Do Hedge Funds Manipulate Stock Prices?

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Abstract

We find evidence that hedge funds significantly manipulate stock prices on critical reporting dates. We document that stocks held by hedge funds experience higher returns on the last day of the quarter, followed by a reversal the next day. For example, the stocks in the top quartile of hedge fund holdings exhibit abnormal returns of 30 basis points on the last day of the quarter and a reversal of 25 basis points on the following day. Using intraday data, we show that a significant part of the return is earned during the last minutes of the last day of the quarter, at an increasing rate towards the closing bell. This evidence is consistent with hedge funds' incentives to inflate their monthly performance by buying the stocks they hold in their portfolios. Evidence of manipulation is stronger for funds that have higher incentives for improving their ranking relative to their peers and a lower cost of doing so. Such dislocations of market prices constitute a negative externality for agents using end-of-month market prices for benchmarking, contracting, or trading purposes.

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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, noise traders cause non-fundamental shocks to prices while sophisticated investors (arbitrageurs) absorb these shocks and stabilize the market. However, recent research challenges this view by pointing out that arbitrageurs such as hedge funds can be constrained by agency frictions (see Gromb and Vayanos 2010 for a survey). Not only can these frictions limit arbitrage activity, but they can also be the very source of non-fundamental demand shocks. As an example, after an initial negative shock to their returns, arbitrageurs may be forced to liquidate their positions by margin calls and redemptions. This liquidation spiral amplifies the original negative shock to prices (Shleifer and Vishny 1997, Gromb and Vayanos 2002, Brunnermeier and Pedersen 2009).

Our paper contributes to this emerging literature by documenting a novel dimension along which arbitrageurs' relation with their capital providers generates non-fundamental demand shocks. Based on the mounting evidence that hedge funds manipulate their reported performance (e.g., Agarwal, Daniel, and Naik 2011), we ask whether the incentive to attract and retain capital interferes with hedge funds' contribution to market efficiency. We provide evidence suggesting that hedge funds pump up end-of-month prices of the stocks they own in order to improve their performance. This apparent "signal jamming" leads to substantial distortions of end-of-month market prices and is not restricted to specific periods; rather, it constitutes a permanent negative externality for anyone using end-of month prices (e.g., for benchmarking, contracting or trading purposes). Similar to Brunnermeier and Nagel (2004), who document that hedge funds rode the Internet bubble, our results call into question the widely accepted idea that hedge funds improve the quality of market prices.

The study has two parts. First, based on the quarterly holdings data of hedge funds that we match to daily and intraday stock prices, we document that stocks held by hedge funds experience 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. 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. We find evidence that manipulation is concentrated in illiquid stocks, consistent with the idea that hedge funds can devote only a limited amount of capital to pushing up stock prices.

In the second part of the paper, we document that the stock level effect is reflected in hedge funds' equity portfolios, which exhibit an abnormal positive return at the end of the quarter and a decline on the next day. This pattern is more likely to occur with small hedge funds that have concentrated portfolios. In addition, manipulating hedge funds rank at the top in terms of year-to-date performance. This result is consistent with the evidence in Carhart, Kaniel, Musto, and Reed (2002) that mutual funds that manipulate stock prices are those with the best past performance. These 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. We also report a persistence in manipulation at the fund level, i.e., funds that have manipulated in the past are more likely to do so in the future. Finally, while manipulation patterns exist consistently throughout the sample period, they are stronger in quarters in which market returns were low, potentially because these occasions present opportunities for hedge funds to demonstrate their skill to investors.

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 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.

We run a battery of robustness checks to rule out alternative explanations for our findings. First, we test whether our documented effect is not generated mechanically by portfolio reallocation, resulting either from asset inflows or rebalancing. When we lag our hedge fund holding measure by one month or control for current and future inflows, the relation remains strong. Second, there is no overlap with price manipulations by mutual funds, 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.

Hedge funds typically report performance figures to their investors monthly. Several studies have raised doubts about the reliability of these reports, as hedge funds have an incentive to modify their numbers in order to boost performance fees and attract capital. The recent paper by Agarwal, Daniel, and Naik (2011) presents strong evidence of performance manipulation. They mostly focus on the funds' incentive for generating 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 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 consequences in the stock market of price manipulation by hedge funds and show that hedge funds' actions are likely to cause important distortions to monthly stock prices. We are able to find strong evidence of 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. Bollen and Pool (2009) document a discontinuity in the total returns distribution of hedge funds around zero. Jylhä (2010) elaborates on this result by showing that the discontinuity 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.[1] A complementary explanation for some of these results is that many of the assets held by hedge

[1] Other studies examine stock market manipulation through a broader scope. 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 a desired direction; as a result, prices are distorted and have higher volatility.

funds are illiquid, and their valuations could therefore be imprecise, with the autocorrelation due to smoothing of imputed returns (Getmansky, Lo, and Makarov 2004).

Hedge funds' manipulation of end-of-month prices 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 noise added to stock returns by hedge funds distorts other contract signals and consequently imposes a negative externality in aggregate. It is important to note that, although the distortion induced by hedge funds' manipulation is shown to revert quickly, we show that it does not cancel out within the 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.

More broadly, our paper joins 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 down pressure on prices in the last moments of trading before the end of the year.

Closely related to our work, Carhart, Kaniel, Musto, and Reed (2002) document that the prices of stocks owned by mutual funds exhibit positive abnormal returns at the end of the quarter. Consistent with the results of Duong and Meschke (2008), we find no evidence for such manipulation by mutual funds in our sample period (2000Q1 to 2010Q3). This suggests that the increased scrutiny on mutual funds following the initial publication of the results has led to a decrease in mutual funds' manipulation intensity. It is also important to note that mutual funds report their performance daily, which makes manipulation easier to detect. This can also explain the disappearance of manipulation after the evidence was first published. In contrast, hedge funds report monthly, requiring a data-intensive effort to reveal manipulation to the broader public. This paper fulfills this task.

