The Long-Short Wars:

Evidence of End-of-Year Price Manipulation by Short Sellers

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ABSTRACT

Thus this paper identifies one of the few situations in which there are clear, ex-ante predictions about exactly how short sellers would manipulate prices, and in this setting, we find patterns consistent with end-of-year price manipulation by short-sellers. Specifically, we find stocks with high short interest experience abnormally low returns on the last trading day of the year. This effect is strongest among stocks that are easily manipulated, strongest during the last hour of the trading, and the effect reverses at the beginning of the year; four findings that are consistent with temporary price manipulation by short sellers. Furthermore, we find a large increase in end-of-day short sales on the last day of the year, giving direct evidence that short sales contribute to the return pattern. We show that hedge funds' portfolios are closely related to the market-wide short interest, and we argue that hedge funds' convex pay structure generates incentives that may lead to the behavior we observe. Finally, we show that if mutual funds' long positions and short-sellers short positions are of similar size, then there are decreases in volume consistent with short-sellers and mutual funds avoiding each other's target stocks. We also see that, on average, upward manipulation pressure by mutual funds outweighs downward pressure by short-sellers, but among stocks with high holdings and among stocks with high end-of-day volume, downward pressure is stronger than upward pressure.

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In the popular press, short-sellers are often accused of manipulating prices.[1] In response to the perceived manipulation, regulators have limited the trading behavior of short-sellers in a variety of ways (e.g. the uptick rule or the recent short-selling ban on financial stocks). Despite the outcry and the government action, beyond a handful of anecdotes there are no academic studies that (1) identify manipulation opportunities specifically for short-sellers and (2) find evidence consistent with manipulation. This paper is the first to do so.

Oddly enough, our evidence of short-seller manipulation *does not* justify the singling out of short-sellers by regulators and media. In fact, quite the opposite is true. We find that short-sellers manipulate in the same way long-only traders manipulate: in response to period-end incentives.

A large body of literature finds that mutual fund managers manipulate closing prices by trading to put upward pressure on closing prices at the end of the year (e.g., Carhart, Kaniel, Musto and Reed (2002), Bernhardt and Davies (2005) and Zweig (1997)). Even though the resulting price impact is transitory, top-performing managers have the incentive to make these trades because of the convex flow-to-performance relationship.[2]

While the mutual fund literature finds a strong relationship between *mutual fund holdings* and *high* end-of-year returns, here we find a string relationship between *short interest* and *low*

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[1] See, for example: "Are Short Sellers to Blame for the Financial Crisis?", Bill Saporito, Time, September 18, 2008 or "Did Short Selling Contribute To The Financial Mess?", Wendy Kaufman, National Public Radio, September 19, 2008.

[2] Evidence on responses to incentives includes Brown, Harlow and Starks (1996) and Busse (1999), among others.

end-of-year returns. In other words, stocks for which there are a large number of short positions perform poorly on the last trading day of the year. The effect that we document is strongest among firms that are easiest to manipulate (small, illiquid stocks), and is strongest in the last hour of the last day of trading. Using the Regulation SHO intra-daily data on short sales (as described in Diether, Lee and Werner (2007)), we find significantly more short-selling in the last hour of trading for stocks that have large short interest. We also find strong evidence that stocks with high short interest experience reversals at the beginning of the year, undoing the low returns experienced at year-end with high returns at the beginning of the year. This suggests that the poor returns experienced by high short-interest stocks at the end of the year are temporary.

All of these results are consistent with trading by short-sellers who have strong end-of-year incentives to manipulate prices. Furthermore, previous literature has shown that hedge fund managers have strong end-of-year incentives arising out of the convex relationship between returns and compensation, primarily driven by performance contracts. So hedge fund traders are a natural examples of short sellers with strong end-of-year incentives. Although data concerning hedge fund short positions are sparse, we do find a strong relationship between our short interest variable and the aggregate short positions of hedge funds that we can observe. We also find that our main result – high short interest leads to low year-end returns – is strongest in years in which the hedge fund industry was the largest.

After providing both time-series and cross-sectional evidence of end-of-year manipulation by short-sellers, our paper then considers situations in which stocks are subject to upward manipulation pressure by mutual funds and downward pressure by short-sellers, a set of stocks which we call “battlefield” stocks. We show that when mutual funds’ long positions and short-sellers positions are of similar size, then a number of interesting results emerge in two distinct variables: volume and price. First, we find overall decreases in volume that are consistent with the notion that short-sellers and mutual fund managers avoid each other’s territory for year-end trading. Even though the average pattern is consistent with each group avoiding trading against the other, a refinement of the results shows that when both groups have large positions, volume increases significantly.

When we turn our attention to prices, and we see that the battlefield stocks show either no pattern on year ends, or they show a price increase, consistent with the idea that for the average battlefield stock, upward manipulation pressure by mutual funds is relatively strong compared with downward pressure by short-sellers. However, when we focus on the difference between holdings in battlefield stocks, we find that downward manipulation pressure is significantly stronger among stocks with high holdings. This result indicates that when the two sets of traders have large exposures to the stock, downward pressure by short-sellers dominates. Furthermore, when we examine stocks with high trading volume in the last half hour of the day, or stocks where battles between mutual funds and short-sellers may have taken place, we find that returns for high-volume stocks are below returns for low-volume stocks. In other words, when battles appear to have taken place among relative matches, downward pressure is stronger, relatively, than upward pressure.

Our conclusion is that short-sellers are not unique, but rather that flow-based and compensation-based incentives motivate traders regardless of whether they are long or short. We also find interesting return and price dynamics when the incentives of both long and short traders align.

The balance of this paper proceeds as follows. Section II describes the existing literature upon which our paper builds, Section III details our hypotheses, Section IV describes our data, Section V reports our findings and Section VI concludes.

II. Background

The motivation for this paper arises out of three distinct strands of the existing literature. In Section A, we summarize the literature on hedge fund managers' incentives. In the Section B, we describe the literature's main findings on period-end trading patterns, and in Section C, we describe the literature on price manipulation.

A. Incentives

Incentives are central to the hypothesis that hedge fund trading is associated with period-end trading patterns. Incentives may arise from three sources: reporting, flows and contracts. First, reporting refers to the idea that hedge funds may report their returns to databases and investors. To the extent that reporting makes monthly, quarterly and annual performance periods more important than other periods, hedge funds will have an incentive to manipulate prices at the ends of these periods. Second, flows into funds from new investors may reflect past performance over specified periods. In hedge funds, this flow to performance relationship may be more closely tied to quarterly and annual performance because of the existence of redemption periods which limit investors' ability to withdraw funds between performance measurement periods. Finally, managers' performance contracts are one of the key distinguishing features of hedge funds, and these contracts generate relatively strong incentives. Performance contracts are not only functions of assets under management, but as shown in Hodder and Jackwerth (2007), hedge fund contracts typically include performance fees that are tied to performance. The fact that managers' contracts are more closely tied to performance increases managers' incentives to manipulate end-of-period prices. In the following paragraphs, we will explain these three sources of year-end incentives in more detail.

In the popular press, Eisinger (2005) argues that reporting is a key driver in an apparent pattern in month-end prices; the article documents upward spikes in the month-end prices of several stocks. The article argues that hedge funds are likely responsible for the pattern on the last day on the month, quarter or year. The article shows that prices increase before the end of the period and recede in the first days of the following period, and the article argues that recent proliferation of hedge funds, combined with the fact that many hedge fund investors get monthly updates, explains a recent increase in the end-of-month return pattern. Furthermore, Ackermann, McEnally and Ravenscraft (1999) explain that hedge funds send audited reports to investors which include monthly returns, and that these returns are the same returns the funds supply to the databases.

Similarly, fund flows have been shown to be an important determinant of manager behavior, especially in the area of mutual funds. Brown, Harlow and Starks (1996) shows that mutual fund managers increase risk when their performance is below that of their peers. Specifically, managers whose mid-year performance is above the median fund's performance have a lower standard deviation through the rest of the year than funds with mid-year performance below the median. Papers such as Brown, Harlow and Starks (1996) are measuring risk shifting that would be a natural outcome of the incentives generated by the convex flow-performance relationship identified in Chevalier and Ellison (1997) and Sirri and Tufano (1998). Despite the fact that hedge fund contracts typically pay benchmark-based performance fees, Brown, Goetzmann and Park (2001) provides evidence that relative performance, or competition among managers in the hedge fund industry, still influence managers' choice of risk. The paper argues that managerial career concerns are the primary driver of increased risk taking. However, Fung and Hsieh (1997) show that reputational concerns and contractual constraints may reduce the incentive to increase risk.

The existence of subscription and redemption periods may also increase the importance of period ends (e.g. Ackermann, McEnally and Ravenscraft (1998) and Aragon (2007)). Unlike mutual funds, hedge fund investors are only allowed to withdraw funds at pre-specified times. Ackermann, McEnally and Ravenscraft (1999) show that 85% of hedge funds allow multiple redemption periods each year, based on net monthly returns. Interestingly, they show that subscription and redemption periods do not necessarily correspond to incentive fee periods, which are quarterly or annual.

