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Do Arbitrageurs Amplify Economic Shocks?

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Abstract: We test the hypothesis that arbitrageurs amplify economic shocks in equity markets. The ability of speculators to hold short positions depends on asset values: shorts are often reduced following good news about a stock. Therefore, the prices of highly shorted stocks are excessively sensitive to shocks compared to stocks with little short interest. We confirm this hypothesis using several empirical strategies including two quasi-experiments. In particular, we establish that the price of highly shorted stocks overshoots after good earnings news due to short covering compared to other stocks.

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1. Introduction

We examine whether arbitrageurs amplify exogenous economic shocks in asset markets. This issue is related to a large literature dating back to Friedman (1953) on the role of speculators in affecting asset price dynamics. A number of theories suggest that asset prices are excessively sensitive to economic news when arbitrage is limited in various ways such as leverage constraints or agency problems arising from delegated money management.[1] For instance, the market turmoil of 1998 is widely viewed as having been exacerbated by the forced selling of assets by Long Term Capital Management and other hedge funds that were pursuing similar strategies. The turbulence in the summer of 2007 has been attributed to the forced selling by many multi-strategy quantitative funds.[2] And throughout the current crisis since the collapse of Lehman Brothers in September 2008, many market observers have pointed to the forced unwinding of highly-levered trades as an explanation for the collapse and extreme volatility of financial markets.[3]

Despite the wide acknowledgment of the importance of this amplification mechanism in financial markets, there is relatively little systematic evidence on whether fundamental shocks are magnified by such speculative activity. An understanding of the effects of speculators on asset price dynamics has never been more important from both academic and public policy perspectives.

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[1] A few examples include Delong, Shleifer, Summers and Waldmann (1990); Shleifer and Vishny (1997); Kyle and Xiong (2001); and Gromb and Vayanos (2002).

[2] See, for example, Khandani and Lo (2008).

[3] For example, *Reuters Newswire* reported on October 24, 2008: "The manager of the world's biggest bond fund said on Friday that forced liquidations, based on margin calls, are driving stocks lower, and not fear. Bill Gross, chief investment officer of Pacific Investment Management Co. or Pimco, said on CNBC television that margin calls were driving the selling that has resulted in a long-term deleveraging of assets not seen since the 1930s." Echoing this theme, Jim Rogers in an interview with the *Financial Times* on November 17th, 2008 said: "A forced liquidation like we are now experiencing has occurred only 8 or 9 times in the past 150 years."

We tackle this issue in the context of short arbitrage in equity markets by examining if the presence of short arbitrage in a stock heightens the reaction of its price to quarterly earnings news. There are a couple of reasons why short selling in equity markets is a useful setting to study this issue. First, there are plentiful panel data on the amount of short selling, and most short sales are undertaken by professional speculators such as hedge funds as opposed to retail investors. This stands in contrast to the difficulty of measuring levered long speculative positions in equities. Second, in practice, the ability of arbitrageurs to hold on to short positions depends on asset values: shorts are often reduced (increased) following good (bad) news about a stock for a variety of reasons. This has been confirmed by earlier work on this mechanism (see, e.g., Lamont and Stein (2004)). Short sales tend to be highly levered transactions that require having enough funds in the margin account.

Indeed, the financial press often speaks of “short covering” (the cutting down of short positions through the purchase of shares) causing excess volatility in markets. One example is for the internet stock eBay, which reported better earnings than expected in the summer of 2005. Its stock price soared dramatically the same day. The press pointed to short covering as a likely source of the price movement (see Nassar (2005)). More recently, on October 28, 2008, hedge funds shorting the car maker Volkswagen (VW) were forced to cover their short positions when news came out that Porsche had bought up much of VW's remaining free float. Shares in the German car maker, that began the day trading at €420 a share hit an intraday high of €1,005.01, valuing the company at €296.06 billion euros ($370.4 billion) based on ordinary stock: more than that of the world’s next largest company at the time Exxon Mobil Corp's $343 billion market value. VW’s share price reverted to €393 per share by November 3rd after the hedge funds finished buying all the shares they needed to cover their speculative positions.