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 used to do so. Section 4 presents the daily and intraday empirical evidence of end-of-month manipulations and relates it to stock-level characteristics. Section 5 studies the determinants of hedge fund behavior and investigates cross-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 funds (by Thomson-Reuters), mandatory institutional quarterly portfolio holdings reports (13F), and information about hedge fund characteristics and performance (TASS). The same dataset, albeit for a shorter period, was used by Ben-David, Franzoni, and Moussawi (2011).

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).[2] Form 13F requires that all institutions with investment discretion over $100 million of qualified securities (mainly publicly traded equity, convertible bonds, and options) at the end of the year report their long holdings in the following year.[3] 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.[4]

[2] 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…."

[3] 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.

[4] 13F filings have been used intensely in research concerning the role of institutional investors in financial markets. Brunnermeier and Nagel (2004) explore the behavior of hedge funds during the Internet bubble. Campbell,

We match the list of 13F institutions in Thomson-Reuters with a proprietary list of 13F hedge fund managing firms and other institutional filers provided by Thomson-Reuters. Relative to the self-reported industry lists commonly used to identify hedge funds, the Thomson list is certainly more comprehensive, as it classifies all 13F filers.[5] Moreover, the Thomson-Reuters hedge fund list identifies hedge funds at the disaggregated advisor 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 advisors within Blackstone that reported their holdings under the same filing.[6,7] 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 bias that occurs when relying on TASS and other self-reported databases for hedge fund identification (Agarwal, Fos, and Jiang 2010).

Ramadorai, and Schwartz (2009) combine 13F filings with intraday data to explore the behavior of institutional investors around earnings announcements.

[5] 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 the 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).

[6] There are three advisor entities within Blackstone Group L.P. that report their holdings in the same consolidated Blackstone Group report. Among the three advisors included, GSO Capital Partners and Blackstone Kailix Advisors are classified by Thomson-Reuters as Hedge Funds (which an ADV form confirms), while Blackstone Capital Partners V LP is classified as an Investment Advisor. 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

[7] For brevity, we will from now on refer to the observational unit in our data set as a 'hedge fund'. However, it should be clear that 13F provides asset holdings at the management firm level or at the advisor entity level. Each firm/advisor reports consolidated holdings for all the funds that it has under management.

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 advisors within a management company. Fifth, 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 advisors 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 advisors 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 advisors 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 advisors since 2006, when available.[8] We match those filings by advisor 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 Advisory Business) of Form ADV. Therefore, we believe that our final list of hedge funds contains only

[8] ADV forms are filed by investment advisors. In these forms, advisors provide information about the investment advisor's business, ownership, clients, employees, business practices, affiliations, and any disciplinary events for the advisor 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 advisor ADV filings are available on the SEC's investment advisor public disclosure website:
http://www.adviserinfo.sec.gov/IAPD/Content/Search/iapd_OrgSearch.aspx.

institutions with the majority of their assets and reported holdings in the hedge fund business, which we label "pure-play" hedge funds.

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" and "Live" databases.[10] We use hedge fund company names in TASS and map them to the advisor 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 strategy level. We aggregate the TASS data at the management company level, on a quarterly frequency, and match it to the 13F dataset using the consolidated management company name.[11] We exclude hedge funds 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. We let the sample start in the first quarter of the year 2000, as we want to focus on the impact of hedge funds in the stock market in recent years. The sample-end coincides with the end of 13F data availability (2010Q3). In (unreported) analysis, we verified that the results hold for earlier samples as well.

In Panel A of Table 1, we provide annual statistics for our sample of hedge funds. Our initial sample includes pure play hedge funds in 13F. In 2000, 295 such hedge funds filed 13F forms with their equity holdings; this figure peaked at 2008, when 745 hedge funds filed 13F forms. Following the financial crisis, the number of hedge funds declined and reached 608 in 2010. The merged dataset of 13F and TASS yields between 100 and 186 hedge funds per year. We estimate that in terms of reported equity assets, our sample covers about 80% of the number of 13F institutions that have *any* hedge fund business, and 25.3% of the aggregate equity portfolio owned by the same institutions.

The average equity portfolio size managed by hedge funds in our sample is about $0.5 billion to $1 billion. On average, hedge funds hold portfolios with about 100 stocks; however, about half of hedge funds hold relatively undiversified portfolios of less than 45 stocks.

[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 included hedge fund names).
[10] TASS started retaining information on 'dead' funds only in 1994; our analysis starts in 1990. We have run the regressions that use TASS data excluding the period before 1994; the results are largely unaffected. The reason for this is likely because most of our crisis periods occur after 1994.
[11] We used strategy assets under management as weights in aggregating fund characteristics and total reported returns.

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 Daniel, Grinblatt, Titman, and Wermers (1997), 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 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.

For the price impact of trading analysis (Section 6), we use TAQ trading data for January 2000 until December 2009. We keep only data for the last ten seconds of trading in 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 the end-of-quarter price manipulation. In this sample, hedge fund ownership is 2.6% on average; mutual 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 quarter (-0.13% and -0.06%, respectively).

Panel C describes the hedge fund-quarter sample used for studying the characteristics related to stock manipulation. The information in this panel is based on TASS data. The average of the logarithm of assets under management by hedge funds is 5.44, which corresponds to $230.4m. The average age of hedge funds in our sample is 7.8 years. The other variables in Panel C are introduced later in the text.

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 talent or their real performance (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 highly 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 costs of manipulation presumably would primarily include the transaction costs and the risk of detection and legal indictment.[12]

Since the signal that 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 sources: first, to be effective, the manipulation needs to last until month end; beginning a manipulation earlier could be unnecessarily costly. Moreover, 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 sooner rather than later.

There is some anecdotal evidence for portfolio pumping in the hedge fund industry. In an interview with TheStreet.com (cited as the epigraph),[13] 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.*

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 therefore can be manipulated at a lower cost. This prediction is consistent with Comerton-Forde and Putnins (2010), who suggest

[12] There are several reported cases where hedge fund managers have been indicted by the SEC for inflating 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).