Finally, contracts are likely to play a strong role in hedge fund managers' incentives at the end of the performance measurement period. As Brown, Goetzmann and Park (2001) indicate, there are two components to manager compensation: a fixed percentage of assets under management and a performance-based fee. Ackermann, McEnally and Ravenscraft (1999) show that the median percentage of assets that is paid annually as a non-performance-based management fee is 1.25%, and Goetzmann, Ingersoll and Ross (2003) say it is "nearly axiomatic" for managers seek to increase the size of assets under management. But perhaps the strongest incentive to manipulate prices arises from the performance fee. Carpenter (2000), Goetzmann, Ingersoll and Ross (1997), Grinblatt and Titman (1989) and Kaniel and Cuoco (2007) all show that hedge fund performance contracts have option-like payoffs that increase the incentive to take risk. McEnally and Ravenscraft (1999) state that in the "overwhelming majority" of cases, fees are calculated on an annual basis. Therefore, year-end price manipulation could be considered one form of risk taking, and Agarwal, Daniel and Naik (2007) say "hedge funds are compensated by incentive fees that are paid at the end of the year based on annual performance exceeding pre-specified thresholds. Thus, there exist strong incentives for managers to improve performance as the year comes to a close."

B. End-of-Period Return Patterns

The finance literature has identified several patterns in returns around period ends. Keim (1983) and Roll (1983) identify excess returns in small stocks over a five-day period a starting with the last day of the year. Attempted explanations for this anomaly include tax-loss selling (e.g. Roll (1983) and Ritter (1988)) and window dressing (e.g. Haugen and Lakonishok (1988) and Musto (1997)). However, these explanations relate to the first days in the new year, and they have no specific implications for the last day (or especially, the last minutes) of the previous year. Similarly, Ariel (1987) identifies excess returns over a nine-day period a starting with the last day of the month. Furthermore, Harris (1989) shows that prices rise at day-ends, and he finds this pattern is strongest at month-ends.

Carhart, Kaniel, Musto and Reed (2002), Bernhardt and Davies (2005), Duong and Meschke (2008) and Zweig (1997) show that mutual funds manipulate year-end prices. Furthermore, aside from differences in hedge fund preferences (e.g., Griffin and Xu (2008)), any upward manipulation by mutual funds is likely to be indistinguishable from upward manipulation by hedge funds, and that upward manipulation plays an important role in our setting. Everything else being equal, we would expect hedge funds to manipulate year-end prices for the same reasons mutual funds do, but the manipulation would look different because of the prevalence of short positions in hedge funds. Furthermore, hedge funds are, by definition, less regulated than mutual funds. As a result, we may expect even more manipulation due to the relative lack of supervision, and we may expect some manipulation at the expense of mutual funds as in Chen, Hanson, Hong, and Stein (2008).

One potentially important aspect of market microstructure that affects our analysis is the calculation of closing prices. Hillion and Suominen (2004) show closing auctions significantly changed trading patterns associated with manipulation on the Paris Bourse. Similarly, Duong and Meschke (2008) show manipulation peaks in the 1997-2001 period. On the NASDAQ, price determination changed from a last-trade mechanism to a closing price auction in April, 2004. The change, documented in Smith (2005), makes it more difficult to manipulate closing prices (e.g. Comerton-Forde and Putniņš (2008)). Interestingly, we do not find any significant difference when we proxy for this change in our analysis.

One additional way hedge funds could improve period-end performance is to trade in non-equity securities. Aragon and Martin (2008) show that hedge funds have many option positions. Hedge funds could possibly avoid contention with mutual fund closing trades by trading in non-equity markets such as the options market.

C. Manipulation

This work also touches on the theme of enforcement cases in the area of stock price manipulation. Aggarwal and Wu (2006) show that stock characteristics such as exchange listing, market capitalization and liquidity are related to manipulation. In the sample used by Aggarwal and Wu (2006), there are 17 SEC enforcement actions on NASDAQ listed securities and only 3 enforcement actions on NYSE securities. Similarly, Comerton-Forde and Putniņš (2008) construct a model that estimates the likelihood of manipulation. The model is calibrated using 160 enforcement cases of closing price manipulation, and they find that price, volume and liquidity all play an important role in predicting the likelihood of closing price manipulation.

The literature on enforcement of manipulation cases echoes the literature on the potential for manipulation. The literature on enforcement actions suggests that more manipulation actually takes places in situations where manipulation is easier, such as small, illiquid stocks traded on the NASDAQ.

III. Hypothesis Development

We intend to show that short interest before the end of the period is related to end-of-period returns, and this pattern is a result of end-of-period trading by hedge funds. We will start by breaking this pattern up into testable hypotheses. First, we need to show that short interest is negatively related to end-of-year price movements.

H1. High short interest is negatively correlated with end-of-year returns.

Next, we can take advantage of the recently released intraday short sales volume data to show that short interest is related to end-of-year short sales volume.

H2. Short interest is positively correlated with end-of-year short sales volume.

Finally, to reinforce the result that the price and trading patterns are the result of intentional manipulation, we need to show that the trading and return patterns are most evident in settings where manipulation is likely to be most effective. Starting with the exchange, we can rely on evidence form Aggarwal and Wu (2006) to show that manipulation is more likely on the NASDAQ. It is interesting to note that end-of-period prices may be affected by information and/or trading in other markets. So, volume and selling pressure are not necessary for a price effect.

H3a. Price, volume and selling pressure are all more evident on the NASDAQ than the NYSE.

Also following Aggarwal and Wu (2006), we would expect liquidity to be an important factor.

H3b. Price, volume and selling pressure are all more evident on stocks where liquidity is low.

While somewhat overlapping with a measure of liquidity, we expect that smaller cap stocks will be more easily manipulated as well.

H3c. Price, volume, and selling pressure are all more evident on smaller cap stocks.

Finally, following Carhart, Kaniel, Musto and Reed (2002), we expect manipulation to be more effective at the end of the period, a result that is supported by the prevalence of enforcement actions examined in Comerton-Forde and Putnins (2008).

H4. Price, volume and selling pressure effects are all more evident at the end of the last day of trading relative to earlier in the day and relative to other days of the year.

Overall, our hypotheses take the basic idea that hedge funds put downward pressure on prices to increase the value of short positions and split it up into testable hypotheses.

IV. Data

We employ a number of databases to examine short selling around period ends. In addition to the usual data on stock prices and accounting variables, we use short interest, intraday short sales transaction data, intraday trade and quote data and a database on hedge fund short positions. In this section we will describe each database and our process of preparing the data for analysis.

We obtain short interest from June 1, 1988 to December 31, 2007. Short interest is reported is monthly until August 2007, and it is reported semi monthly from September 2007 through the end of 2008. Compustat provides the data from March 2003 to the present, and the older data are from historical releases from the exchanges.

We employ a database of intraday short sales transaction data from January 2005 through July 2007. As described in Diether, Lee and Werner (2007), our short sales database is a transaction level record of short sales. The data were made available as part of the Securities and Exchange Commission's Regulation SHO, which required exchanges to make short sales transaction data publicly available. It is worth noting that the short sales volume is only one part of a large collection of databases on short sales. As described in Boemer, Jones and Zhang

(2008) one important deficiency of the short sales volume database is the fact that these data are short sale initiations, and this database provides no information on the duration of short positions.

We also employ the NYSE Trade and Quote data (TAQ) to examine the intraday evidence on closing price patterns. We employ the TAQ data for two primary reasons. First, the TAQ data shows whether trading patterns at the end of the day differ from trading patterns throughout the rest of the day. Second, given the fact that the short selling transaction data is only available for a relatively short period, the TAQ data allows us to estimate sales volume for a much longer period. Although we will not be able to disentangle short sales from long sales, the Lee and Ready (1991) algorithm helps measure the relative selling pressure at the end of the day. All transactions are aggregated into 30 minute intervals through the trading day. Out of hours trades are excluded. Trade volume for an individual interval is dollar weighted at the transaction level.

To obtain accurate measures of price manipulation, we only consider transaction executed on the listing exchange of each stock. We obtain monthly data from CRSP which we compare with the TAQ data, keeping only the transactions which occur on the home exchange.

We obtain institutional ownership data from the Thomson Reuters s34 database, which provides all institutional ownership of all 13f institutions, and we use the term "institutional ownership" to refer to these 13f institutions, not individual mutual funds. To compute excess returns, we employ the value-weighted market return and the benchmark described in Daniel, Grinblatt, Titman, and Wermers (1997). Mutual Fund holdings computed for the "Battlefield" section are from the Thomson Reuters s12 database at a quarterly frequency, and the percentage is computed by aggregating mutual fund positions in a single stock and dividing by shares outstanding.

Aggregate hedge fund data comes from two sources. We obtain Net Asset Value (NAV) and Returns from TASS prior to 2006, and obtain Funds Under Management (FUM) from HedgeFund.net. Data is available by fund along with fund style. We take all fund styles except Fixed Income Arbitrage, Emerging Markets, and Managed Futures as funds of interest for short selling. NAV and FUM are each summed monthly to obtain an aggregate growth measure of hedge funds. We believe NAV to be the more accurate measure and so we use them separately and then create an aggregate measure where we take NAV first and supplement with FUM only when NAV is not available.

