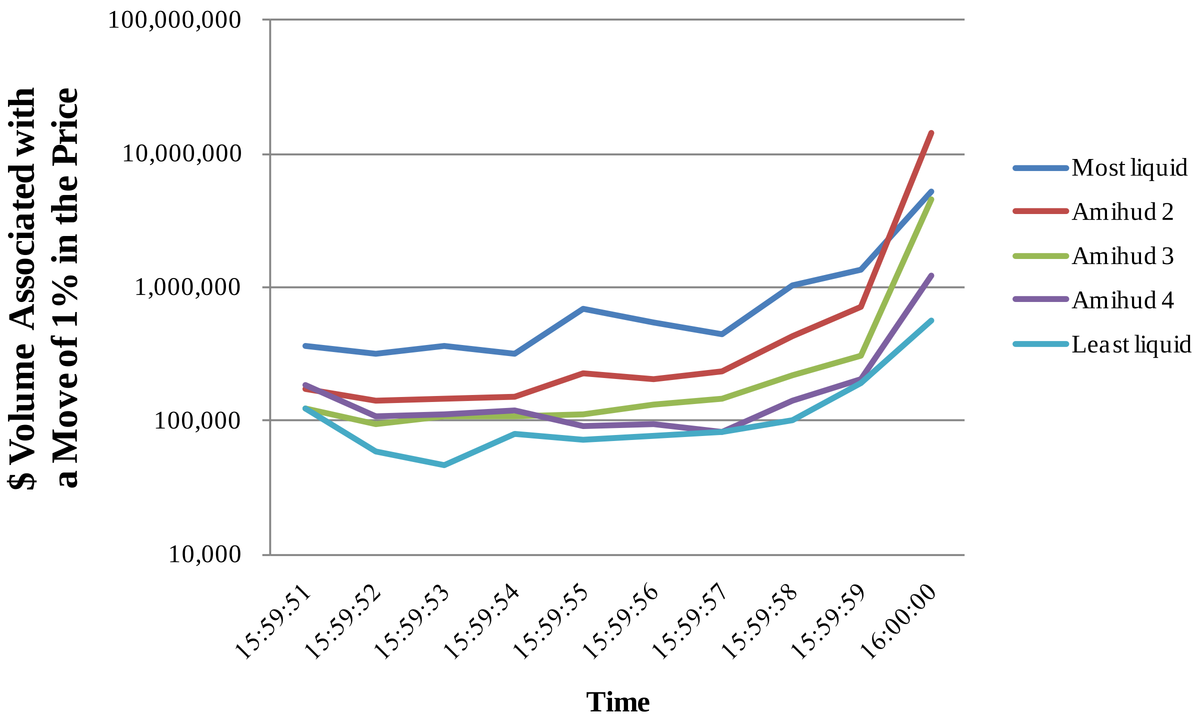


Figure 4. Blip and Market Returns

The figure shows the average adjusted blip for hedge fund management companies (last-day-of-the-month returns on the long-equity portfolio minus the first day-of-the-month returns on the same portfolio, adjusted for market returns) for each quarter-end as a function of monthly stock market returns, in the last month of the quarter. The sample period is 2000Q1 to 2010Q3. The straight line is a linear fit and the shaded area is the corresponding 95% confidence interval.

Figure 5. Dollar Volume Needed to Move the Price by 1%

The figure reports the inverse of the slope from regressions of returns (in percent) on signed dollar volume. The regressions are run for each quintile of stocks sorted on the lagged Amihud (2002) liquidity measure, for each second of the last 10 seconds of the trading day. Only the last days of the month are included for all months from January 2000 through December 2009. The reported series can be interpreted as the dollar amount associated with a one-percent move in the price.



Internet Appendix for "Do Hedge Funds Manipulate Stock Prices?"*

Itzhak Ben-David, Francesco Franzoni, Augustin Landier, Rabih Moussawi

In this Internet Appendix, we report additional tests to buttress the main analysis carried out in the paper.

1. Do Manipulating Management Companies Have Higher Total Returns?

In Appendix Table 1, we provide an additional robustness analysis to Table 9 (in the paper). The purpose of the test is to verify that hedge fund management companies that show a pattern consistent with manipulating their equity returns also exhibit higher total returns (as reported in TASS). In Appendix Table 1, we regress management companies' total returns (which result from aggregating TASS returns at the company level) on an indicator of the company being in the top 10% of the blip distribution, as well as controls. We find that the companies at the top of the blip distribution indeed have a higher monthly return (by 30 bps). The coefficient on *High Blip* is significant after controlling for the company's incentives to manipulate. This is to be expected as incentives to manipulate are correlated with a lower performance. In other words, the managers with a lower performance in a given month tend to manipulate (see Table 9) at the month end. We include the controls used in Table 9, Panel A, to control for incentives. We also show that controlling for "I(Bad month)" (a dummy equal to 1 if the month's returns are below -2%) is enough for the coefficient on *High Blip* to be significant.