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

that illiquid stocks with a high degree of information asymmetry are the most prone to manipulation. Therefore:

H2: Illiquid stocks are more likely to be manipulated.

Next, we wish to characterize those hedge funds that engage in manipulation activity. We conjecture that manipulation is more likely for hedge funds with less diversified portfolios. For these funds, 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.

H3: Manipulation is more likely for hedge funds with less diversified portfolios.

We also analyze the incentives that lead hedge funds to manipulate stock prices. For hedge funds, the month's, quarter's, and year's ends are important dates for two reasons. First, hedge fund 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 funds value improved rankings more than others do: top performing funds may manipulate stock returns more than others, 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, hedge funds that were bad performers in a previous quarter but that have caught up to their peers might have a stronger incentive to attract investors' attention. Funds that had a low YTD (Year-to-Date) ranking in the *past* quarter but that in the current quarter have a high YTD ranking might be especially eager to boost earnings in order to get noticed by investors and potentially be "re-categorized" from losers to winners.

Certain circumstances are likely to make investors' impression of a fund more elastic. For example, investors' belief regarding young funds might be more elastic to performance due to the funds' shorter track records. Thus young funds 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 elastic to monthly performance (because year-to-date performance is, on average, smaller earlier in the year).

Finally, 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 manipulation is related to the stock market's recent performance, as investors may benchmark hedge fund performance relative 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.[14] For this reason, we expect that on average, hedge funds will be more prone to manipulation in months when the market performs badly.

To summarize, we conjecture that:

H4: Manipulation aimed at boosting performance rankings is stronger for:

a. *Top performing hedge funds;*

b. *Hedge funds with a currently good but poor past relative performance;*

c. *Young hedge funds;*

As well as:

d. *Earlier in the calendar year;*

e. *When market returns are low.*

We expect to observe persistence in manipulating behavior over time. 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 manipulation activities. Thus, conditional on observing evidence of

[14] 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.

manipulation for a particular fund at quarter-end *t*, the fund is statistically more likely to exhibit such evidence again in the next period. A second reason for persistence is that once a fund has manipulated returns for strategic purposes, it might be tempted to continue to "undo" the negative impact of the previous quarter's manipulation on this quarter's performance.

H5: Manipulation activity is persistent over time at the hedge fund 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 small hedge funds, i.e., moving stock prices before the closing does not require much capital.

H6: Traders can move prices at the end of the month by investing relatively small amounts of capital.

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 hedge funds manipulate the price of the stocks in their portfolio at the end of the quarter. Using 13F information, for each stock and quarter we compute the fraction of market capitalization held by hedge funds. 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 in the four days around the quarter end (the second-to-last, last, next-to-last, and second-after-the-last days of the quarter) onto the hedge fund ownership indicators. Returns are risk-adjusted using the Daniel, Grinblatt, Titman, and Wermers (1997, DGTW) approach. Standard errors are clustered at the date level in these regressions as well as in the other stock level regressions in this section.

Panel A of Table 2 shows a strong pattern in the last day of the quarter as well as a reversal on the following day (the first day of the following quarter). 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 that hedge funds may be 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 which we present below indicates that the impact on fund returns remains stable throughout the year (see Table 7).

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 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 out this possibility, 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 is evidence that manipulation occurs on a monthly basis, although we observe holdings on a lower frequency. In other words, since a hedge fund's current holding is correlated with its future holdings (for stocks that were not sold by hedge funds), and because the current holding is correlated with one- and two-month future end-of-month returns, as Table 4, Panels A and B show, one can reasonably conclude that manipulation occurs on a monthly frequency.

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 hedge funds that are in the top tercile of the flow (in percentage of assets under management) for that quarter. Then we create an indicator variable for stocks with above-median ownership by high-flow funds. We include this dummy in the original specification, which also has the above-median ownership 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 fund 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. The results show that hedge fund ownership retains its significance and magnitude when controlling for mutual fund ownership. Consequently, hedge funds seem to add an independent layer of manipulation relative to what has already been found for mutual funds.[15] We do not find a significant coefficient on the mutual fund ownership dummy effect, 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 net, 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 regressions from Table 1 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 the last day of the month is practically zero. Further, the correlation between the returns around the turn of the month and hedge fund ownership remains unaffected.

4.2. Intraday Returns

To minimize the cost of inflating the stock price, hedge funds 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

[15] 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 this sample period.

when the pumping-up 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 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, columns are labeled by the start time of the time 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).

Figure 1 summarizes the results. Figure 1a shows the cumulative return over the last day of the quarter for stocks with above- and below-median hedge fund ownership. The figure shows the departure of returns of stocks with above-median hedge fund ownership in the last minutes of trade. Figure 1b shows that on the first day of the quarter, high hedge fund ownership stocks display lower returns, which start materializing right at the opening bell. In other words, as would reasonably be expected, if the price changes are a pure liquidity effect, the reversal begins as soon as the market opens.

4.3. Which Stocks Are Prone to Manipulation?

Next, we explore the characteristics of stocks that exhibit manipulation patterns. According to Hypothesis H2, stocks are more likely to be manipulated by hedge funds if they are relatively illiquid. To test this hypothesis, we regress 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 the main effects.[16] We also control for the size indicator and its interaction with the hedge fund ownership indicator. The results in Table 6 are strongly consistent with the prediction of Hypothesis H2. Above-median illiquid stocks with above-

[16] 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.

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

4.4. Hedge-Fund-Level Evidence of Quarter-End Manipulation

Having provided evidence of manipulation at the stock level, we now turn to the fund-level evidence by looking at the behavior of the stock portfolios held by hedge funds at quarter ends. We have a double objective: first, we seek to confirm that the pattern of manipulation we have documented at the stock level does indeed translate into higher hedge fund portfolio returns. Our second objective is to explore which hedge funds tend to engage in price manipulations at month end, and the circumstances under which they do it.