Data on position-level hedge fund holdings come from the Morningstar US Open Ended Funds database. This database allows us to gather holdings of hedge funds from 1988 to 2009. The database, similar to that used by Aragon and Martin (2009), covers hedge funds that qualify as 13(f) institutions, namely managers with holdings "having an aggregate fair market value on the last trading day of any month of any calendar year of at least $100,000,000". Using these data, we construct aggregate holdings for hedge funds in each stock. The data frequency is quarterly, though there are some additional observations available for intervening months for some funds.

We combine these databases with stock price and volume data from CRSP and financial statement data from Compustat. We use different time horizons for each experiment, but in the cross section our databases cover 16,668 unique equities in over the period from 1988 to 2007. Additional summary statistics are provided in Table I.

V. Results

If hedge funds trade to affect the closing prices of their positions, it will be relatively straightforward to find statistical evidence of these actions. In this section, we will describe our approach of testing for patterns of manipulation and we will analyze our results.

A. Patterns in Prices

In our first set of experiments, we will be looking for patterns in closing prices. Our hypotheses are distinct from the "marking the tape" hypothesis in that we focus on short positions rather than long positions. In this sense, our paper is the first to identify the use of closing price trading strategies by short sellers. Specifically, we know from Carhart, Kaniel, Musto and Reed (2002) that there are positive abnormal returns for mutual fund long holdings on the last day of the year, so our approach is to look for distinct return patterns in stocks where there are substantial short positions. Of course, short interest is such a measure, so as a first pass, we will look at the effect of short interest on end-of-year returns.

Figure 1 shows the end-of-year return pattern graphically. We plot excess returns in 30-minute intervals for year-ends and non-year-ends. On days that are not year-ends, the returns are relatively flat, and returns for stocks with high short interest and low short interest are close to one another. This indicates that these two sets of stocks have relatively similar return patterns on non-year-end days. However, the solid lines indicate short interest plays a large role in the return pattern, especially at the end of the day. The grey line captures the return pattern documented in Carhart, Kaniel, Musto and Reed (2002); for stocks with low short interest returns increase 61 basis points in the last half-hour, consistent with mutual fund managers trading to increase the closing price. The black line, which plots returns for stocks with high short interest, shows the dramatic difference from Carhart, Kaniel, Musto and Reed (2002); for stocks with high short interest, returns fall by 24 points in the last half-hour. The dramatic difference between the two sets of stocks, primarily in the last half-hour of the day, is consistent with institutional managers trading to improve the annual performance of their portfolios, but in distinct ways depending on whether portfolio positions are short or long.

When we turn our attention to stocks that are more easily manipulated in Panel B of Figure 1, we see that there is even stronger evidence for the marking the tape hypothesis; stocks with low short interest have a 95 basis point increase in returns at the end of the year. Interestingly, we see that stocks with high short interest have a less dramatic decrease among stocks that are more easily manipulated. As we will explore in a later section, the smaller difference may be the result of an increased proportion of stocks where both long- and short-position holders are trading to change prices.

Our first statistical approach to testing the statistical significance of the pattern is a pooled time series and cross sectional regression. The regression has daily risk-adjusted returns for individual stocks on the left hand side, and indicator variables for period ends and short interest on the right hand side. Specifically, *Month End* is an indicator for month-ends which are not quarter- or year-ends, *Quarter End* is an indicator for quarter-ends which are not year-ends, and *Year End* is the last trading day of the year. *Short Interest* is the number of open short positions normalized by the number of shares outstanding. To ensure that possible correlation between short interest and mutual fund holdings is not driving the results, we control for institutional ownership in the regressions to capture the distinct effect of short interest on end-of-period returns. *Hedge Fund NAV* is a monthly aggregate Hedge Fund Net Asset Value of hedge fund styles likely to engage in short selling. We employ this variable to test whether *Short Interest* is a good proxy for Hedge Funds engaging in short selling. Hypothesis H1, the hypothesis that there is negative correlation between short interest and returns at year-ends, will be tested by asking whether there is a statistically positive coefficient estimate on the interaction between *Short Interest* and *Year End*.

Table II shows the results. The coefficient estimates of the period-end indicator variables are mixed for the whole sample, but in the later portion of the sample, there is a strong positive relationship between returns and *Year End*, as expected from Carhart, Kaniel, Musto and Reed (2002). However, this relationship does not condition on the degree of long or short holdings. In fact, one of the central findings of this paper reverses the Carhart, Kaniel, Musto and Reed (2002) result for stocks with high short interest. The negative and statistically significant coefficient estimate of -106.091 in the overall sample indicates that for stocks with a large amount of short interest, year-end returns are significantly negative. Economically, the coefficient is relatively large; a one standard deviation increase in short interest is associated with a decline of 1 basis point in the daily return, but on the last day of the year, that same one standard deviation increase in short interest leads to a 7 basis point decrease in returns.

Although the result is large and statistically significant in overall sample, the effect of short interest on end-of-year returns is particularly strong from 2001 through 2007. This later period, which corresponds with a dramatic increase in hedge fund assets, has a particularly strong coefficient estimate of -220.806. Here, a one standard deviation increase in short interest is associated with a decline of 1 basis point in the daily return, but on the last day of the year, that same one standard deviation increase in short interest leads to a 13 basis point decrease in returns.

We test the correlation of hedge funds and our proxy variable in the final regression. Again, we use the whole sample and find that it enters the regression negatively and significant at the 10% level. This gives at least some evidence that hedge funds matter in this end of year effect.

As Aggarwal and Wu (2006) demonstrate, manipulation is not equally likely among stocks. Specifically, that paper shows that manipulation is more likely among NASDAQ stocks than NYSE stocks, and manipulation is more likely among small and illiquid stocks. As a test of Hypothesis H3a, we show in Table III that the year-end return pattern is only statistically significant for NASDAQ traded equities. The statistically significant coefficient estimate of -

316.607 on the NASDAQ compared with the insignificant estimate on the NYSE shows that the effect is surprisingly strong on the NASDAQ relative to the NYSE.

Similarly, we show that the effect is concentrated in illiquid stocks. As a test of Hypothesis H3b, we show that the year-end return pattern is statistically significant for the lowest two terciles of illiquidity as measured by Amihud (2002). The effect is particularly strong for the lowest tercile, where the statistically significant coefficient estimate is -622.974, also in Table III. When we pool all stocks, we find that the indicator variable for stocks in the lowest tercile of Amihud (2002) liquidity is significantly negative when interacted with *Short Interest* and *Year-End* as shown in Table IV. Overall, we find that the end of the year price effect is significantly stronger among illiquid stocks.

Finally, we show that the effect is concentrated in small stocks. As a test of Hypothesis H3c, we show that the year-end return pattern is statistically significant for small stocks as predicted.. The lowest tercile of stocks, which comprises stocks with an average market cap of $41MM, has a statistically significant coefficient estimate of -456.523. As with exchange listing and liquidity, we show the difference is statistically significant in Table III. When we pool all stocks, we find that the indicator variable for stocks in the lowest tercile of market capitalization is significantly negative when interacted with *Short Interest* and *Year-End* in Table IV. Overall, we find that stocks traded on the NASDAQ, illiquid stocks and small stocks all have a significantly larger price effect, a finding consistent with the Aggarwal and Wu (2006) findings more the end of the year price effect is significantly stronger among illiquid stocks. A summary of these results can be found in Table IV.

To confirm that the movement in prices we observe is manipulation rather than information-based trading, we must show that prices reverse in the subsequent first trading day in the next period. Thus, we now employ a leading return as our dependent variable, and the contemporaneous return in addition to our standard set of independent variables. We show the results of our test with an Excess Return measure in Table V. Similar to our main result, we see a reversal on the whole sample of 36%, but when we limit the sample to 2001-2007, we find stronger evidence of reversals, as evidenced by a coefficient of -0.679 and an increase in significance from 10% to 5%. With raw returns, we do not have a significant result on the entire sample, but find strong evidence of reversals in the 2001-2007 subsample with a coefficient of -1.015, significant at the 1% level. We see this as further evidence that hedge funds play a role in end-of-year manipulation as their growth has been tremendous since 2001. Results are summarized in Tables V and VI.

B. Patterns in Volume

Figure 2 shows the pattern graphically. Following Carhart, Kaniel, Musto and Reed (2002), we first define abnormal short selling volume as short selling volume relative to short selling volume in the surrounding symmetric 120-day window. We do this over distinct 30-minute intervals throughout each day. Next we compare abnormal short selling volume among stocks with high short interest to stocks without high short interest. As Panel A shows, on days that are not year-end, the dashed lines are flat and close to one another. This indicates that these two sets of stocks are relatively similar in terms of short sales on a typical day. However, the solid lines indicate short sales volume on the last day of the year. The black line, which plots short volume for stocks with high short interest, is higher than the grey line throughout the day, and the difference is particularly large in the last hour of the day. In other words, the trading patterns of stocks with high short interest are normally similar to other stocks, but on the last day of the year, there is substantially more short-selling among stocks with high short interest, especially at the end of the day. The pattern in Panel A of Figure 2 is striking, but it is somewhat unfocused because it includes stocks regardless of whether manipulation is feasible. Following the evidence in Aggarwal and Wu (2006), we refine our sample of stocks to small stocks on the NASDAQ exchange, and we find that the pattern is similar, if not more dramatic.