These results support our argument that hedge funds distort equity prices in order to boost the return that they report to investors. In particular, since long-equity portfolios are only a fraction of the total portfolios held by these management companies, it is reassuring to see that the blip measured on the long-equity portfolios does have a significant impact on the total company returns.

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2. Discontinuity at Zero for Total Returns: Robustness

We provide a robustness test for the discontinuity analysis in Table 10. In Appendix Table 2, we vary the polynomial degree and the number of bins used in the analysis. In Column (1), we repeat the analysis from Table 9 in the paper, but use a 2nd degree polynomial instead of the 3rd degree polynomial used in the paper. In this column, we also use a narrower band: only 20 bins (instead of the 40 in the paper). In Columns (2) and (3), we experiment with other variations: 20 bins and a 3rd degree polynomial (Column (2)) and 30 bins and a 3rd degree polynomial (Column (3)).

Overall, the findings are consistent with the results reported in the paper. All specifications report a discontinuity in the density of return observations at zero. There is a greater number of return observations in positive bins than there is in negative bins; this effect is concentrated among hedge fund management companies with a high blip indicator (the top 10% of hedge fund management companies).

3. Hedge Fund Management Companies' Adjusted Blip and Performance

In Section 5.4 of the paper, we explore alternative explanations for the results that show a relation between management companies' adjusted blip and the YTD performance. The concern we address is that the relation between these variables might come from a reverse causal relationship, in which the high blips are themselves the cause of the high YTD performance. Note that the endogeneity of the YTD performance only occurs if the current-month manipulation affects the current-month relative performance. Hence, the endogeneity concern can be addressed by including in the regression the management company's relative performance for the current month.

In Appendix Table 3, we include quintile dummies as controls for the company performance. The regression shows that after controlling for these variables, the relation between the adjusted blip measure and the YTD performance variables remains as strong as it is in Table 9 of the paper.

Hence, we conclude that the relation between the adjusted blip and YTD performance is not driven by reverse causality.

4. Alternative Tests of Return Discontinuity around Zero

We perform an additional test for the discontinuity around zero returns, following the methodology developed in Bollen and Pool (2009). The idea is to first estimate a smooth kernel density (under the null that the density is smooth) and then look at whether the realized frequencies around zero are statistically compatible with the distribution being that kernel density. We apply the Bollen and Pool technique to both the sample of "High Blip" observations and "Non High Blip" observations. A critical parameter to pick to apply this smoothness test is the bandwidth of the kernel density estimation. Following Silverman (1986) and Bollen and Pool (2009), we set a bandwidth that equals to: $\times 1.364 \times \min\left(\sigma, \frac{Q}{1.34}\right) N^{-1/5}$, where σ is the empirical standard deviation of returns, Q is the interquartile range, N is the number of observations and α is a scalar set to be 0.776, corresponding to a normal distribution. In our data, $\sigma = 0.044, Q = 0.028$. The number of observations is N=631 for the High Blip sample, which yield a recommended bandwidth of 62 bps, which we round to 60 bps for simplicity. We also use this bandwidth for the High Blip sample, to be able to compare the histograms and kernel densities of both samples. This bandwidth is higher than that from the Bollen and Pool (2009) sample, due to the lower number of observation in our sample. As recommended by Bollen and Pool (2009), the bin size for the histogram estimates used in the test is identical to that of the kernel bandwidth and we use Gaussian kernel functions.

The test consists of checking that the frequency in Bin 0 (resp. Bin -1), which corresponds to returns falling in the $[0, 60bps)$ returns bracket (resp. $[-60bps, 0)$), is statistically significantly higher (resp. lower) than the kernel density estimate. This test allows establishing that some funds artificially "transform" some small negative returns (Bin -1) into small positive returns (Bin 0). The frequency of observations observed in a given bin interval is distributed around the integral of the density function estimate over that interval (p) with asymptotic standard deviation $\sqrt{\frac{p(1-p)}{N}}$ (see Bollen and Pool (2009), p. 2269). This allows us to draw the histogram and the predicted histogram with its 95% confidence interval. The test consists in checking whether the observed histogram is out of the confidence interval for the predicted histogram.