Focusing on December hedge fund returns, Agarwal, Daniel, and Naik (2011) find only marginal evidence of a spike in monthly returns that is reversed in the following month. We include in our tests all quarter ends, not just December, and perform the analysis at a daily frequency. The idea, which is supported by the stock level analysis, is that if manipulation takes place on the last day of the quarter and its effect is reversed the next day, tests that are based on daily returns will have more power to detect it. Hedge funds do not report their returns daily. However, using portfolio holdings from the 13F filings at the end of the quarter, we construct daily returns for the long equity portfolio. The drawback is that we need to use the same portfolio holdings for the three days around the quarter end (the next to last day, last day, and first day of the next quarter). This may reduce the power of our test as it introduces measurement error.

Specifically, for each hedge fund in the intersected dataset of 13F and TASS, we calculate *ret(last day)*, the return of the fund's long equity portfolio, weighted by dollar holdings as reported in the fund'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 identify manipulations 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 fund pushes its returns upwards 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 hedge fund level the anomaly we reported earlier at the stock level. In Table 7, we report the descriptive statistics of these last four variables, calculated at the hedge fund level and averaged at the quarter level. In line with what one would expect if a fraction of the funds were engaging in monthly return pumping on 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 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. Finally, based on untabulated results, we note that the time-series of the average adjusted blip for each date appears to be positive for roughly 90% of the quarters of the sample.[17]

Thus, we confirm at the fund 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.

[17] Table 3 suggests that, at the stock level, the evidence of manipulation increases over the year, whereas the fund level blip in Table 7 does not display such a 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 7, the stocks are given the weight that they have in each hedge fund's portfolio. Further, the returns in Table 7 are equally weighted across funds. In conclusion, the difference in weighting schemes does not allow a direct comparison between the two tables.

5. Characteristics of Manipulating Hedge Funds

5.1. Link with Incentives to Improve Returns

In order to better understand the economics of stock manipulation, we try to identify the hedge funds that exhibit the strongest manipulation patterns. Having described the blip measure for each fund-quarter, we now examine the fund-level characteristics that relate to high levels of blip Since, for purely statistical reasons, more volatile hedge fund portfolios are more likely to experience a blip, a more accurate fund-level signal of manipulation is the volatility-adjusted blip ($Blip/volatility_{i,t}$), where we divide $Blip_{i,t}$ by the volatility of the daily returns of fund i's portfolio, estimated using the daily returns during the quarter finishing at time *t* (and using the quarter-end weights). This volatility-adjusted variable, which will be used to detect manipulation in the data, is distributed independently of volatility and, absent manipulations or other end-of-month anomalies, would be centered around zero.

In Table 8, Columns (1) to (4), we regress the fund-level volatility-adjusted blip on a set of hedge fund characteristics. Our regressions include time 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 fund's assets under management (AUM) at the end of quarter *t*; *log(Equity portfolio size)*$_t$ is the logged number of stocks held by the fund as a measure of diversification at the end of quarter *t*. Both variables are constructed using the funds' 13F filings. Using TASS data, we compute the percentage of flows out of lagged assets under management *Fund flows / lag(AUM) (%)*.

The results in Table 8 show that hedge funds 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 funds to move their portfolio performance. In contrast, a highly diversified fund cannot generate a high impact on its returns by pushing a small number of stocks (Hypothesis H3).

To test Hypothesis H4, that links the incentives to manipulate with manipulation activity, we consider relative and absolute performance measures constructed using the TASS data. We call *I(Bad month)*$_t$ a dummy equal to one if the fund'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 funds according to their year-to-date performance: *YTD performance quintile* X_t is an ordinal discrete variable that distributes funds 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 funds within the year. For instance, HSBC's "Hedge Weekly" report provides "Top list" and "Bottom list" of funds according to their YTD performance.

The results in Table 8 confirm that hedge funds in the highest year-to-date performance quintile exhibit higher blips (Hypothesis H4a). 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 funds having a bad month (less than -2%) are more likely to experience a blip, which can be explained by the concern that an overly negative return might tarnish the fund's track record (e.g., by increasing volatility). 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 about ten percent 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 8, 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 funds that are experiencing a bad month or that are in the highest quintile of YTD performance have last-day returns that are around 15 bps 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 manipulating hedge funds. In

Hypothesis H4b-d, we test whether manipulation is stronger for: (i) hedge funds with a currently good relative performance but a poor past relative performance, (ii) young hedge funds, and (iii) early months in the calendar year.

As Table 9 shows, we find supportive evidence for all three hypotheses: hedge funds 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)), $Low\ reputation_t$ 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*). Funds where *Low reputation* = 1 were thus perceived, as of last quarter, to be substandard performers and were more likely to be included in poor-performer lists. If a fund 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)), $Young_t$ is a dummy equal to one if the fund's age (measured from the first date of 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 relates 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 7. Rather, it means that the incentive to manipulate that originates from the YTD performance rankings is stronger at the beginning of the year.

5.2. Time-Series Evidence

Next, we explore the time-series dimension of price manipulation. First, we would like to verify that manipulation takes place consistently over time and is not limited to a single episode in the decade being examined. Figure 2 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 H4e), we compute for each quarter-end month the average market-adjusted blips and test whether these aggregate blips are stronger when the market performs poorly. We find evidence that this is indeed the case (Table 10): the aggregate adjusted blips are significantly negatively correlated with monthly market performance. 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). Since the sample is small, we present a scatter plot of the scaled blip, as a function of market returns in Figure 3. The figure shows that the result is not driven by outliers, but rather 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.

5.3. Robustness and Alternative Explanations

We now address a few potential concerns regarding the fund-level results' interpretation. First, the link between YTD performance and blips 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 fund's relative performance for the current month. We report this robustness check in Appendix Table 1: *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 8 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 funds 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 fund at quarter end, *Fund flows / lag(AUM) (%)*. Following the literature standard (Chevalier and Ellison 1997, Sirri and Tufano 1998, Agarwal, Daniel, and Naik 2011, among others), we compute fund flows as the quarterly difference in AUM at quarter end minus the dollar return on the previous quarter AUM. Fund flows are then scaled by the lagged AUM. Columns (4) and (8) of Table 8 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 (in unreported regressions, we also included forward and lagged measures of monthly net flows, with similar results), relaxing the concern that price-impact at month end is a driving force in these regressions.