To capture this amplification mechanism caused by short covering, we begin by developing a simple three date model, based on Shleifer and Vishny (1997), of asset price dynamics in which arbitrageurs have a profitable opportunity to short an over-priced stock subject to positive sentiment.[4] The key ingredient is that the ability of arbitrageurs to hold on to short positions depends on asset values (i.e., the past performance of these positions). There is also an earnings announcement that may affect the sentiment for the stock. Our joint hypothesis is as follows: Suppose the firm has good earnings news, forcing arbitrageurs to short cover. This short covering will temporarily boost a firm's stock price as the extra buying pressure leads to an overshooting of price to earnings news that is reversed in the long run.

We derive three key predictions that we test using monthly data on short sales in U.S. equities from 1994 to 2007. The first prediction is that the price sensitivity to earnings news is higher for a stock with positive short selling (i.e., arbitrage presence) than for a stock with no short selling (i.e., no arbitrageurs). We measure the sensitivity of the stock price to earnings news as the regression coefficient of the stock return around the earnings announcement date on the earnings surprise (or the difference between the earnings and the consensus forecast scaled by previous price). We define a highly shorted stock as one in the top 33% of the short ratio (short interest to shares outstanding) distribution for stocks in our sample for that quarter and a stock with little short selling as the rest of the stocks in our sample for that quarter. The premise behind this cutoff is that only those with substantial short ratios are likely to be subject to genuine valuation-motivated arbitrage activity.

[4] Our short-selling set-up is consistent with empirical studies on the source of short seller profits. Dechow *et.al.* (2001) and D'avolio (2002) argue that the source of profits for short sellers is that they short mis-priced stocks: short sales increase with price-to-earnings ratios, and short sellers cover as the mis-pricing corrects (i.e. as price converges towards earnings).

We test this prediction by running a pooled regression of cumulative abnormal returns around (quarterly) earnings announcement dates (from one trading day before to one day after) on a high earnings surprise dummy variable (equal to one if the stock is in the top 33% of the earnings surprise distribution for stocks in our sample for that quarter and zero otherwise), a dummy variable for whether a stock is highly shorted before the earnings date and the highly shorted dummy interacted with the high earnings surprise dummy. The coefficient for the interaction term then tells us the difference in the sensitivity of the stock price to news between highly shorted stocks and stocks with little short interest.

In estimating this relation, we worry about unobserved heterogeneity: e.g., highly shorted stocks may be more in the "media spotlight" than other stocks and hence their prices respond more to news. To deal with this issue, we estimate this regression specification (and indeed all the other specifications below) in a variety of ways such as controlling for a number of stock characteristics (e.g. interacting news with stock characteristics such as firm size and institutional ownership) and using stock fixed effects. Regardless of how we estimate this relation, we find that the price of a highly shorted stock is more sensitive to earnings news than a stock with little shorting. For stocks with little short interest, our basic results suggest that having a high earnings surprise leads to a higher cumulative abnormal return of about 3.27 percentage points (or 327 basis points). In contrast, for highly shorted stocks, the comparable figure is around 382 percentage points. The difference of 55 basis points (about 17% larger for highly shorted stocks) is economically and statistically significant. We verify that this relation (as well as all the other ones established below) is robust to a variety of different specification checks such as ways of measuring abnormal returns and earnings surprises.

The second prediction is that the change in the short interest ratio of a stock should be negatively correlated with the earnings surprise (e.g., a positive earnings surprise should lead to a fall in this ratio). Here, we are merely extending earlier work by Lamont and Stein (2004) and Savor and Gamboa-Cavazos (2005); they have already shown that the monthly short interest ratio falls on good news to stock prices and rises on bad news to stock prices. Ideally, we want to measure the sensitivity of changes in daily short interest to unexpected earnings announcements; unfortunately, we can only observe short interest at a monthly frequency. As we discuss below, such monthly changes are a noisy and likely biased way to pick up the short covering effect around earnings dates. Therefore, we use a stock's abnormal turnover around the earnings announcement as a proxy for changes in the short interest ratio. Consistent with our model, we find that for highly shorted stocks, abnormal turnover is more sensitive to earnings news than for little shorted stocks.[5]