Of course, the pattern in the figure may or may not be statistically significant after controlling for various factors. So, in Table VII, we turn to a regression framework in which the dependent variable is abnormal volume in each of the last four hours of the day. That is, the dependent variable is the natural logarithm of each hour's short selling volume minus the natural logarithm of short selling volume from 9:30 A.M. to 12:00 P.M. on the same day.[3] The fact that each hour's normalization comes from an early period in the same day not only controls for

[3] We obtain qualitatively similar results when we use percent changes rather than log differences for the dependent variable.

cross-stock and cross-day differences in trading patterns, but it also allows us to include one observation per day in the regression framework in a setup similar to Table III. The coefficient estimates show that short selling volume is not abnormally high from 12:00 P.M. through 3:00 P.M., but from 3:00 P.M. to 4:00 P.M., there is a significant increase in short selling among stocks that have high short interest on the last day of the year. This finding is confirms Hypothesis H4. We see that short selling is abnormally high only in the last hour of trading, which is consistent with short sellers trading in an effort to influence the closing price.

C. The Role of Hedge Funds

The patterns described in the preceding sections of this paper are based on short interest data, and as such, they cover a number of different types of market participants, including individuals, proprietary trading desks and hedge funds. In this section, we provide some evidence that the behavior of hedge funds contributes to the pattern.

Table VIII shows that hedge fund holdings are closely correlated with short interest. Specifically, we present the estimates from regressions of short interest on hedge fund holdings from Morningstar from 2001 to 2009. Each observation in the regression represents a unique reporting date on which we have aggregate hedge funds' holdings for a given stock, and for that observation, we identify the market-wide short interest data for that stock that is most closely matched in calendar time. In the normalized regressions, short interest, hedge fund holdings and institutional ownership are normalized by shares outstanding.

We see a positive and significant relationship between hedge fund ownership and short interest, even controlling for institutional ownership and market capitalization. The relationship is strong and the magnitude of the coefficient estimates is intuitive. The coefficient estimate in the last column of Panel A, 2.279, indicates that for a 10% increase in shares held by hedge funds, short interest increases by 22.79%. In other words, the regression indicates market-wide short positions are closely correlated holdings that holdings by hedge funds, and hedge funds comprise only a fraction of the market's overall short positions.

Ideally, we could study hedge fund behavior more closely by looking at holdings data in much the same way Carhart, Kaniel, Musto and Reed (2002) employ mutual funds' holding data. Namely, we could use stock-level hedge fund holdings to predict year-end patterns in prices and returns.[4] However, this potential experiment suffers from several shortcomings. First, the \$100,000,000 cutoff significantly restricts the sample of hedge funds. Specifically, or sample comprises 330 hedge funds whereas Lipper/TASS database indicates that there are at least 3863 unique hedge funds over this period. Second, we suspect that those funds that do report may be modifying their behavior because of the reporting itself. We see a significant amount of cash holdings in the holdings database, 26% on average (with a median of 16%) whereas other sources, such as Lipper/TASS indicate that the average hedge fund has a leverage ratio of over 50%. This holdings difference may a result of window dressing.

[4] In unreported results, we replicate Table II with hedge fund holdings instead of short interest. We find insignificant results, and we attribute some of the difference between these results and the Table VIII results to a lack of power. The number of observations falls from 6.2M with short interest to 739K with hedge fund holdings.

In the end, it is not surprising that the lightly-regulated pool of hedge fund assets has sparse, and potentially non-representative, reporting. In fact, similar databases are used by several recent papers because, despite the limitations, these data give an unprecedented view into hedge fund holdings.[5] Overall, we see that the short positions of those hedge funds for which we do have data are closely correlated with market-wide short interest, but the hedge funds data are too sparse to use in a direct test of whether specific hedge funds manipulate stocks in which they have short positions.

D. *Battlefield Stocks*

Carhart, Kaniel, Musto and Reed (2002) show that fund managers trade to increase year-end prices, and the evidence above indicates that hedge fund managers trade to decrease year-end prices. What happens when both types of managers are trading in the same stock? In this section, we answer this question by analyzing stocks where mutual fund managers and hedge fund managers both have a strong interest in the year-end prices, stocks we will call battlefield stocks.

Our first goal is to identify these stocks, and we do this by comparing short interest to institutional ownership on a stock by stock basis. To get an accurate gauge of holdings without including shares bought and sold on the last day of the quarter, we take institutional ownership in the previous quarter and the last short interest report in the previous quarter. We then calculate

[5] e.g. Aragon and Martin (2008) and Griffin and Xu (2007)

two measures for each stock: institutional ownership scaled by shares outstanding and short interest scaled by shares outstanding. We then identify stocks where these measures are roughly equal based on two notions of equality: relative and absolute. Our relative measure identifies stocks where the percentile ranking of institutional ownership is equivalent to the percentile ranking of short interest. In other words, we round each percentile ranking to the nearest percentage point, and we look for stocks where those rounded percentages are equal. We will call this our ***rank match***. Our absolute measure is similar, except we do not rank institutional ownership or shares outstanding in order to get a measure that captures matches on a number-of-shares held basis. In other words, the absolute measure identifies stocks where the number of shares held by mutual fund managers matches the number of shares held by hedge fund managers. We will call this our ***size match***. We will use this bold italic font to indicate our battlefield matches on rank and size.

The results of a Wilcoxon test of means are presented in Table IX. The first set of findings that emerge from the examination relate to volume. We use two measures of volume over the last half hour of the day, *Excess Volume* and *Excess Dollar-Weighted Volume*, which is defined as the increase in volume in the last half-hour of trading on quarter ends over the 120 moving average for that half hour. As seen in Table IX in the ***rank match*** on the whole sample, we do not see a statistical difference in our ***rank match*** measure of battles, though we will continue using it for comparison. In the ***size match***, however, we get very large negative Z scores of 23.44 and 24.78 for our two measure of volume, indicating that this is a significant division.

The matching definition allows matches where short interest and institutional ownership are equal and *low* as well as matches where short interest and institutional ownership are equal and *high*, but we have little reason to expect end-of-quarter trading when these variables are low, because trading will have a relatively small effect on the overall performance when holdings are low. To examine differences between high matches and low matches, we form groups for both types of matches; specifically, we define a low match as a match where the relative ranking percentile is in the lowest tercile of matched battle stocks, which is less than the 25th percentile, or the number of absolute shares is below 1%. We define a high match as a match where the relative ranking percentile is in the highest tercile, greater than 70th percentile, or the absolute number of shares is above 4%. We then compare volume for high matches and low matches in rows 2 and 4 of Table IX. Interestingly, we get opposing results. Under the ***rank match*** measure, we see that higher holdings lead to lower excess volume. But, when the absolute number of shares is matched in our ***size match*** measure, the significant Z-score of 7.39 indicates that these stocks have significantly more volume. In other words, the overall results show that hedge funds and mutual funds generally stay away from each other's territory, but when both groups have large positions, volume increases significantly, indicating that hedge funds may have higher enough incentives to push prices downward or perhaps just prevent mutual funds from moving prices up against their large short positions. Our last comparison is on quarter-end versus year-end. We find that with the ***rank match*** measure, volume in general decreases at year end, with an insignificant decreasing using the ***size match*** measure. In Table XI, we show that a multivariate analysis yields similar results, with the ***rank match*** correlating higher holdings with lower volume, whereas the ***size match*** correlates higher holdings with higher volume. The ***rank ma***again shows a decrease in volume at year-end, indicating avoidance, which now is corroborated by the ***size match*** when we interact *Year End* with *High Holdings*.

The second set of findings relate to price, where we again have a Wilcoxon Test of Means in Table X. If higher volume indicates that a battle is happening, then the movement of the price will tell us who is winning. We consider two measures: *Afternoon Return,* which is computed with the price difference from 12:00 P.M. to close and *Late Afternoon Return*, which is computed with the price difference from 2:30 P.M. to close and again subdivide into the same *Low Holdings* and *High Holdings* groups as before. We first look at prices in the full sample of stocks with somewhat mixed results. The ***rank match*** is insignificant for the full afternoon, but in *Late Afternoon*, we see a significant decrease, indicating that Hedge Funds may be depressing prices. But when we look at the ***size match***, we get strong results in the other direction, with both *Afternoon* and *Late Afternoon Returns* increasing when there is a battle. In all cases, *High Holdings* is associated with a significant Z score indicating downward pressure on prices. This seems to indicate that the higher the stakes, the more hedge funds are willing to fight in general. If we look solely at *Year End*, however, we see the familiar result of Carhart, Kaniel, Musto and Reed (2002) emerges; where in all four cases we see upward pressure at *Year End*. Table XI again provides multivariate results, but there are no significant results on the interaction terms.

In total, we see a pattern emerging. With a relative match, pitting the largest mutual fund positions against the largest hedge fund short interest positions, we see evidence of avoiding a fight as evidenced by insignificant differences overall, and specifically low abnormal volume when the stakes are particularly high. But when we look at prices, we see some evidence of downward pressure in general until we consider *Year End*, when it is clear that the mutual funds push prices upward.