We reproduce the corresponding graph and present it in the Internet Appendix Figure 1a. In both the High Blip and Non High Blip samples, we observe that Bin 0 (the $[0, 60) bps\ returns$) is significantly abnormally high. Graphically, the anomaly looks bigger for the High Blip sample, but the significance of the kernel frequency estimate is also lower due to the smaller sample size. The t-stats for the discontinuity test can be computed using the formula $(freq - p)/\sqrt{p(1-p)/N}$, where $freq$ is the empirical frequency (the blue bar in the histogram) and p is (as before) the integral of the estimated kernel density over the bin's interval. We find the following *t*-stats:

t-stat	Non High Blip	High Blip
Bin -1	-1.45	-1.83*
Bin 0	3.11***	2.49**

The *t*-stats show that, as expected, for high-blip bins, Bin -1 is negative and statistically significant; Bin 0 is positive and statistically significant. These results are consistent with the idea that Bin 0 has a higher concentration of returns for the high-blip hedge fund management companies. For the non-high blip hedge fund management companies, there is also a jump at Bin 0, and it is statistically significant on the positive side. We note, however, that the number of observations for the non-high blip group is higher by a factor of 9 (high blip are the funds with the top 10% of BlipVol).

Next, we apply the same analysis to long-short equity funds. This analysis is interesting since long-short equity funds hold liquid assets and therefore cannot engage in misreporting of valuation, such are sometimes performed with illiquid assets (which could potentially explain the findings of Getmansky, Lo, and Makarov 2004). Figure 1b of the Internet Appendix presents a histogram of the returns and the predicted values. The results of the test are as follows:

t-stat	Non High Blip	High Blip
Bin -1	0.13	-0.23
Bin 0	0.47	2.14*

These findings confirm the result from the paper that for this category of funds, the discontinuity at zero is only significant for "High Blip" funds. This suggests that portfolio pumping is one of the only means of manipulation available to these funds.

All in all, using the Bollen and Pool (2009) discontinuity test confirms that (1) both High Blip and Non High Blip funds have a significant discontinuity at zero, (2) the discontinuity is larger in level for High Blip funds, and (3) within long-short equity funds, only the High Blip funds exhibit a discontinuity at zero that is significant at 95% confidence level.

5. Hedge Fund Trades over the Quarter and Manipulation-Consistent Activity

To supplement the analysis in Section 4.3 of the paper, we provide an additional test for the relation between intraday trades and quarterly hedge-fund-management companies' trades, as evidence that hedge funds are involved in price pumping. The test directly adapts the methodology in Campbell, Ramadorai, and Schwartz (2009) to our context. Like Campbell, Ramadorai, and Schwartz (2009), our goal is to find a correlation between changes in 13F ownership and intraday activity in TAQ. However, unlike these authors, we are interested in a specific subset of institutional investors (hedge funds), and restrict our attention to the intraday activity of the trading hours around the turn of the quarter, when manipulation arguably plays out.

The intuition behind the test is as follows. If hedge funds manipulate the closing price of some stocks, these stocks should experience large buying pressure and a price reversal at the turn of the quarter. Therefore, our test focuses on a significant positive relation between the increases in management company holdings over the quarter and the interaction between buying pressure and a high price reversal at the turn of the quarter.

In a similar fashion, we expect that in the following quarter hedge funds would unload any stocks they have pumped up. Therefore, we should observe a negative relation between decreases in management companies' holdings and selling pressure for stocks that experienced a high price reversal at the turn of the quarter.

Using the 13F filings, we compute the following variables for each stock-quarter (j,q) and scale them by total shares outstanding for that stock:

- *Hedge fund net trades:* is the net cumulative change in holdings of a given stock over the quarter across all hedge fund management companies divided by total shares outstanding:

$$HF\ Net\ Trade_{j,q} = \frac{\sum_{i \in \{HF\}} \left(Shares\ Held_{i,j,q} - Shares\ Held_{i,j,q-1} \right)}{Shares\ Outstanding_{j,q}}.$$

- *Hedge fund buys*: is the sum of all hedge fund management company buys (or positive net trades) into a particular stock divided by total shares outstanding:

$$HF\ Buys_{j,q} = \frac{\sum_{i \in \{HF\}} \left(Shares\ Held_{i,j,q} - Shares\ Held_{i,j,q-1} \right)^{+}}{Shares\ Outstanding_{j,q}}.$$