5.4. Persistence of Manipulation Behavior

In the final part of the hedge fund-level analysis, we investigate whether manipulation patterns are persistent within hedge funds (Hypothesis H5). To this end, we regress the current quarterly blip on the lagged blip of the same hedge fund. Table 11 documents that blips are indeed significantly persistent from one quarter to the next: volatility-adjusted blips have an autocorrelation of around 0.11. This persistence remains significant even when controlling for all the variables that have been seen as predictors of manipulation, as Column (3) indicates. This suggests that manipulating returns is a "habit" that tends to persist over time at the fund level.

6. Feasibility Analysis

We argue that the economic mechanism that drives the end-of-month returns is stock manipulation on the part of hedge funds. A necessary condition for this mechanism is that the manipulation of stock prices is feasible with a reasonable amount of capital. That is, we would like to see that the amount of money necessary to move prices by the observed magnitudes is 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%?

We verify that hedge funds can actually manipulate prices by examining the association between 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 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 at the 2^{nd} and 98^{th} 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 4 (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 prices 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 H6 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 holdings data to validate the conjecture that hedge funds manipulate stock prices before the close of trading at the end-of-month by buying some of their stock holdings before market close. This claim is supported by high end-of-month returns and a consequent reversal on the following day, as well as by intraday data, where we find that returns are especially high in the last minutes of trading. We document that manipulations are likely to take place in cases where the manipulation is likely to be most effective.

Our paper joins previous literature that discusses stock price manipulation before the bell for other investor populations. 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).

It is difficult to evaluate the welfare costs induced by hedge funds' manipulations of monthly returns: the price effects are large, but they revert quickly. A major source of the economic costs of these manipulations stems from the fact that many contracts and performance measures in the economy are likely to rely on monthly returns. By jamming the signals on which their own performance is evaluated, hedge funds add noise to a widely used signal, thus imposing a negative externality on the rest of the economy.

Although it is beyond our study's scope, one wonders whether contracts can be designed to reduce the incentive to manipulate prices by hedge funds. Two simple solutions, with opposite ramifications, seem feasible. The first solution is that investors could reduce the frequency of performance reporting, say, to an annual frequency. This solution, however, seems at odd with the general trend towards more frequent performance reporting in financial markets (e.g., investors having online access to their pension fund accounts) and the need for investors to perform a statistical analysis of track-records for monitoring and risk-management purpose. The second solution is that investors demand reports at a higher frequency, for instance, on a daily basis, as mutual funds do. With such a high reporting frequency, manipulations would become easy for investors to detect, which might eliminate the practice. Of course, this solution is likely to make the most sense for hedge funds that invest in highly liquid securities such as equity.

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Table 1. Summary Statistics

The table reports summary statistics. Panel A presents aggregate summary statistics about the universe of hedge funds available in the 13F filings as well as the subset that could be matched with TASS. Panel B presents summary statistics of stock-day observations of the last day of the month (summary statistics of other days around the turn of the month are very similar). Panel C presents summary statistics at the hedge-fund-quarter level. The sample period is 2000Q1 to 2010Q3.

Panel A: Summary Statistics of the Hedge Fund Universe

	Number of Mgrs.		Total AUM	Equity portfolio ($m, TASS match)	Equity portfolio ($m, whole sample)			Number of Stocks per manager		
Year	13F	TASS match	in Tass ($bn)	Mean	Mean	Median	St. dev.	Mean	Median	St. dev.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
2000	295	101	42	1,251	1,037	272	2,920	108	55	195
2001	315	110	48	878	756	207	2,081	104	49	198
2002	351	126	65	612	595	151	1,697	95	47	174
2003	388	138	78	688	696	190	2,118	106	47	201
2004	479	156	117	746	754	254	1,810	103	47	197
2005	562	177	138	685	851	278	1,996	105	45	215
2006	648	186	175	765	901	259	2,285	106	41	235
2007	737	184	219	1,030	1,011	287	2,762	101	39	228
2008	745	145	246	675	667	163	1,872	80	28	203
2009	658	107	149	594	611	139	1,605	81	29	200
2010	608	100	144	752	886	221	2,106	92	36	211

Panel B: Stock-Day Level Summary Statistics

	N	Mean	Std Dev	Min	p25	p50	p75	Max
Return last day (%, DGTW adjusted)	128841	0.021	3.772	-74.251	-1.361	-0.067	1.260	14.469
Return first day (%, DGTW adjusted)	128868	-0.126	3.728	-81.250	-1.539	-0.072	1.398	14.469
Return second day (%, DGTW adjusted)	128800	-0.059	3.612	-94.788	-1.451	-0.070	1.358	14.469
Return second-to-last day (%, DGTW adjusted)	128844	-0.019	3.484	-71.286	-1.288	-0.060	1.224	14.469
HF ownership (%)	128910	2.615	3.803	0.000	0.440	1.258	3.246	100.000
Mutual Fund ownership (%)	128910	13.637	9.481	0.000	6.095	12.303	19.656	100.000
Ownership by high-inflow funds (%)	128910	0.640	1.829	0.000	0.000	0.043	0.456	100.000
Amihud illiquidity measure	128910	0.310	0.974	0.000	0.001	0.008	0.072	5.000
Market capitalization ($k)	125861	4.08E+09	1.77E+10	-1.03E+09	1.60E+08	5.40E+08	1.89E+09	5.71E+11