When both institutional ownership and short interest are approximately the same percent of shares outstanding (***rank match***), there is more likely an increase in abnormal volume, indicating that mutual funds and hedge funds are fighting to push the prices in different directions. Looking at the whole sample, we see general downward pressure on prices, but at *Year End* compared to quarter-end, the movement changes to upward pressure, indicating that the mutual funds are winning when it matters the most.

VI. Conclusion

In this paper, we find trading patterns consistent with price manipulation by hedge funds. We start by identifying stocks for which hedge funds have a strong incentive to manipulate prices because of their large aggregate short positions: stocks where there is high short interest. Year-end returns are significantly lower in this sample of stocks. Furthermore, the effect is significantly stronger in later periods and stronger for stocks that are more easily manipulated. We also look at end-of-day short sales transactions, and we find that an increase in short sales may be responsible for the return pattern. Specifically, when there are relatively large short interest positions, we see a significant increase in short selling in the last half hour of trading. Overall, we find hedge funds respond to annual performance incentives in much the same way mutual funds do, but they take the opposite actions. Instead of buying shares to increase portfolio values, hedge funds short sell to decrease end-of-year prices of stocks already held in short positions.

But what if mutual funds and hedge funds are trying to manipulate the closing prices in opposite directions? We show that when mutual funds' long positions and hedge funds' short positions are of similar size, there are decreases in volume consistent with hedge funds and mutual funds avoiding each other's target stocks. However, when both groups have similarly large positions, volume increases significantly. In other words, if both groups have equal holdings, and the incentives are relatively strong, then there is an increase in trading volume. When we turn our attention to prices, we see that on the average, upward manipulation pressure by mutual funds is relatively strong compared with downward pressure by hedge funds. However, we find that downward manipulation pressure is significantly stronger among stocks with high holdings, and we find that returns for high-volume stocks are below returns for low-volume stocks. In other words, upward manipulation dominates on average, but when incentives are especially strong, or when there is a lot of volume, downward pressure is stronger than upward pressure.

This paper also makes a novel contribution to our understanding of short selling. We present evidence consistent with the idea that short sales are used in two ways. First, we show that a significant portion of short interest is likely held by institutional investors, such as hedge funds managers, who hold the short positions overnight and who are subject to the same incentives as other, better understood, institutional investors such as mutual fund managers. Second, we show that the convex relationship between performance and remuneration leads hedge fund managers to use short selling in order to temporarily decrease prices, especially in easily manipulated stocks.

Furthermore, the paper shows that short sellers manipulate prices. Whereas previous literature (e.g. Securities and Exchange Commission (2006) and Shilko, Van Ness, and Van Ness (2008)) identifies potential manipulation based on price and volume patterns, this paper uses one of the few situations in which there are clear, ex-ante predictions about exactly how short sellers would manipulate prices, and we find that short sellers do indeed manipulate prices. However, the results in this paper do not indicate that short sellers manipulate prices more than buyers, just that short sellers manipulate prices in much the same way buyers do. If anything, we find that when short sellers and buyers are both likely to be manipulating prices, the upward pressure from buyers outweighs the downward pressure of sellers on average.

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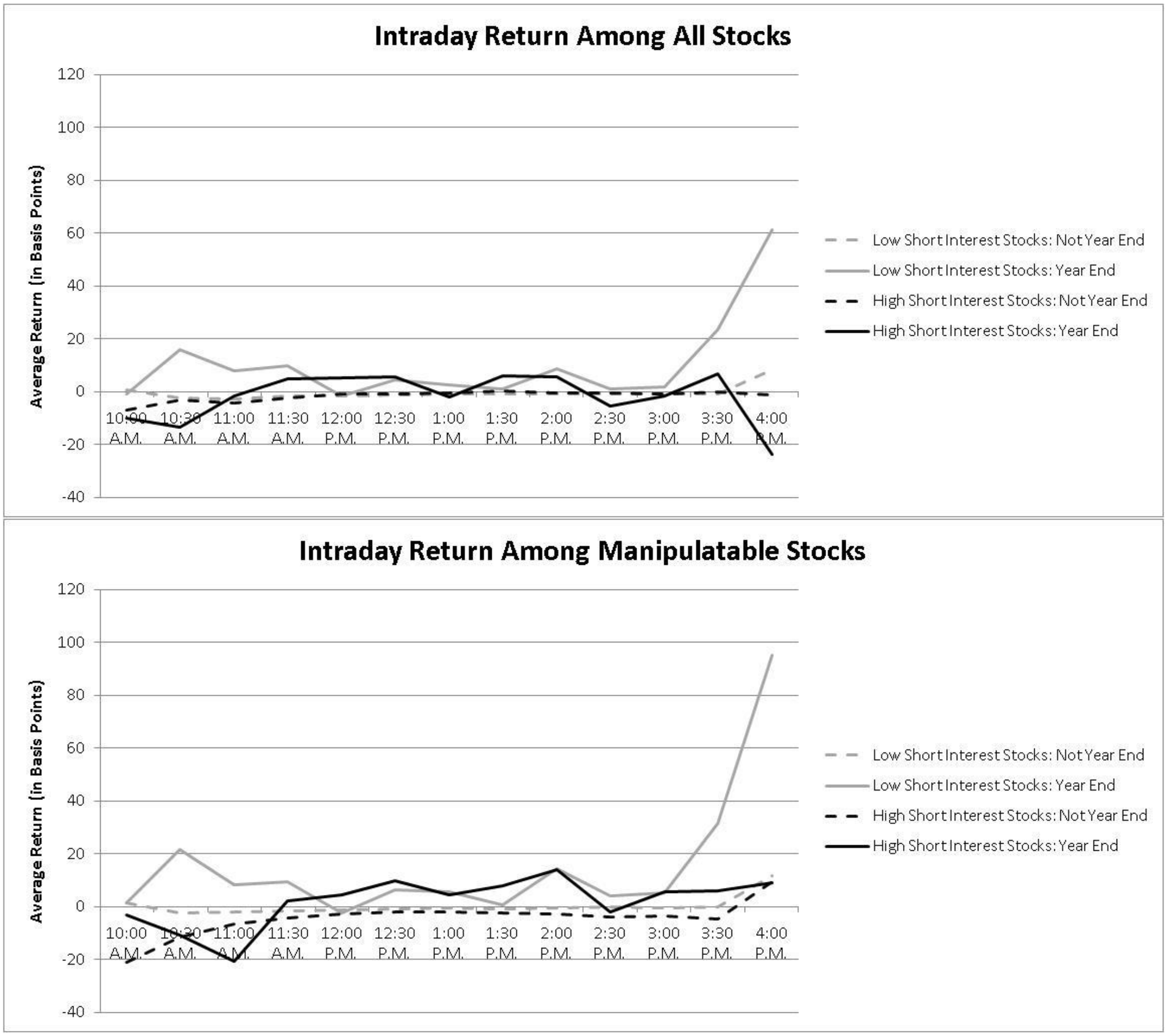

Figure 1: Intraday Return

Both panels plot the average excess half-hour return (excess is with respect to the value-weighted market return) for year-end and non-year-end days. Excess returns are winsorized at the 1st and 99th percentile . The top panel plots these for stocks sorted into high/low quintiles based on short interest. The bottom panel plots the same but is restricted to "manipulable" stocks. Manipulable stocks are those that trade on NASDAQ and have market capitalizations that are in the bottom tercile of our sample. The data cover the period of January 2001 – December 2007.