- *Hedge fund sales*: is equal to the cumulative sum of the shares sold by hedge fund management companies over the quarter for a particular stock divided by total shares outstanding.

$$HF\ Sales_{j,q} = \frac{\sum_{i \in \{HF\}} \left[-\left(Shares\ Held_{i,j,q} - Shares\ Held_{i,j,q-1} \right) \right]^{+}}{Shares\ Outstanding_{j,q}}.$$

We next approximate buying and selling pressure using the buy-sell order imbalance (BSI). Applying the Lee and Ready (1991) algorithm to the TAQ data, we classify transactions into buyer-driven (transaction price above the mid-quote), seller-driven (transaction price below the mid-quote), and unclassified (transaction at the mid-quote without a recent uptick or downtick). We limit the analysis to transactions taking place in the last hour of quarter and the first hour of the following quarter. These are the time periods when most of the action seems to be taking place (see Figure 1). For each of the two periods, we compute the buy-sell order imbalance as the difference between the total number of shares that are buyer-driven and the total number of shares that are seller-driven, scaled by total shares outstanding. A positive BSI denotes buying pressure on the stock in that time interval. Unclassified volume is also scaled by total shares outstanding. BSI is the same order flow variable used by Campbell, Ramadorai, and Schwartz (2009).

Then, for each stock, we calculate a stock-quarter manipulation proxy as the return on the last day of the quarter minus the return on the first day of the following quarter (return reversal). We define a high-return-reversal dummy variable that indicates whether the return reversal is in the top quartile of the distribution.

Our analysis is presented in Appendix Table 4. We conduct two tests: for buying pressure at the end of the quarter and for selling pressure at the beginning of the following quarter. In the analysis of the current quarter (Quarter q), we search for a relation between management companies' trades over the quarter and quarter-end buying pressure for high-return-reversal stocks. Therefore, we regress the aggregated trades from 13F (either net trades, buys only, or sales only) on the high-return-reversal indicator interacted with the BSI variable. We include in the regression the main effects of BSI and the high-return-reversal variable. Following Campbell, Ramadorai, and Schwartz (2009), we also include ownership of hedge fund management companies at the beginning of the quarter, previous-quarter hedge fund trades, and the fraction of the unclassified volume. In addition, we add calendar quarter fixed effects. Standard errors are clustered at the quarter level.

The results are presented in Appendix Table 4, Panel A. Our test focuses on the significance of the interaction between the high-return-reversal dummy and the BSI variable. The table shows that net trades and buys by hedge funds are higher for stocks with a high return reversal and high buying pressure (Columns (1) and (2)). This is evidence that the buying activity of hedge fund management companies is associated with an end-of-month stock price increase. The significance of the interaction variable in Column (3) is not evidence against our hypothesis. Rather, it may suggest that hedge funds also manipulate those stocks with holdings that have decreased during the quarter, but that are still present in their portfolios. It might also reflect the fact that some hedge funds act as liquidity providers, thereby selling when spikes of buying pressure occur. In any case, we find it reassuring that the coefficient of the hedge fund buy transactions (Column (2)) is twice as large as the coefficient for the sell transactions (Column (3)).

Next, we focus on selling pressure in the first day of the following quarter. Specifically, we examine the relation between hedge fund trades in Quarter q+1 and the order imbalance in the first hour of the first day of Quarter q+1. In this case, we expect to find that hedge funds decreased their holdings more intensely for stocks experiencing a high return reversal around the turn of the quarter and large selling pressure in the first hour of the quarter. Similar to the previous analysis, we regress trading (net trades, buys, and sales) by hedge fund management companies in Quarter q+1 on the interaction of the high–return-reversal indicator and the BSI variable. We include the same control variables as above.

The results are reported in Appendix Table 4, Panel B. As expected, we find a significant correlation between the sell trades of hedge funds (from 13F) and the selling pressure of high-return-reversal stocks (from TAQ) in the first hour of Quarter q+1. Note that the significant coefficient for the sales specification (Column (3)) is twice as large as its counterpart for buys (Column (2)), which is not significant. The negative sign is what we would expect as BSI measures buying pressure.

These results are consistent with the claim that hedge funds are involved in applying buying pressure at the end of the quarter. Also, the hedge funds are likely to unload the stocks at the beginning of the following quarter.