Our third and perhaps most important prediction is that arbitrageurs are forced to cover short positions that would have been profitable; i.e., the stock price subsequently declines. This means that for highly shorted stocks, a short position initiated after the event date should be more profitable after good earnings news forces short covering. We find that for stocks with little shorting, good news leads to higher subsequent returns (from 2 days after to 126 trading days after the announcement) to holding the stock (about 157 basis points). This is consistent with the well-documented post earnings announcement drift (see, e.g., Bernard and Thomas (1989, 1990)). However, for highly shorted stocks, good news leads to excess returns of *negative* 110 basis points: 267 basis points lower than for little shorted stocks. In other words, a short position in these stocks initiated after good earnings news is profitable.

[5] These findings control for level differences in turnover between highly-shorted stocks and other stocks. Consistent with our model, highly-shorted stocks have higher turnover than other stocks. However, this could also be consistent with other asset pricing models without our effects.

It is this third prediction that cuts strongly against a number of alternative stories. For instance, one possible reason for price being more sensitive to news for highly shorted stocks is that short sales are informed bets that there are going to be negative earnings surprises. As a result, good news means these bets are wrong and price naturally reacts more to good news. If this alternative explanation is correct, then one would *not* expect to find that the greater price increase observed on the event date following good news is subsequently reversed (i.e., that the stock price declines in the months following the good news). This post-announcement return finding is difficult to reconcile with alternative explanations.

Finally, to better identify our amplification mechanism, we consider two quasi-experiments. Our first quasi-experiment is that the above findings ought to be stronger for NASDAQ stocks than NYSE stocks because historically it was easier to short NASDAQ stocks than NYSE stocks for regulatory reasons before 2007 (and particularly before 2001). We find empirical support for our hypothesis using this quasi-experiment. Our second quasi-experiment builds on the work of Hanson and Sunderam (2008), who show a striking increase in the short interest ratio since the early 2000s concentrated among small stocks. They argue that this is due to the rise of hedge funds. If our hypothesis is correct, then we expect to find that the destabilizing effects shown above ought to have increased among small stocks since 2002 compared to large stocks that did not witness such growth. Although our estimates are imprecise, we find that this is indeed the case.

There is a growing literature testing the implications of limits to arbitrage models. Work most closely related to ours includes Savor and Gamboa-Cavazos (2005), who find that short sellers cover their positions after suffering losses and increase them after experiencing gains (measured using past returns). This relation is very strong for positions established due to perceived overvaluation; expected returns do not explain the documented short seller behavior. Similarly, Lamont and Stein (2004) show a strong negative correlation between market returns and the change in the aggregate short interest ratio.

The main innovation of our paper relative to these and other empirical papers in the literature is that we show that arbitrage activity directly influences asset prices through at least one channel: the amplification of fundamental shocks.[6] The important point is that this paper is one of the first to directly show the economic mechanism that leads to destabilizing speculation in asset markets.[7] However, the idea that short sales can influence stock price reaction to news is also in Reed (2007), who shows that short-sales constraints lead price to under-react to bad earnings news. We show in contrast that stock prices over-react to good news due to short covering.

Our paper is also closely related to empirical papers looking at the relation between leverage and asset prices.[8] Lamont and Stein (1999) test a similar hypothesis to ours but in the context of the housing market. Their principal finding is that in cities where a greater fraction of homeowners are highly leveraged, house prices react more sensitively to city-specific shocks such as changes in per capita income. In contrast to their paper, our setting provides a tighter test of the amplification-of-fundamental-shocks hypothesis.

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[6] Other recent examples related to testing limits of arbitrage models include Brunnermeier and Nagel (2004), who examine the holdings of certain hedge funds during the Internet bubble and Gabaix, Krishnamurthy and Vigneron (2007), who argue that prices of mortgage-backed securities are determined by specialized arbitrageurs.

[7] We do not take a stand on why short arbitrageurs cut their positions following good news. We have naturally framed this short covering in terms of leverage, risk management or more general agency issues, but it could very well be due to other factors such as behavioral biases that lead arbitrageurs to cut their losses.