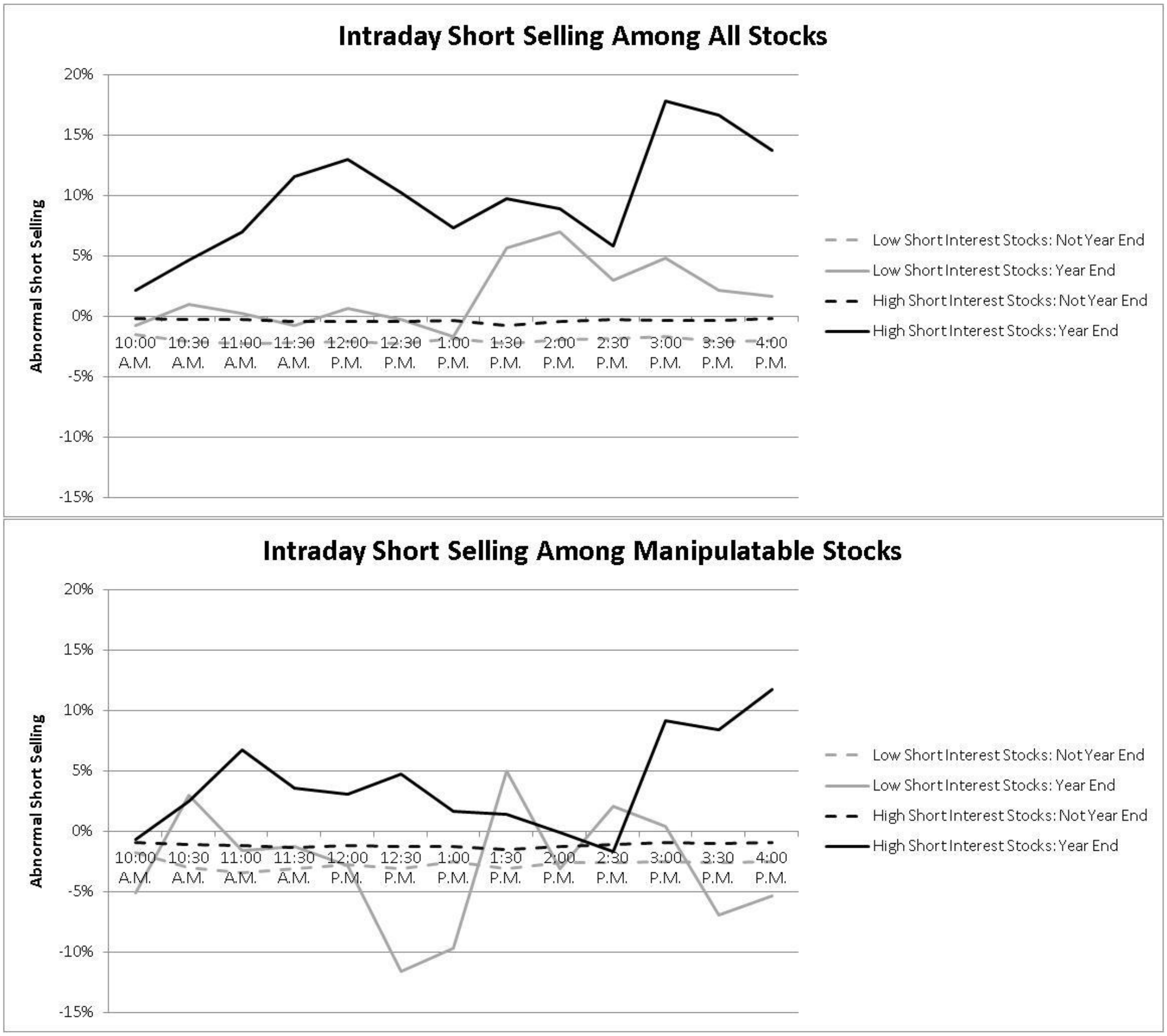

Figure 2. Intraday Short-Selling.

The top panel plots Excess Short-Sales Volume for stocks sorted into high/low quintiles based on short interest. Excess Short-Sales Volume is defined as Short-Sales Volume less its 120 day symmetric moving average over that moving average. The bottom panel plots the same but is restricted to "manipulable" stocks. Manipulable stocks are those that trade on NASDAQ and have market capitalizations that are in the bottom tercile of our sample. The data cover the Regulation SHO period of January 2005 – May of 2007 where we have intraday short-selling data. Excess Short-Sales Volume is winsorized at the 1st and 99th percentile.

Table I
Summary Statistics

Short Interest over Shares Outstanding is referred to as “Normalized Short Interest and Institutional Ownership over Shares Outstanding is called “Institutional Ownership.” All data is for 1988 through 2008 except short sales volume which is January 2005 through July 2007. Unique stocks are unique tickers across the entire data period. Total data set is 26.5M unique stock-days. Mean is reported with Median in parentheses underneath except where otherwise indicated.

	Overall	NASDAQ	NYSE
Short Interest/Shares Outsanding	0.027	0.018	0.037
	(0.0026)	(0.0013)	(0.0065)
Institutional Ownership/Shares Outstanding	0.38	0.32	0.51
	(0.29)	(0.23)	(0.51)
Normal Volume	329 M	260 M	469 M
	(28 M)	(17 M)	(72 M)
Short Sales Volume	8.7 M	7.7 M	9.3 M
	(2.3 M)	(1.3 M)	(3.4 M)
Number of Unique Stocks	16,668	10,245	4,835

Table II
Year-End Short Interest Effects by Period

The dependent variable in each regression is the DGTW characteristic-adjusted return, computed daily. All data are daily observations except as follows: Short Interest is normalized by Shares Outstanding observed mid-month contemporaneously with Short Interest. "Daily" short interest amounts are for the month in which they were reported mid-month. Institutional ownership is reported quarterly and duplicated daily for the entire previous quarter in which it was reported. White standard errors are in parentheses. *, ** and *** represents significance at the 10%, 5% and 1% level.

	Dependent Variable: Abnormal Return				
Period:	1988 - 2007	1988 - 1993	1994 - 2000	2001 - 2007	1988 - 2007
Intercept	2.577***	6.127***	3.101***	2.055***	3.701***
	(0.208)	(0.731)	(0.712)	(0.160)	(0.465)
Short Interest (Normalized)	-21.399***	-30.338***	-10.899*	-24.614***	-16.007**
	(5.619)	(10.458)	(5.792)	(3.013)	(7.625)
Institutional Ownership	-0.057**	-8.187***	-1.401	-0.028***	-1.612**
	(0.025)	(1.585)	(1.340)	(0.007)	(0.713)
Month End Dummy	1.707**	-2.742	2.351*	3.355***	1.482
	(0.848)	(2.083)	(1.423)	(1.179)	(0.906)
Quarter End Dummy	0.461	-6.147*	1.466	2.058	0.055
	(1.401)	(3.439)	(2.283)	(2.109)	(1.513)
Year End Dummy	3.481	-7.900	-1.019	14.680***	-4.265
	(2.837)	(6.091)	(5.056)	(2.948)	(4.224)
*Short Interest * Month End*	-18.895	2.890	-13.761	-37.779**	-15.852
	(14.493)	(68.848)	(22.367)	(17.566)	(16.268)
*Short Interest * Quarter End*	24.515	110.312	-4.756	29.968	24.815
	(18.610)	(149.651)	(22.662)	(27.604)	(21.251)
*Short Interest * Year End*	-106.091*	-16.585	-51.381	-220.806***	-54.733
	(54.859)	(112.794)	(110.703)	(34.927)	(112.029)
Hedge Funds					-0.001***
					(0.000)
*Short Interest * Hedge*					0.003
					(0.005)
*Year End * Hedge*					0.012***
					(0.003)
*Short Int * YrEnd * Hedge*					-0.121*
					(0.067)
Observations	13,571,010	2,303,227	5,039,227	6,228,556	11,842,700
Clusters (firms)	10,744	3,292	6,548	6,484	10,148
R-Square	0.000008867	0.000022	0.000003718	0.000024	0.0000092

Table III
Year-End Short Interest Effects sorted by Easiest-to-Manipulate Characteristics

The dependent variable in each regression is the DGTW characteristic-adjusted return and the sample is restricted to the 2001 – 2007 time period. Data is the same as in Table II. The Amihud illiquidity measure is calculated as in Amihud (2002) by taking the yearly average of absolute daily return divided by volume. White standard errors are in parentheses. *, ** and *** represents significance at the 10%, 5% and 1% level.

	Dependent Variable: Abnormal Return							
	Exchanges		**Liquidity**			**Size**		
	NYSE	NASDAQ	Low	Medium	High	Small	Medium	Large
Intercept	0.387	2.428***	3.911***	1.680***	-1.965**	-0.577*	9.394***	3.298***
	(0.604)	(0.221)	(0.411)	(0.366)	(0.780)	(0.303)	(0.486)	(0.500)
Short Interest (Normalized)	-18.926***	-28.473***	-3.796	-24.100***	-26.910***	-151.959***	-36.642***	35.265***
	(4.998)	(4.162)	(9.937)	(5.796)	(4.798)	(15.246)	(5.638)	(4.516)
Institutional Ownership	1.751**	-0.030***	-4.409***	-0.022**	4.885***	-0.040**	-8.515***	-2.401***
	(0.843)	(0.005)	(1.088)	(0.011)	(1.071)	(0.018)	(0.841)	(0.710)
Month End Dummy	4.688***	3.305**	3.910*	3.230	4.927***	4.947**	-0.445	5.397***
	(1.329)	(1.657)	(2.261)	(2.522)	(1.675)	(2.275)	(1.745)	(1.338)
Quarter End Dummy	7.854***	-0.302	-6.929*	-0.780	15.457***	-8.597**	10.798***	10.027***
	(2.172)	(3.103)	(3.677)	(4.641)	(2.860)	(4.059)	(3.271)	(2.491)
Year End Dummy	-1.336	20.328***	22.520***	13.986**	-0.273	39.854***	-6.524*	-0.989
	(2.622)	(4.063)	(6.160)	(5.434)	(2.730)	(6.232)	(3.648)	(1.944)
*Short Interest * Month End*	8.314	-72.537***	25.431	-41.248	-49.893*	-79.165	-1.113	-64.196**
	(26.143)	(23.690)	(62.294)	(34.147)	(25.465)	(63.506)	(20.911)	(25.894)
*Short Interest * Quarter End*	-58.912*	71.985*	95.854	15.670	-83.656***	178.267*	-43.820	-60.353
	(30.804)	(39.758)	(158.602)	(53.594)	(31.660)	(97.842)	(32.234)	(49.787)
*Short Interest * Year End*	10.642	-316.607***	-622.974***	-255.690***	-49.465	-456.523***	-48.888	-100.698***
	(46.194)	(43.988)	(132.975)	(68.782)	(42.010)	(149.028)	(43.775)	(35.876)
Observations	2070251	3781834	1649671	1556909	1801299	2070448	2062766	2095342
Clusters (firms)	1712	4246	2724	2786	2157	3707	3435	2355
R-Square	0.000043	0.000032	0.000025	0.000022	0.000073	0.000145	0.000197	0.00007

Table IV
Comparison of "Manipulable" Variables

Data are all the same as in Table II. "Manipulation Dummy" below is how each column "Manipulable" variable is used in each regression.