6. How Many Hedge Funds Engage in Manipulation?

In general, this is a difficult question to answer since hedge funds can manipulate sporadically, e.g., only when the incentives are strong enough. Moreover, all we have is a noisy signal of whether or not a fund is manipulating at month end. In the paper, we present evidence about the persistence of manipulation by hedge funds. Here, we can provide some additional intuition.

Our estimation is based on the *AdjBlip* variable. This variable measures the return on the last day of the quarter minus the return on the first day of the following quarter. Each daily return is in excess of the market return for that day. This adjustment takes care of anomalous end-of-month behavior in the market. The null hypothesis of no manipulation implies that the mean of the random variable *AdjBlip* is zero. Also, one can assume that in the absence of manipulation, the distribution of *AdjBlip* is symmetric around zero. Under this null hypothesis, the fraction of quarters in which *AdjBlip* is larger than zero for each management company should be 50%. That is, *AdjBlip* is above zero by pure luck fifty percent of the time. In Figure 2, we plot the distribution of the fraction of quarters in which *AdjBlip* is positive at the management company level, restricting the sample to companies that have at least two quarters.

The mean and median of the distribution are 61.3% and 62.5%, respectively. These figures appear to be far from the null hypothesis of no manipulation. It is also interesting that the distribution seems to have two lumps of probability mass: one around 40%-50% and another around 60%. That is, the distribution seems to be bimodal. As a matter of interpretation, the lower cluster of probability mass seems to be associated with companies that do not manipulate, while the higher cluster is more likely to be associated with firms that manipulate. We note that more probability mass seems to be present around the rightmost cluster, consistent with the claim that manipulators are not uncommon in the population. Interestingly, a non-negligible 4.2% of companies display an *AdjBlip* that is positive in all quarters (the last bar in the histogram displayed in the figure), which raises the possibility that some funds are frequent manipulators.

This analysis, however, is subject to an important caveat. Hedge funds tend to hold portfolios that partly overlap with each other. As a consequence, even if a fund does not manipulate, it may display a blip in returns if another fund with a similar portfolio is manipulating. Counting the number of funds with a positive blip in returns is therefore bound to misrepresent the actual number of manipulators.

Appendix Table 1. Manipulation and Company Performance

This table reports fund-level OLS regressions. The universe is all hedge fund management companies in TASS for 2000Q1 to 2010Q3 that can be matched to a 13F filing. The dependent variable is the management company's monthly return for end-of-quarter months; *High Blip* is a dummy variable equal to one if a company experiences a volatility-adjusted blip in the top 10% of the distribution of that variable for that month (Blip/Volatility is defined for each company-quarter as the difference between ret(last day) and ret(last day + 1) divided by the daily volatility of the portfolio over the quarter). The other explanatory variables are: the log of the company's assets under management reported to TASS (*log(AUM)*), the log of the number of stocks reported in the 13F (*log(# Stocks in equity portfolio)*), a dummy variable (*I(Bad month)*) for whether the current month's performance is below -2%, and the YTD performance (as of quarter end) by quintiles (*YTD performance quintile X*). *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the fund level and time fixed effects are included.

Dependent variable:	Total return (%)		
	(1)	(2)	(3)
I(High blip)	0.003	0.003**	0.004***
	(1.603)	(2.367)	(3.144)
log(AUM)	0.001***	0.001***	
	(3.604)	(3.223)	
log(# Stocks in equity portfolio)	-0.001	-0.001	
	(-1.201)	(-1.618)	
YTD performance Q2		0.004***	
		(3.036)	
YTD performance Q3		0.006***	
		(4.776)	
YTD performance Q4		0.012***	
		(9.090)	
YTD performance Q5		0.031***	
		(23.853)	
I(Bad month)		-0.059***	-0.065***
		(-44.712)	(-49.735)
Calendar date fixed effects	Yes	Yes	Yes
Observations	6,649	6,598	6,649
Adjusted R^2	0.208	0.482	0.423

Appendix Table 2. Discontinuity at Zero for Total Company Returns

The table presents a discontinuity analysis of monthly hedge fund management company returns around zero. The dependent variable is the density in a return bin. Hedge fund management company returns are distributed to 20 bins (Columns (1) and (2)) or to 30 bins (Columns (3)), each with a width of 20 basis points. The dependent variable is the fraction of observations in each bin. *High blip hedge fund* is defined above. *Positive returns (I(i≥ 0))* is an indicator as to whether the returns are positive. The regression includes two separate 2nd or 3rd degree polynomials for positive and negative returns. *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. We use robust standard errors.