Panel C: Hedge Fund-Quarter Level Summary Statistics

	N	Mean	Std Dev	Min	p25	p50	p75	Max
Adj ret(last day) (%)	6649	0.368	1.558	-8.527	-0.400	0.063	0.725	14.743
Adj ret(last day + 1) (%)	6649	0.002	0.020	-0.138	-0.007	0.003	0.012	0.118
Adj ret(last day - 1) (%)	6649	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) (%)	6649	0.008	0.044	-0.553	-0.006	0.008	0.022	0.746
log(AUM, $m)	6649	5.439	1.742	-5.163	4.498	5.490	6.512	10.915
log(# Stocks in equity portfolio)	6649	3.885	1.281	0.000	3.219	3.892	4.575	7.839
Fund flows / lag(AUM) (%)	5741	0.010	0.041	-0.311	-0.003	0.003	0.019	0.237
Hedge fund age (years)	6649	7.803	4.484	0.000	4.343	7.124	10.567	25.421
Blip/vol	6649	0.012	1.484	-1.006	-0.186	0.904	-3.982	8.637

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 Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW) approach. Four specifications are reported for which the dependent variables are the stock return in the second-to-last, last, next-to-last, and second-after-the-last days of the 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 of 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)
High 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 HF Ownership Stocks, by Quarter

The table reports results from OLS regressions in which the dependent variable is the daily percentage return adjusted using the Daniel, Grinblatt, Titman, and Wermers (1997) 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 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 Daily Return Analysis

The table reports results from OLS regressions in which the dependent variable is the daily percentage return adjusted using the Daniel, Grinblatt, Titman, and Wermers (1997) approach. Four specifications are reported in which the dependent variables are the stock return in the second-to-last, last, next-to-last, and second-after-the-last days. In Panels A and B, the dependent variable is one- and two-month future returns relative to end-of-quarter ownership, respectively. The explanatory variable in Panels A and B are indicators 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 Hedge Funds 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, last, next-to-last, and second-after-the-last days of the 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. 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 Daniel, Grinblatt, Titman, and Wermers (1997) approach. The dependent variables are the stock return in the second-to-last, last, next-to-last, and second-after-the-last days of the 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 7. Fund-Level Evidence of Abnormal Month-End Returns

The table reports the average market-adjusted daily returns for equity portfolios held at quarter's end by hedge funds. *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 TASS hedge funds 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 + 1) - Adj ret(last day)	0.52%	0.50%	0.59%	0.55%	0.44%
	(5.38)	(2.58)	(2.43)	(2.80)	(2.83)

Table 8. Which Hedge Funds Manipulate Prices? Volatility-Adjusted Blips

The table reports fund-level OLS regressions of the volatility-adjusted quarter-end "blips" of hedge fund portfolios. Specifically, the dependent variable in Columns (1) to (4), *Blip/volatility*, is defined for each fund-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 Panel B is *ret(last day of quarter)*, which is the quarter-end daily returns of their equity portfolio (based on holdings reported in 13Fs). *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 determinants are: the log of assets under management reported to TASS (*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)*) for whether the current month's performance is below -2%, and the YTD performance (as of quarter end) by quintiles (*YTD performance quintile X*). The universe is all TASS hedge funds for 2000Q1 to 2010Q3 with a match to 13F filings. *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:	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)
Fund 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. Manipulations and Incentives to Attract Attention

The table reports fund-level OLS regressions of the volatility-adjusted quarter-end "blips" of hedge fund portfolios. Specifically, the dependent variable, *Blip/volatility,* is defined for each fund-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 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 determinants are: the log of assets under management reported to TASS (*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)*) for whether the current month's performance is below -2%, and the YTD performance (as of quarter end) by quintiles (*YTD performance quintile X*). Year-to-date performance is interacted with three characteristics: whether the fund's age is below median (dummy *Young*), whether the YTD performance as of the last quarter was in the lower two quintiles (dummy *Low reputation*) and whether the current quarter ends in March (dummy *March*).The universe is all TASS hedge funds for 2000Q1 to 2010Q3 with a match to 13F filings. *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: 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)
Fund 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. Stock Price Manipulation and Market Direction

The table reports OLS regressions of the cross-sectional average of quarter-end "blips" of hedge fund portfolios. Specifically, the dependent variable is the average across hedge funds at a given quarter-end of *AdjBlip* and *AdjBlip/volatility*. These variables are constructed for all TASS hedge funds for 2000Q1 to 2010Q3 with a match to 13F filings in the following manner: *Adj ret (last day)* is the market-adjusted return of this portfolio on the last trading day of the quarter and *Adj ret (last day* – 1*)* (*Adj ret (last day* + 1*)*) is the returns of the same portfolio on the previous (next) 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 right-hand-side variable *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 during 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 11. Serial Manipulation? Autocorrelation of Abnormal Quarter-End Blips

The table reports fund-level OLS regressions of the volatility-adjusted quarter-end "blips" of hedge fund portfolios. Specifically, the dependent variable, *Blip/Volatility*, is defined for each fund-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 this 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 fund as last quarter's measure of *Blip/volatility*. The universe is all TASS hedge funds for 2000Q1 to 2010Q3 for which the 13F is known. *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 Cumulative Returns

The figure reports the cumulative intraday returns (in percents) for stocks that have above- and below-median hedge fund ownership in the quarter. The two panels focus on the last day of the quarter and the first day of the next quarter, respectively. The sample period is 2000Q1 to 2010Q3.