	Dependent Variable: Abnormal Return		
Manipulation Dummy Variable	NASDAQ	Illiquid	Small
Intercept	1.674***	1.529***	4.993***
	(0.193)	(0.191)	(0.199)
Short Interest (Normalized)	-24.446***	-20.911***	-43.818***
	(3.007)	(3.111)	(3.640)
Manipulation Dummy	0.617**	1.485***	-6.766***
	(0.240)	(0.320)	(0.337)
Institutional Ownership	-0.026***	-0.021*	-0.063*
	(0.009)	(0.012)	(0.035)
Month End Dummy	2.816*	3.128**	1.230
	(1.492)	(1.304)	(1.117)
Quarter End Dummy	5.821**	7.015***	9.363***
	(2.338)	(2.558)	(2.000)
Year End Dummy	4.091	10.818***	-4.935**
	(3.801)	(3.006)	(2.164)
*Short Interest * Month End*	28.380	-41.540**	-4.115
	(25.534)	(18.021)	(16.995)
*Short Interest * Quarter End*	-34.198	-13.161	-29.747
	(32.309)	(28.792)	(26.569)
*Short Interest * Year End*	-43.349	-171.606***	-47.232
	(50.372)	(35.258)	(31.409)
*Manipulation Dummy * Month End*	0.625	0.682	4.919*
	(2.231)	(2.604)	(2.521)
*Manipulation Dummy * Quarter End*	-5.987	-14.044***	-16.758***
	(3.871)	(4.450)	(4.503)
*Manipulation Dummy * Year End*	16.373***	11.609*	45.990***
	(5.557)	(6.811)	(6.608)
*Manipulation Dummy * Month End * Short Interest*	-104.957***	78.734	-183.114***
	(35.091)	(66.645)	(64.642)
*Manipulation Dummy * Quarter End * Short Interest*	102.142**	120.613	99.951
	(50.448)	(157.256)	(98.601)
*Manipulation Dummy * Year End * Short Interest*	-277.297***	-441.142***	-517.392***
	(66.325)	(140.144)	(150.191)
Observations	6,228,556	6,228,556	6,228,556
Clusters (firms)	6,484	6,484	6,484
R-Square	0.00003	0.000032	0.000115

Table V
Reversals using Excess Return Measure

Return is Excess Return over DGTW benchmark as in Table II. The dependent variable is the same return measure, one day ahead of the independent variable, such that it will be the first day of the year when T = Year End. White standard errors are in parentheses. *, ** and *** represents significance at the 10%, 5% and 1% level.

	Dependent Variable: 1 Day Lead Excess Return			
	1988 – 2007	1988 – 1993	1994 – 2000	2001 – 2007
RETURN	-0.165***	-0.255***	-0.166***	-0.097***
	(0.006)	(0.005)	(0.005)	(0.003)
Inst Ownership	-0.066**	-10.296***	-2.117	-0.026***
	(0.033)	(1.994)	(1.564)	(0.007)
Month End	-0.906	-3.596*	-0.748	0.564
	(0.809)	(2.071)	(1.270)	(1.068)
Qtr End	-1.368	0.343	-6.132***	2.037
	(1.273)	(2.884)	(2.093)	(1.848)
Year End	-0.722	4.280	-3.154	-2.320
	(2.478)	(5.435)	(4.503)	(2.870)
Short Interest	-22.991***	-48.008***	-12.076	-24.709***
	(7.824)	(9.996)	(8.923)	(2.660)
*RETURN *Month End*	-0.014**	0.010	-0.017*	-0.038***
	(0.007)	(0.021)	(0.010)	(0.010)
*RETURN *Qtr End*	-0.061***	0.008	-0.077***	-0.101***
	(0.012)	(0.021)	(0.017)	(0.022)
*RETURN *Year End*	-0.021	-0.040	-0.002	-0.011
	(0.016)	(0.026)	(0.023)	(0.022)
*Month End*Short Int*	-10.597	244.477***	21.100	-59.417***
	(13.955)	(66.162)	(14.141)	(15.644)
*Qtr End*Short Int*	-69.757***	-43.926	-69.794**	-83.228***
	(20.390)	(116.747)	(30.817)	(25.806)
*Year End*Short Int*	-59.221	-114.667	20.359	-66.077
	(50.533)	(101.658)	(93.480)	(47.115)
*RETURN *Short Int*	0.692**	1.470***	0.411	0.707***
	(0.288)	(0.273)	(0.260)	(0.040)
*RETURN *Month End*Short Int*	-0.338***	0.394	-0.310**	0.075
	(0.070)	(0.411)	(0.154)	(0.101)
*RETURN *Qtr End*Short Int*	-0.149	-1.254***	-0.148	0.267
	(0.290)	(0.394)	(0.301)	(0.227)
*RETURN *Year End*Short Int*	-0.361*	0.163	-0.296	-0.679**
	(0.185)	(0.541)	(0.209)	(0.304)
Observations	13,571,009	2,303,227	5,039,227	6,228,555
Clusters	10,744	3,292	6,548	6,484
R-Square	0.02551	0.06291	0.0268	0.008173

Table VI
Reversals using Raw Return Measure

Same as in previous table, but Return measure is a raw return in basis points. White standard errors are in parentheses. *, ** and *** represents significance at the 10%, 5% and 1% level.

	Dependent Variable: 1 Day Lead Raw Return			
	1988-2007	1988 - 1993	1994 - 2000	2001 - 2007
RETURN	-0.150***	-0.246***	-0.151***	-0.084***
	(0.006)	(0.006)	(0.006)	(0.003)
Inst Ownership	-0.148	-15.423***	-6.269***	-0.060***
	(0.103)	(2.071)	(1.581)	(0.020)
Month End	17.306***	17.645***	23.125***	13.232***
	(0.859)	(2.264)	(1.431)	(1.186)
Qtr End	-10.256***	2.902	-34.881***	4.195*
	(1.532)	(3.229)	(2.413)	(2.239)
Year End	24.816***	73.028***	24.950***	1.946
	(2.922)	(6.823)	(5.433)	(2.943)
Short Interest	-44.532***	-53.361***	-16.602	-56.311***
	(15.068)	(10.467)	(11.523)	(3.581)
*RETURN *Month End*	-0.022***	0.004	-0.027***	-0.047***
	(0.007)	(0.021)	(0.010)	(0.010)
*RETURN *Qtr End*	-0.084***	0.004	-0.084***	-0.149***
	(0.013)	(0.020)	(0.017)	(0.024)
*RETURN *Year End*	-0.004	-0.038	0.020	-0.009
	(0.015)	(0.027)	(0.021)	(0.022)
*Month End*Short Int*	3.606	271.079***	74.465**	-74.890***
	(13.485)	(73.447)	(36.487)	(17.034)
*Qtr End*Short Int*	20.585	-12.608	-105.323***	78.392***
	(27.710)	(121.489)	(38.792)	(29.500)
*Year End*Short Int*	-302.929***	-760.720***	-347.242***	-107.625**
	(55.841)	(204.406)	(120.447)	(49.792)
*RETURN *Short Int*	0.725**	1.627***	0.431	0.712***
	(0.297)	(0.297)	(0.277)	(0.037)
*RETURN *Month End*Short Int*	-0.455***	0.149	-0.371*	0.126
	(0.093)	(0.420)	(0.196)	(0.103)
*RETURN *Qtr End*Short Int*	-0.268	-1.418***	-0.056	-0.045
	(0.311)	(0.409)	(0.309)	(0.265)
*RETURN *Year End*Short Int*	-0.184	0.037	0.118	-1.015***
	(0.199)	(0.537)	(0.208)	(0.313)
Observations	13,571,009	2,303,227	5,039,227	6,228,555
Clusters	10,744	3,292	6,548	6,484
R-Square	0.02133	0.05832	0.02253	0.006496

Table VII
Incentive-Driven Intraday Short-Selling

The dependent variable in each regression is the natural logarithm of that hour's short-selling volume minus the natural logarithm of the morning's short-selling volume (9:30 A.M. to 12:00 P.M.). See Table III for a description of the other variables. Abnormal short selling is Excess Short Sales Volume as defined in Figure 2. Note that independent variables are all daily observations, while dependent are intraday intervals. White standard errors are in parentheses. *, ** and *** represents significance at the 10%, 5% and 1% level.