[8] This leverage mechanism has been pointed out in a number of other settings including stocks (Garbade (1982)), corporate asset sales (Shleifer and Vishny (1992)), land (Kashyap, Scharfstein and Weil (1990)); Kiyotaki and Moore (1997)) and housing (Stein (1995)).

Our paper proceeds as follows. We present a simple model to derive the main predictions in Section 2. The data is presented in Section 3 and the empirical findings in Section 4. We conclude in Section 5. All proofs are in the Appendix.

2. Model

This section presents a simple three-period model based on Shleifer and Vishny (1997). Whereas Shleifer and Vishny (1997) look at levered longs by arbitrageurs in an initially under-priced stock, we consider the case of arbitrageurs shorting an initially over-priced stock. The model illustrates how an informed arbitrageur faced with leverage and/or risk management constraints must cut back on positions following adverse price moves and that such actions tend to amplify the price reaction to an economic shock.

There is a single asset (the stock) available in unit net supply. There are three dates numbered 0, 1, and 2. At date 2, the asset is liquidated with payoff v, which may take on the value $\bar{v}$ or $\underline{v}$ with equal chance. At date 1, the value of v is announced to all. We denote the price at time t by p_t.

There are two sets of agents in the economy: noise traders and risk neutral rational speculators (e.g., hedge funds). The noise traders over-estimate the fundamental payoff by an amount $S > 0$ at time 0. This sentiment (optimism) may widen or narrow to $S(v)$ at time 1 (depending on the nature of the earnings announcement) and disappears completely by time 2. More formally, we assume that aggregate noise trader demands at time 0 and 1 are given by (in share terms)

$$Q_0^N = \frac{E_0[v]+S}{p_0} = \frac{\frac{1}{2}\bar{v}+\frac{1}{2}\underline{v}+S}{p_0} \qquad (1)$$

and

$$Q_1^N = \frac{E_1[v] + S(v)}{p_1} = \frac{v + S(v)}{p_1} \tag{2}$$

respectively.

Arbitrageurs undertake short positions to partially counteract the noise traders, but we assume their resources in the two periods, given by F_0 and $F_1(v)$, are insufficient to bring prices to fundamental value. For simplicity, initial aggregate speculator demand is given by

$$Q_0^S = -\frac{F_0}{p_0} \tag{3}$$

where $F_0 < S$. (In the Appendix, we solve the more general model in which arbitrageurs can determine how much of their resources ($D_0 \le F_0$) to invest at time 0. The remainder is invested in cash and yields a zero net return as a safeguard against running out of funds at time 1.) At time 1, all uncertainty has been resolved and speculators take the maximum possible short position, yielding a demand of

$$Q_1^S = -\frac{F_1}{p_1} \tag{4}$$

provided $F_1(v) \le S(v)$. Due to the unit net supply assumption, the short demand of speculators in this model is also the short ratio or the ratio of shares shorted to total shares outstanding.

We also make the following assumption regarding the time evolution of the arbitrageurs' resources

$$F_1(v) = F_0 + aF_0\left(1 - \frac{p_1(v)}{p_0}\right), \tag{5}$$

where $a > 1$. If the arbitrageurs do not short at time 0, then $F_1(v) = F_0$. But since they are assumed to short an amount F_0, their capital at time 1 depends on the return of shorting, $\left(1 - \frac{p_1(v)}{p_0}\right)$, between time 0 and 1. How sensitive their resources are at time 1 to asset values or past returns (i.e. their ability to hold on to shorts) is given by the parameter a. We do not take a stand as to why $a > 1$. Most naturally, it reflects the fact that short sellers tend to be levered. Also plausibly, it may be an internal risk management control, or it might be imposed on the speculators by fund inflows and outflows from outside investors (Shleifer and Vishny (1997)). For instance, one interpretation is that there are loss-limits at the position level or related value-at-risk (VAR) considerations and, when a short position suffers a loss, the position is dramatically cut back. (Plentiful anecdotal evidence (cited in the Introduction) seems to bear this assumption out.)