Figure1a: Last Day of the Quarter

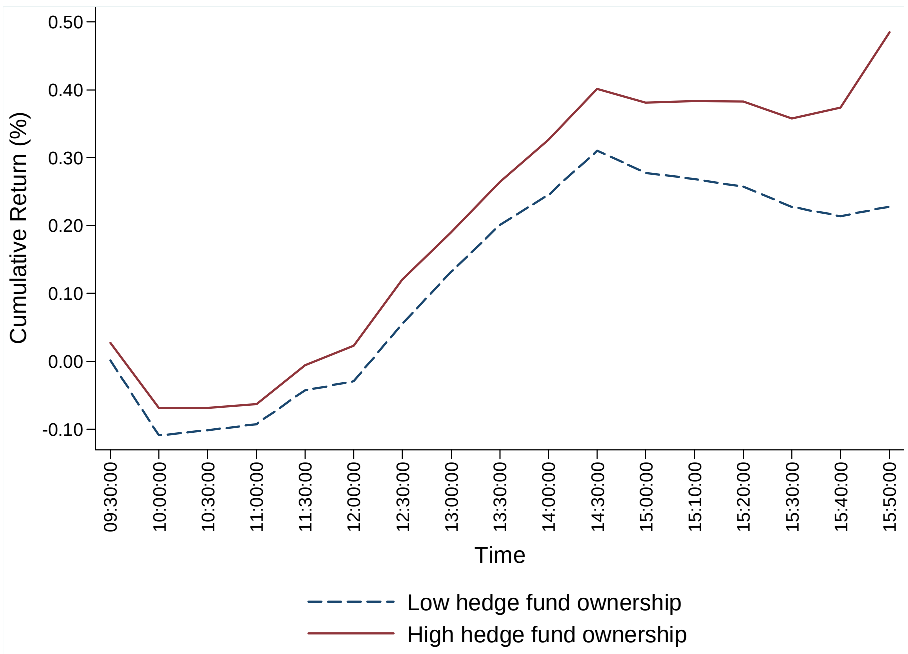


Figure1b: First Day of the Quarter

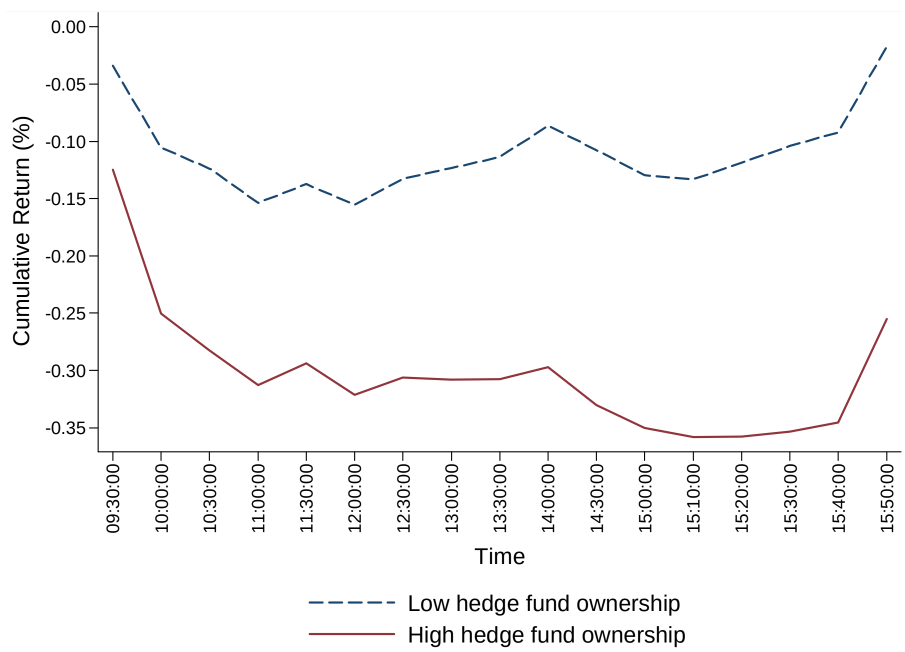


Figure 2. Time-Series of the Returns in the Last Day of the Quarter

The chart presents the time series average adjusted returns for stocks with high and low ownership by hedge funds. Adjustment is made using the Daniel, Grinblatt, Titman, and Wermers (1997) approach. The sample period is 2000Q1 to 2010Q3.

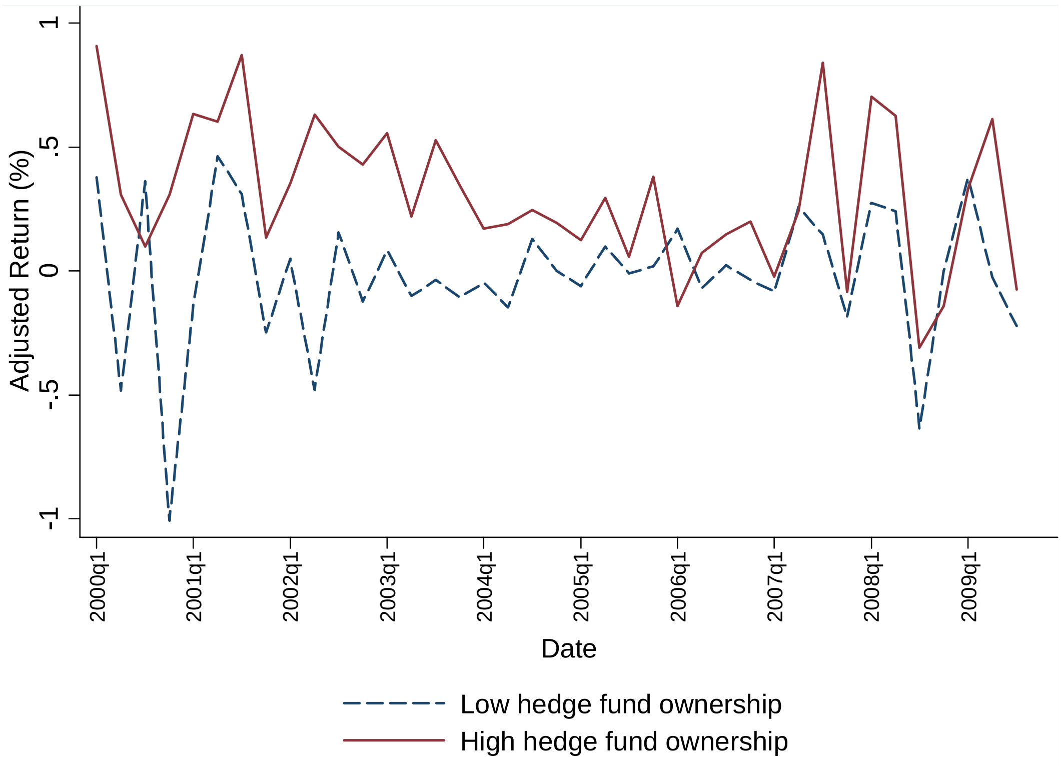


Figure 3. Blip and Market Returns

The figure shows the average adjusted blip for hedge funds (last day-of-the-month returns minus first day-of-the-month returns, 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.