Dependent variable:	Density in bins		
Sample:	All hedge funds	All hedge funds	All companies
	(1)	(2)	(3)
Positive returns (I(i ≥ 0))	0.005	0.003	0.003
	(1.497)	(0.633)	(0.950)
High blip company	-0.019***	-0.025***	-0.020***
	(-4.533)	(-2.976)	(-4.330)
High blip company × Positive returns (I(i ≥ 0))	0.017***	0.027***	0.020***
	(3.072)	(2.851)	(3.333)
Bin range	[-10, 9]	[-10, 9]	[-15, 14]
Polynomial degree	2nd	3rd	3rd
Observations	40	40	60
Adjusted R^2	0.744	0.717	0.828

Appendix Table 3. Robustness: Current Relative Performance Control

The table reports fund-level OLS regressions similar to the specifications in Table 9. We add a new control: the current month's relative performance expressed by quintiles of monthly performance. For the last month of all quarters, *Current performance X* is the quintile of the hedge fund management company's performance for this month. The universe is all management companies in TASS for 2000Q1 through 2010Q3 with a match to 13F filings. *t*-statistics are clustered at the fund level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Time fixed-effects are included.

Dependent Variable:	Blip/volatility			ret(last day of quarter)		
	(1)	(2)	(3)	(4)	(5)	(6)
log(AUM)	-0.001	-0.002	-0.003	-0.023*	-0.025**	-0.025*
	(-0.056)	(-0.164)	(-0.237)	(-1.854)	(-2.013)	(-1.729)
log(# Stocks in equity portfolio)	-0.030**	-0.028**	-0.030**	-0.041**	-0.038**	-0.040**
	(-2.136)	(-2.020)	(-1.972)	(-2.352)	(-2.165)	(-2.188)
Flows / lag(AUM) (%)			0.275			-0.016
			(0.823)			(-0.042)
I(Bad month)		0.111***	0.103**		0.211***	0.227***
		(2.606)	(2.216)		(3.921)	(3.745)
YTD performance Q2	0.017	0.027	0.017	-0.025	-0.007	0.005
	(0.492)	(0.788)	(0.457)	(-0.618)	(-0.167)	(0.115)
YTD performance Q3	-0.009	-0.000	0.000	-0.026	-0.009	0.011
	(-0.269)	(-0.010)	(0.013)	(-0.620)	(-0.212)	(0.244)
YTD performance Q4	0.021	0.029	0.011	0.039	0.055	0.066
	(0.567)	(0.797)	(0.261)	(0.955)	(1.339)	(1.467)
YTD performance Q5	0.085**	0.091**	0.089**	0.130***	0.142***	0.172***
	(2.049)	(2.223)	(1.979)	(2.907)	(3.185)	(3.501)
Current performance Q2	0.028	0.064*	0.047	-0.013	0.056	0.059
	(0.859)	(1.953)	(1.325)	(-0.347)	(1.497)	(1.478)
Current performance Q3	-0.032	0.019	0.001	-0.030	0.067*	0.066
	(-0.962)	(0.551)	(0.021)	(-0.728)	(1.711)	(1.513)
Current performance Q4	0.007	0.060	0.043	-0.075*	0.026	0.015
	(0.192)	(1.566)	(1.024)	(-1.813)	(0.678)	(0.345)
Current performance Q5	0.002	0.056	0.029	-0.088**	0.014	-0.003
	(0.042)	(1.347)	(0.661)	(-2.087)	(0.342)	(-0.070)
Calendar quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,598	6,598	5,710	6,598	6,598	5,710
Adjusted R^2	0.702	0.702	0.700	0.549	0.550	0.542

Appendix Table 4. Linking 13F Data and TAQ Trades

The table links the aggregate quarterly trades of hedge fund management companies, drawn from 13F filings, to intraday trading activity on the last day of the quarter and the first day of the following quarter. The sample is at the stock-quarter level. Panel A focuses on trading activity on the last day of the quarter. The dependent variables are aggregate net trades, aggregate buys, or aggregate sales during the quarter as a fraction of total shares outstanding. The variable of interest is *High return reversal dummy*BSI*. *High return reversal dummy* is an indicator as to whether the stock is at the top quintile of the last day-of-the-quarter returns minus the first day-of-the-following-quarter returns. *BSI (Buy-Sell Order Imbalance)* is the difference between the number of shares identified (using the Lee and Ready (1991) algorithm) as buyer-driven and those identified as seller-driven, scaled by the sum of the two numbers. In Panel A, BSI and unclassified volume are calculated in the last hour of the day. In Panel B, BSI and unclassified volume are calculated in the first hour of the day. *HF Ownership* is the fraction of shares outstanding owned by hedge funds at the beginning of the quarter. Unclassified volume is that fraction of volume that is not classified as either buyer-driven or seller-driven, scaled by total volume on the day. HF trades/buys/sales is the aggregate trades by hedge fund management companies in the preceding quarter. *t*-statistics are reported in parentheses. Standard errors are clustered by date. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Regressions of the Trades in Quarter