We now solve for the asset prices. Date 2 represents the long-run in which price reverts to fundamental value; i.e. by no arbitrage, $p_2 = v$. Because aggregate demand in each period must equal the unit supply, i.e.,

$$Q_t^S + Q_t^N = 1, \tag{6}$$

price at time 0 is

$$p_0 = \frac{1}{2}\overline{v} + \frac{1}{2}\underline{v} + S - F_0 . \tag{7}$$

Equating supply and demand at time 1 and then substituting from equation (5), we get

$$p_1(v) = \frac{v + S(v) - F_0(1+a)}{1 - a\dfrac{F_0}{p_0}} . \tag{8}$$

Finally, we introduce an important variable for our empirical work. This variable, the sensitivity of stock price to earnings news (often called the earnings response coefficient) denoted by β, is:

$$\beta(v) = \frac{\frac{\Delta p}{p_0}}{\frac{\Delta v}{p_0}} = \frac{p_1 - p_0}{v - E[v]} \tag{9}$$

It represents the responsiveness of price to innovations in fundamental value. Higher values of β denote higher sensitivity of prices to news. Alternatively, we can also scale the earnings innovations by the expectation of earnings. The theoretical results are similar and so we stay with the definition in equation (9) because it is the one most often used in papers that measure the sensitivity of price to earnings news.

The following three propositions are the key predictions of the model that we test. For all three propositions, we are assuming that there is not enough capital to bring prices close to fundamental value.

Proposition 1*: The sensitivity of stock price to earnings news, β, is greater for heavily shorted stocks than for little shorted stocks.*

The key amplifying mechanism is that the ability of arbitrageurs to maintain their positions is tied to asset values. The effect is similar to that of leverage constraints for long positions.[9]

[9] Although this model is very stylized, it is possible to perform some back of the envelope calculations to gauge the differential in sensitivity of price to news between highly shorted compared to little shorted stocks (the details of these calculations are available upon request from the authors). The upshot is that the results are sensitive to the unobservable parameter *a* (the amplification parameter) and the differential sensitivity can vary between being 10%

The second proposition is that the change in the short interest ratio of a stock should be negatively correlated with the earnings surprise (i.e., a positive earnings surprise should lead to a drop in the short ratio). Unfortunately, our monthly short interest data is too coarse to capture this short covering effect around earnings announcements, particularly in light of the findings in Diether, Lee and Werner (2009). Due to our inability to measure daily short covering, we show that this short covering effect translates into abnormal turnover being more sensitive to unexpected earnings for highly shorted stocks than little shorted stocks.

Proposition 2*: For shorted stocks, the change in the short ratio is inversely related to the earnings surprise, and share turnover around earnings announcements is more sensitive to (the absolute value of) unexpected earnings for highly shorted stocks than for little shorted stocks.*

It is the latter implication of this proposition that we focus on in our empirical work; that is, we test that turnover is more sensitive to (the absolute value of) unexpected earnings news for shorted stocks.

Finally, the premise of the amplification mechanism is that arbitrageurs are forced to get out of profitable short positions. Proposition 3 formalizes this premise by allowing sentiment to rise even after good news so that the short position remains profitable. This is a modeling device meant to capture the fact that short positions may be fundamentally profitable but arbitrageurs may have difficulty hanging on to short positions if their ability to do so depends on asset values. In a more dynamic set-up with multiple earnings dates, we could also accomplish the same result by introducing transitory earnings shocks.

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to 30% greater for highly shorted stocks (assuming a mean short ratio of 8%, which is roughly what we see in the data) depending on what one assumes about this parameter. Our empirical estimates fall comfortably within this wide range of calibration magnitudes.

Proposition 3: *If sentiment increases proportionally with unexpected earnings news, then for highly shorted stocks, the buying pressure from short covering could push the price to above fundamental value and the expected return to shorting is higher after a good earnings surprise.*

We test Proposition 3 by comparing subsequent stock returns after earnings announcements for highly shorted stocks to little shorted stocks. The only caveat in testing Proposition 3 is that there is the well-documented post earnings announcement drift in the data; i.e., stocks with good or bad news continue to drift in the direction of the news after the announcement (see, e.g., Bernard and Thomas (1989, 1990)). We do not model post earnings announcement drift in this paper, although we could by assuming a degree of under-reaction to news as in Barberis, Shleifer and Vishny (1998) or Hong and Stein (1999). Therefore, we need to account for this drift in testing this proposition. So, another way of posing this proposition is that there should be less post earnings announcement drift in highly shorted stocks compared to other stocks. Positions that were unprofitable (with the positive earnings surprise) are profitable on a point forward basis.