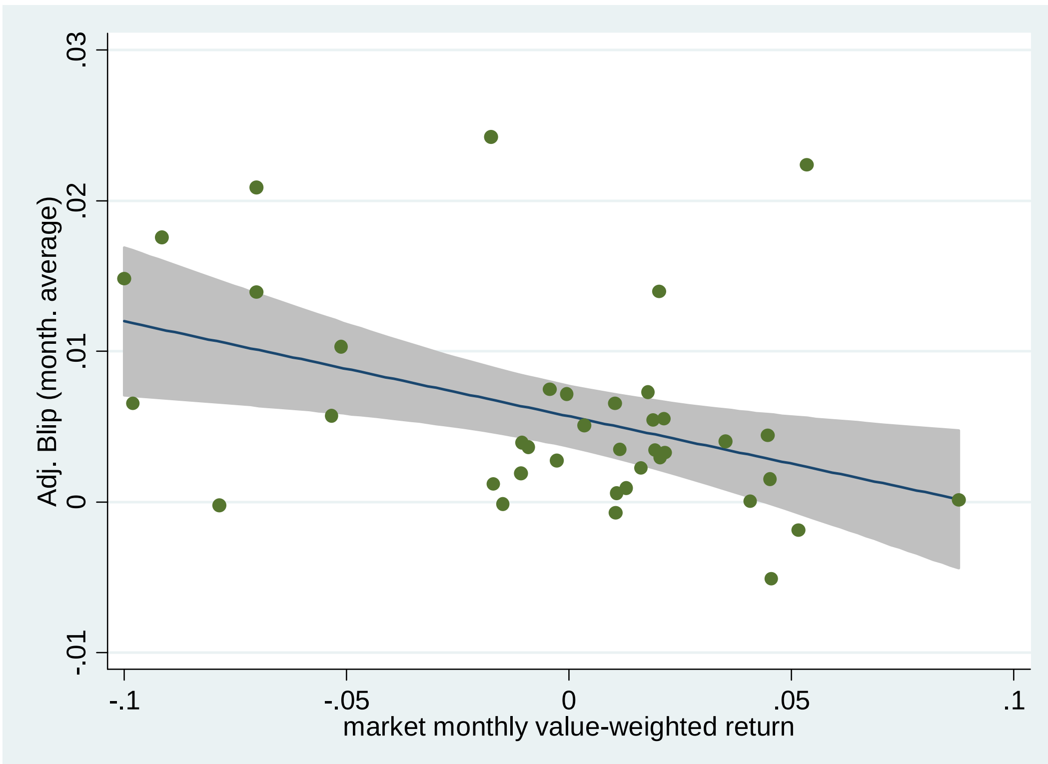
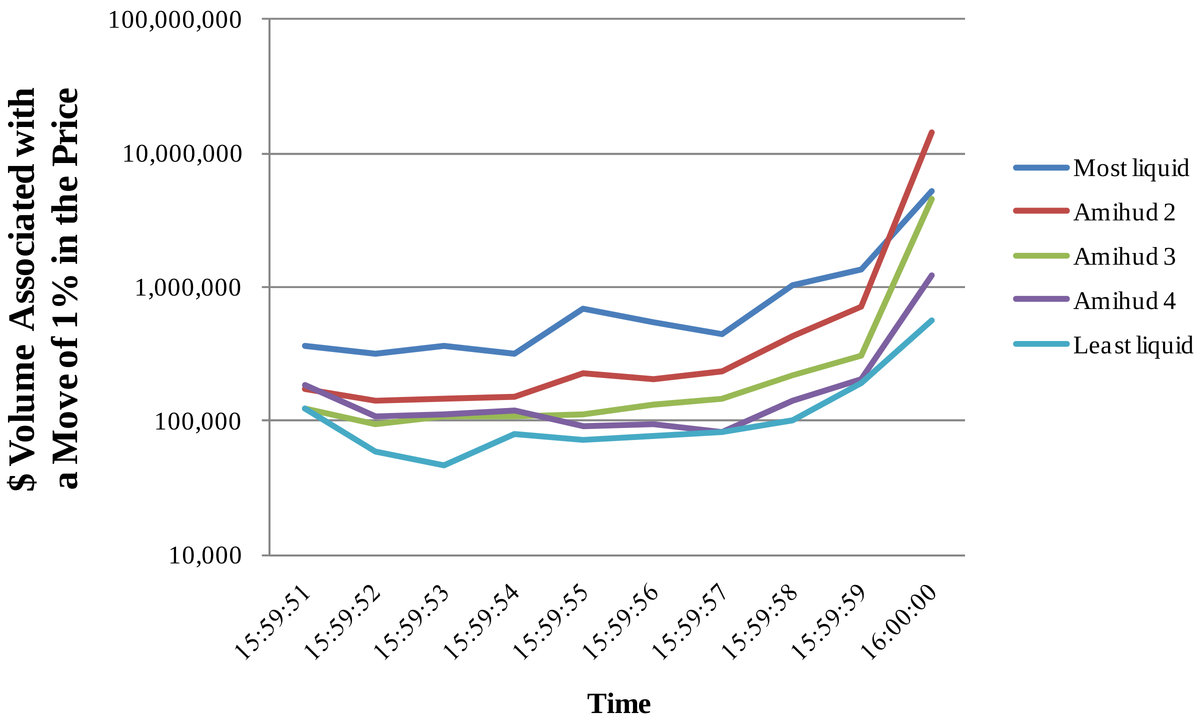


Figure 4. Dollar Volume Needed to Move the Price by 1%

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 stocks sorted based 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.



Appendix Table 1. Robustness: Current Relative Performance Control

The table reports fund-level OLS regressions similar to the specifications in Table 8. We add a new control: the current month's relative performance reported by quintiles of monthly performance. For the last month of all quarters, *Current performance X* is the quintile of the monthly performance of the fund for this month. The universe is all TASS hedge funds 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)
Fund 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