	Trades by hedge funds during quarter q		
	Net Trades	Buys only	Sales only
	(1)	(2)	(3)
High return reversal dummy * BSI (last day of quarter q)	0.618**	0.863***	0.332**
	(2.626)	(3.640)	(2.155)
Buy-sell order imbalance (last day of quarter q)	0.320*	0.470**	0.139
	(1.916)	(2.145)	(1.111)
High return reversal (top quintile dummy)	0.000	-0.001***	-0.001***
	(0.815)	(-2.862)	(-4.511)
HF ownership (beginning of quarter q)	-0.039***	0.060***	0.137***
	(-8.853)	(16.346)	(48.489)
Unclassified volume (last day of quarter)	0.040***		
	(7.692)		
HF trades during quarter q-1	-0.055*	-0.090	-0.023
	(-2.022)	(-1.685)	(-0.974)
HF buys during quarter q-1		0.379***	
		(46.980)	
HF sales during quarter q-1			0.309***
			(30.524)
Calendar date fixed effects	Yes	Yes	Yes
Observations	183,487	183,487	183,487
Adj. R^2	0.032	0.301	0.486

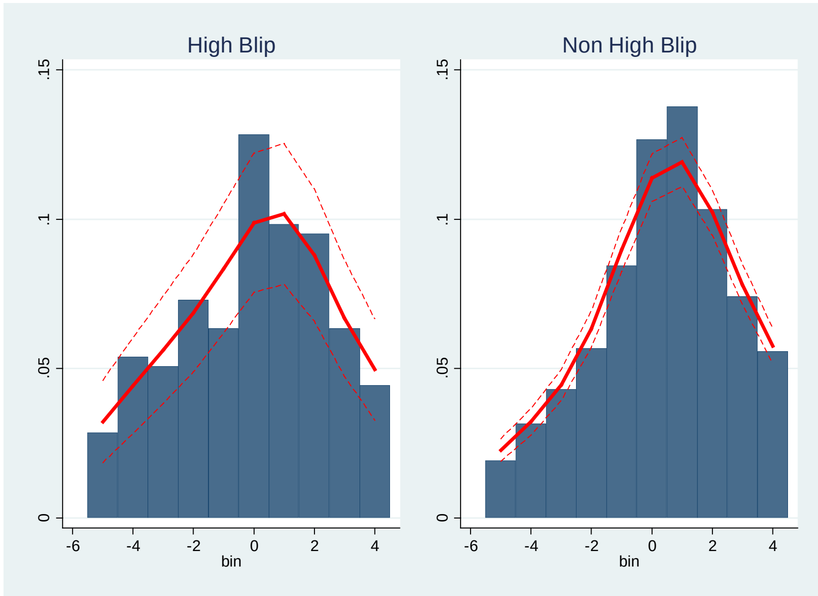
Appendix Table 4. Linking 13F Data and TAQ Trades (Cont.)

Panel B: Regressions of the Trades in Quarter

	Trades by hedge funds during quarter q+1		
	Net Trades	Buys only	Sales only
	(1)	(2)	(3)
High return reversal dummy * BSI (first day of quarter q+1)	0.269	-0.404	-0.792***
	(0.666)	(-1.077)	(-3.140)
Buy-sell order imbalance (first day of quarter q+1)	0.258	1.345***	1.026***
	(1.161)	(4.598)	(4.495)
High return reversal (top quintile dummy)	0.001***	0.000	-0.001***
	(3.640)	(0.400)	(-2.790)
HF ownership (beginning of quarter q+1)	-0.035***	0.063***	0.133***
	(-8.093)	(16.853)	(49.934)
Unclassified volume (first day of quarter q+1)	0.059	-0.013	-0.064
	(0.695)	(-0.165)	(-1.324)
HF trades during quarter q	0.038***		
	(7.468)		
HF buys during quarter q		0.372***	
		(46.683)	
HF sales during quarter q			0.310***
			(30.342)
Calendar date fixed effects	Yes	Yes	Yes
Observations	183,487	183,487	183,487
Adj. R^2	0.029	0.302	0.482