Also, according to our model, the sensitivities of stock prices and turnover to earnings surprises are symmetric with respect to good and bad news as indicated by Propositions 1 and 2. Naturally, good news leads to short covering and hence trading and the extra sensitivity of price to news. Less obviously, the reason bad news also leads to trading is that we assume that short sellers are initially capital constrained; they would ideally like to short more than they can at time 0. When there is bad news at time 1, their positions between 0 and 1 make money and this affords them more capital to take larger short positions at time 1, leading to extra turnover and the extra sensitivity of price to news. This effect is due to the symmetry of our performance-based arbitrage assumption given by equation (5), which says that the arbitrageurs get more money when their positions do well.[10] These predictions are sensitive to our assumption in equation (5), and one could imagine there being asymmetries in these reactions to news if arbitrageurs do not get more capital when their short positions do well. This is largely an empirical question.

Moreover, according to our model (Proposition 3), we should see over-shooting *only* on short covering with very good news. With bad news, the shorts become more profitable between time 0 and 1 and so arbitrageurs do not have to abandon (and might even increase) their short positions at time 1. In other words, we should see an asymmetry in the results for returns subsequent to the earnings announcement. We test to see if there are indeed these patterns in the data.

3. Data

The sample consists of quarterly observations of stocks that are listed on the NYSE/AMEX or NASDAQ exchanges from 1994 through 2007. Observations are dropped if short interest, earnings data, or I/B/E/S forecast data are missing, or if the earnings statement takes place outside the typical earnings announcement season, which we consider to be 30 to 90 calendar days following the end of the fiscal period. All of our cutoff criteria described below are constructed based on this sample.

Our data on monthly short interest, available for the period of 1994 to 2007, are obtained from Bloomberg and NASDAQ. Each month's short interest data represent positions that closed

[10] This is consistent with Lamont and Stein (2004) and Savor and Gamboa-Cavazos (2005), which find that shorting also increases after poor market returns (or good returns to shorting stocks).

on the first business day on or after the 15th of the month. We use this short interest information to construct short ratios for each month; we approximate the short ratio by dividing total short interest positions by shares outstanding (from CRSP) on this day each month. We focus on extremes: highly shorted stocks (the top 33% of the short ratio distribution for our sample in that quarter) compared to little shorted stocks (the rest of the stocks in our sample that quarter). Stocks in this range could be shorted for valuation reasons or for hedging reasons (see, e.g., Chen, Hong and Stein (2002); Asquith, Pathak and Ritter (2005)). We believe this comparison is the cleanest way of identifying our effect. More specifically, we define *HISR* as a dummy equal to one if the stock is in the top 33% of the short ratio distribution for stocks in our sample for the quarter of the observation and zero otherwise. The top 33% cutoff is chosen because among this sub-group there is a relatively high short ratio (about 7.46% on average). Our results are robust to using other cutoffs.

We combine these data with information from three other databases. First, quarterly earnings consensus estimates and actual initial (i.e. unadjusted) earnings releases are collected from the I/B/E/S summary files to calculate unexpected earnings (*UE*). In practice, researchers have a few different ways of calculating unexpected earnings; usually *UE* is the difference between the actual quarterly earnings according to I/B/E/S and the consensus forecast provided by I/B/E/S in the last month before the announcement date scaled by either past price, previous earnings or the consensus forecast (see, e.g., Conrad, Cornell and Landsman (2002) and Kothari (2001)). Here, like most of the literature, we scale *UE* by past price. We define *UEHIGH* as a dummy variable equal to one if a stock's earnings surprise is in the top 33% of the distribution of our data sample for that quarter and zero otherwise.