	Dependent Variable: Abnormal Short Selling			
	12:00 P.M. - 1:00 P.M.	1:00 P.M. - 2:00 P.M.	2:00 P.M. - 3:00 P.M.	3:00 P.M. - 4:00 P.M.
Intercept	-1.363***	-1.375***	-1.175***	-0.607***
	(0.006)	(0.007)	(0.007)	(0.009)
Short Interest (Normalized)	-0.413***	-0.459***	-0.391***	0.183**
	(0.038)	(0.042)	(0.044)	(0.072)
Institutional Ownership	0.000	0.000	0.001	0.002
	(0.000)	(0.000)	(0.001)	(0.002)
Month End Dummy	0.016***	0.016***	0.074***	0.148***
	(0.006)	(0.006)	(0.006)	(0.007)
Quarter End Dummy	0.009	0.009	0.045***	0.321***
	(0.009)	(0.010)	(0.009)	(0.011)
Year End Dummy	0.078***	0.124***	0.214***	0.403***
	(0.018)	(0.018)	(0.018)	(0.018)
*Short Interest * Month End*	-0.102	-0.069	0.047	0.126
	(0.065)	(0.071)	(0.070)	(0.094)
*Short Interest * Quarter End*	0.359***	0.062	0.029	0.337***
	(0.107)	(0.122)	(0.104)	(0.131)
*Short Interest * Year End*	-0.167	-0.325	0.285	0.815***
	(0.213)	(0.223)	(0.211)	(0.215)
Monthly Fixed Effects	YES	YES	YES	YES
Observations	2,148,189	2,150,970	2,192,232	2,361,858
Clusters (firms)	5,820	5,829	5,834	5,880
R-Square	0.001385	0.001372	0.002288	0.004619

Table VIII
Hedge Fund Holdings on Short Interest

The dependent variable is Short Interest, and it is represented as a percentage in columns 3 and 4. HF Own is hedge fund ownership from Morningstar in shares in the first two columns, and also normalized as a percent in columns 3 and 4. Inst Own is the same measure, but for all institutions based on Thomson Reuters. Ln(MktCap) is not normalized in column 3. Data is winsorized at the 1st and 99th percentile, White standard errors are in parentheses, and *, ** and *** represents significance at the 10%, 5% and 1% level..

Panel A: Non-Normalized Data.

	2001 – present (full sample)		**2004 - present**	
Intercept	*-17.91****	*7.055****	-17.59***	7.187***
(x 10^{12})	(4.278)	(0.2833)	(4.176)	(0.2844)
HF Own	21.064	-104.188***	13.771	-108.478***
	(30.878)	(31.291)	(28.045)	(29.344)
Inst Own	14337.000***		13884.000***	
	(2059.000)		(2022.000)	
Ln(Mkt Cap)	10.61***		10.577***	
(x 10^5)	(2.135)		(2.083)	
Observations	38319	38319	30135	30135
Clusters	3154	3154	2997	2997
R-Square	0.3951	0.000006024	0.3982	0.000009044

Panel B: Normalized by Shares Outstanding

	2001 – present (full sample)		**2004 - present**	
Intercept	*0.275****	*0.060****	0.305***	0.064***
	(0.012)	(0.001)	(0.013)	(0.001)
HF Own	1.049***	2.279***	0.951***	2.117***
	(0.119)	(0.130)	(0.125)	(0.137)
Inst Own	0.095***		0.096***	
	(0.005)		(0.005)	
Ln(Mkt Cap)	-0.013***		-0.015***	
	(0.001)		(0.001)	
Observations	38319	38319	30135	30135
Clusters	3154	3154	2997	2997
R-Square	0.2551	0.04002	0.263	0.03755

Table IX
The Battlefield: Volume Differences – Test of Means

Each section tests whether a battle exists on quarter-end data by two different measures. The Rank Match creates a percentile rank on Mutual Fund Holding % vs Short Interest normalized by Shares Outstanding. The Size Match performs a comparison of integer percentages of the same values. High vs. Low Holdings is based on a tercile rank of matched battle stocks only. For the Size Match, the Low Group all have a value of 0, and the High Group are greater or equal than 4%. Year End is an indicator, Not Year End are quarter ends that are not Q4. Last Half Hour Excess Volume is the sum of volume during the last half hour of trading less the 120-day symmetric moving average of last half hour volume over that same moving average. *, ** and *** represents significance at the 10%, 5% and 1% level. All tests use the nonparametric Wilcoxon Two-Sample test of means because a test for normality reveals that the samples are all non-normal.

	Excess Volume			**Excess Dollar Weighted Volume**		
Rank Match						
Whole Sample	*Non-Battle*	*Battle*	*Z Score*	*Non-Battle*	*Battle*	*Z Score*
	0.5754	0.6115	1.32	0.5618	0.6011	1.2
Within Battle Stocks	*Low Holdings*	*High Holdings*	*Z Score*	*Low Holdings*	*High Holdings*	*Z Score*
	0.6758	0.3805	-4.21***	0.6598	0.3787	-4.82***
	Not Year End	*Year End*	*Z Score*	*Not Year End*	*Year End*	*Z Score*
	0.7251	0.3208	-3.34***	0.7029	0.3406	-3.11***
Size Match						
Whole Sample	*Non-Battle*	*Battle*	*Z Score*	*Non-Battle*	*Battle*	*Z Score*
	0.5938	0.3443	-23.44***	0.5802	0.3318	-24.78***
Within Battle Stocks	*Low Group*	*High Group*	*Z Score*	*Low Group*	*High Group*	*Z Score*
	0.234	0.766	7.39***	0.1328	0.3991	7.53***
	Not Year End	*Year End*	*Z Score*	*Not Year End*	*Year End*	*Z Score*
	0.3847	0.24	0.49	0.3703	0.2323	0.27

Table X
The Battlefield: Price Differences

Each section tests whether a battle exists on quarter-end data by two different measures. The Rank Match creates a percentile rank on Mutual Fund Holding % vs Short Interest normalized by Shares Outstanding. The Size Match performs a comparison of integer percentages of the same values. High vs. Low Holdings is based on a tercile rank of matched battle stocks only. For the Percentage Match, the Low Group all have a value of 0, and the High Group are greater or equal than 4%. Year End is an indicator, Not Year End are quarter ends that are not Q4. Afternoon return is the price at 4pm with respect to the price at noon. Late Afternoon Return is the price at 4pm with respect to the price at 2:30pm. The first case listed is where the class variable equals 0. *, ** and *** represents significance at the 10%, 5% and 1% level. All tests use the nonparametric Wilcoxon Two-Sample test of means because a test for normality reveals that the samples are all non-normal.

	Afternoon Return			**Late Afternoon Return**		
Rank Match						
Whole Sample	*Non-Battle*	*Battle*	*Z Score*	*Non-Battle*	*Battle*	*Z Score*
	0.0035	0.0052	0.47	0.0013	0.0017	-1.92*
Within Battle Stocks	*Low Holdings*	*High Holdings*	*Z Score*	*Low Holdings*	*High Holdings*	*Z Score*
	0.0135	0.0014	4.03***	0.0074	-0.0018	6.88***
	Not Year End	*Year End*	*Z Score*	*Not Year End*	*Year End*	*Z Score*
	0.0042	0.0083	-1.266*	0.0015	0.0022	-3.16***
Size Match						
Whole Sample	*Non-Battle*	*Battle*	*Z Score*	*Non-Battle*	*Battle*	*Z Score*
	0.0029	0.0105	7.47***	0.0006	0.0082	17.29***
Within Battle Stocks	*Low Group*	*High Group*	*Z Score*	*Low Group*	*High Group*	*Z Score*
	0.0117	0.0012	-2.29**	0.0095	-0.0007	-5.73***
	Not Year End	*Year End*	*Z Score*	*Not Year End*	*Year End*	*Z Score*
	0.0037	0.0267	7.06***	0.0022	0.0228	4.92**

Table XI
The Battlefield: Regression Analysis of Volume and PriceEffects

The dependent variable is Last Half Hour Excess Volume or Dollar Weighted Volume which is the sum of volume during the last half hour of trading less the 120-day symmetric moving average of last half hour volume over that same moving average. High Holdings is an indicator variable for the highest group for each matching measure. For the Rank Match, it is the top tercile, for the Size Match, it is the High Group which represents matches at 4% or greater. The dataset only includes quarterly observations so Year End is Q4. *, ** and *** represents significance at the 10%, 5% and 1% level.

	Rank Match		***Size Match***		***Rank Match***		***Size Match***	
	Volume	D-W Vol	Volume	D-W Vol	Aft Ret	L Aft Ret	Aft Ret	L Aft Ret
Intercept	0.944***	0.921***	0.944***	0.921***	57.902**	28.415	37.420***	23.255***
	(0.193)	(0.195)	(0.193)	(0.195)	(25.911)	(20.036)	(6.071)	(4.811)
High Holdings	-0.508**	-0.507**	-0.508**	-0.507**	-59.115**	-48.050**	-40.773**	-24.753**
	(0.205)	(0.206)	(0.205)	(0.206)	(26.719)	(20.596)	(16.214)	(11.310)
Year End	-0.561**	-0.540**	-0.561**	-0.540**	-0.268	1.885	232.811	220.012
	(0.237)	(0.243)	(0.237)	(0.243)	(31.733)	(24.907)	(184.565)	(184.849)
*High Holdings * Year End*	0.327	0.390	0.327	0.390	8.394	-24.531	-178.440	-236.678
	(0.284)	(0.294)	(0.284)	(0.294)	(40.056)	(27.397)	(186.530)	(185.755)
Observations	1,242	1,242	1,242	1,242	2,303	2,303	10,279	10,279
Clusters	1,009	1,009	1,009	1,009	1,732	1,732	2,988	2,988
R-Square	0.009011	0.007859	0.009011	0.007859	0.00212	0.00341	0.000407	0.000366