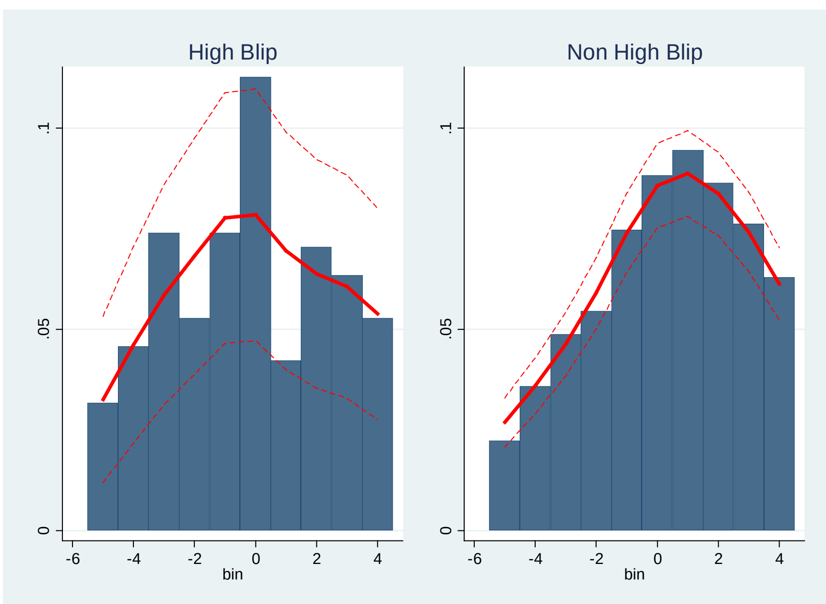
Figure 1. Alternative Tests of Return Discontinuity around Zero

Figure 1a. High-Blip vs. Non-High Blip Management Companies



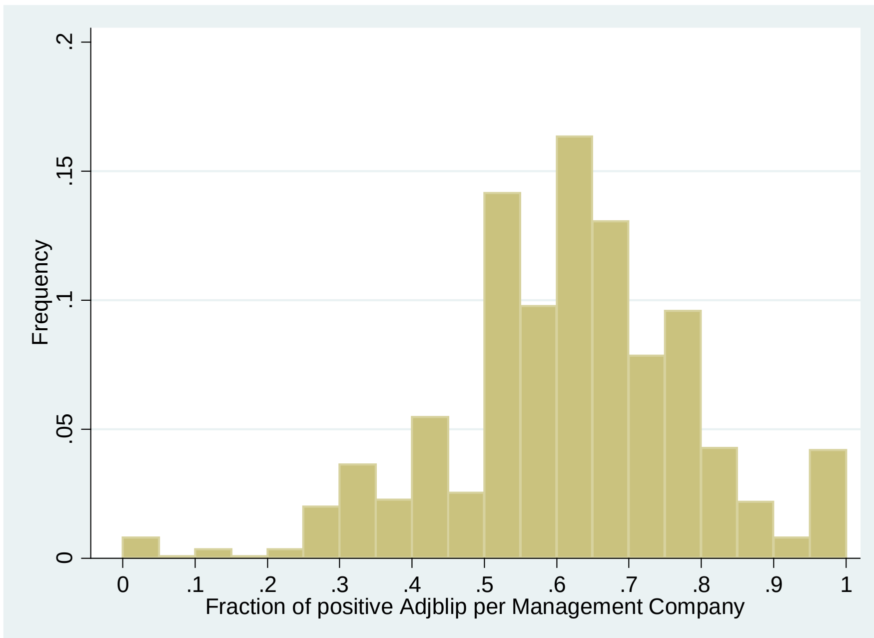
The chart presents a histogram of returns of hedge fund management companies. The dashed lines correspond to the 95% confidence interval around predicted frequencies, which is the plain red line; the blue bars are the frequencies observed in the data.

Figure 1b. High-Blip vs. Non-High Blip Management Companies (Long/Short Equity only)



The chart presents a histogram of returns of hedge fund management companies. The dashed lines correspond to the 95% confidence interval around predicted frequencies, which is the plain red line; the blue bars are the frequencies observed in the data.

Figure 2. Distribution of Fraction of Positive per Hedge Fund Management Company



The chart presents a histogram of the fraction of positive *AdjBlip* per hedge fund management company. For each hedge fund management company we compute the fraction of quarters for which the portfolio *AdjBlip* is positive.