Second, data on daily holding period returns, prices, trading volume and shares outstanding are obtained from the Center for Research in Securities Prices (CRSP). Using these data, we calculate cumulative abnormal returns around earnings announcement dates using a methodology similar to Fama and French (1992) extended to include momentum:

$$CAR_{i,q} = \sum_{j=t_0}^{t_1} R_{i,j} - \sum_{j=t_0}^{t_1} PORT_j \tag{10}$$

where $R_{i,j}$ is the percentage return on stock *i* on date *j* around the earnings announcement in quarter *q*. The window to calculate the cumulative abnormal return begins at date t_0 and ends at date t_1. Similar to Fama and French (1992), we form 18 portfolios based on the intersection of two size-based groups, three book-to-market based groups and three momentum groups (using Fama-French cutoffs). $PORT_j$ is the return on the benchmark size, book-to-market and momentum Fama-French-Carhart portfolio to which stock *i* belongs.

For our main results, we concentrate on two time windows relative to earnings announcements when calculating returns. The first are returns cumulated over the 3-day window from one trading day before until one day after the earnings release date (*CAR*). The second is the cumulative post-announcement returns (*POSTCAR*) using trading days +2 to +126 relative to earnings release.[11] Using the CRSP database, we also calculate daily share turnover (using trading volume and shares outstanding). To account for differences in how volume is computed for NASDAQ-listed firms relative to NYSE/AMEX-listed firms, we adjust NASDAQ volume using the procedure described in Gao and Ritter (2010).[12] We then take the average of this

[11] Because firms occasionally disappear from the CRSP database sometime during the 126 days we are using to calculate *POSTCAR*, we use as many days of returns that are provided (and the delisting return) to measure *POSTCAR* for these firms that leave the database.

[12] As in Gao and Ritter (2010), we divide the volume of NASDAQ listed firms for observations before February 1, 2001 by 2.0. For observations between February 1, 2001 and December 31, 2001, we divide volume of NASDAQ-

adjusted daily share turnover from trading day -1 to day +1 surrounding the day 0 earnings announcement. The timing is set to match that of the *CAR*. We calculate abnormal turnover for a stock (*ABNTURN*) as this turnover around the announcement date minus the average turnover of the stock around all the announcement dates in the sample.

Third, the following annual accounting variables are obtained from the CRSP/COMPUSTAT merged Industrial Annual data file: book equity (data item 60), convertible securities (data item 39), earnings per share (data item 57) and fiscal-year-end closing price (data item 199). The price-to-earnings valuation ratio is calculated as the lagged price as of 21 days before earnings release divided by the previous year's annual EPS.

Finally, firm market capitalization is obtained from CRSP. Monthly return volatility is calculated using daily return data from CRSP. A measure of analyst disagreement, or the dispersion of analyst forecasts (calculated as in Diether, Malloy and Scherbina (2002)), is obtained from I/B/E/S.

The summary statistics for these variables are presented in Table 1. The key statistic is that the mean of the short ratio distribution is about 3.44% and its standard deviation is 4.80%. For stocks in the top 33% of the short ratio distribution, the mean is 7.46% as we mentioned earlier. The statistics for the other variables are similar to those reported in other papers.

4. Empirical findings

4.1. Sensitivity of price to earnings news

We begin by testing Proposition 1, which states that the earnings response coefficient should be higher for highly shorted stocks. We want to measure how the sensitivity of price to

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listed firms by 1.8. For NASDAQ-listed observations during 2002 and 2003, we divide volume by 1.6; beyond 2003 observations, no adjustment is made.

earnings news varies by whether a stock is actively shorted or not. We first measure the overall effect of unexpected earnings shocks on returns: i.e., the price to earnings sensitivity for the typical firm in our sample. This will provide us with a benchmark. To this end, we estimate the following specification:

$$
\begin{aligned}
CAR_{i,t} = {} & \alpha + \beta_1 UEHIGH_{i,t} + \beta_2 HISR_{i,t} + SIZE\,dummies_{i,t} + P/E\,dummies_{i,t} \\
& + DISAGREEMENT\,dummies_{i,t} \\
& + CONVDEBT\,dummy_{i,t} + VOLATILITY\,dummies_{i,t} \\
& + INDUSTRY\,dummies_{i,t} + EXCHANGE\,dummies_{i,t} + QUARTER\,dummies_{t} + \varepsilon_{i,t}
\end{aligned}
\qquad (10)
$$

The left-hand side (LHS) variable is *CAR* (cumulative abnormal return from trading day -1 to +1). The right-hand side (RHS) variable of interest is *UEHIGH*, which equals one if a firm's earnings surprise is in the top 33% of the earnings surprise distribution for stocks in our sample for that quarter and zero otherwise. The other RHS variables include *HISR* (a dummy equal to one if the stock is in the top 33% of the short ratio distribution for stocks in our sample for the quarter of the observation and zero otherwise), *SIZE* (25 dummy variables measuring where a stock's relative market cap is each quarter), *P/E* (price-to-earnings divided into 25 dummies by quarter and one additional dummy variable for negative earnings stocks), *DISAGREEMENT* (the dispersion in analyst forecasts divided into 25 dummies by quarter), *CONVDEBT* (a dummy for the firm having positive convertible debt), *VOLATILITY* (return volatility of firms in the previous month calculated using daily returns divided into 25 dummies by quarter), *INDUSTRY* dummies (SIC at the 2 digit level), *EXCHANGE* dummies and *QUARTER* dummies. We will provide the rationale for each of these control variables as we build up to our specification of interest.[13]

[13] We have also included the age of the firm in all of our cross-sectional regressions as a control and find similar results.

The result for this specification is reported in column (1) of Table 2. As expected, the coefficient for *UEHIGH* is positive and statistically different from zero. The coefficient implies that being in the high unexpected earnings group is associated with a 3.46% abnormal return of the stock (*CAR*). This number is in line with other studies of the sensitivity of stock price to earnings surprises mentioned earlier.

We then estimate the following model, which is the same as the previous one except for the addition of the interaction of *UEHIGH* and *HISR*:

$$\begin{aligned} CAR_{i,t} = {} & \alpha + \beta_1 UEHIGH_{i,t} + \beta_2 HISR_{i,t} + \beta_3 UEHIGH_{i,t} \times HISR_{i,t} + SIZE\ dummies_{i,t} \\ & + P/E\ dummies_{i,t} + DISAGREEMENT\ dummies_{i,t} \\ & + CONVDEBT\ dummy_{i,t} + VOLATILITY\ dummies_{i,t} \\ & + INDUSTRY\ dummies_{i,t} + EXCHANGE\ dummies_{i,t} + QUARTER\ dummies_{t} + \varepsilon_{i,t} \end{aligned} \tag{11}$$

The coefficient of interest is now β_3, which measures the differential sensitivity of highly shorted stocks to unexpected earnings compared to other stocks. The result is reported in column (2). The estimates show that the sensitivity to high unexpected earnings shocks is greater for high short ratio stocks. β_1 suggests that for a low short ratio stock, having a high *UE* is associated with a 3.27 percentage point increase in *CAR*. β_3 is 0.55 and statistically different from zero with a t-statistic of about 4.6. So having a high *UE* increases *CAR* by 0.55 percentage points more for a high short ratio stock than a low short ratio stock. β_3 suggests that the sensitivity of high short ratio stocks to unexpected earnings is about 0.55/3.27 = 17% greater than for low short ratio stocks.

This regression specification controls for a number of stock characteristics, but these controls do not allow for the effect of news to vary by these stock characteristics. Therefore, we estimate the following model, which is the same as the previous one except for the addition of the interactions of *UEHIGH* with the other firm characteristics:

$$
\begin{aligned}
CAR_{i,t} = {} & \alpha + \beta_1 UEHIGH_{i,t} + \beta_2 HISR_{i,t} + \beta_3 UEHIGH_{i,t} \times HISR_{i,t} + SIZE\ dummies_{i,t} \\
& + SIZE\ dummies_{i,t} \times UEHIGH_{i,t} + P/E\ dummies_{i,t} + P/E\ dummies_{i,t} \times UEHIGH_{i,t} \\
& + DISAGREEMENT\ dummies + DISAGREEMENT\ dummies \times UEHIGH_{i,t} \\
& + CONVDEBT\ dummy_{i,t} + CONVDEBT\ dummy_{i,t} \times UEHIGH_{i,t} \\
& + VOLATILITY\ dummies_{i,t} + VOLATILiTY\ dummies_{i,t} \times UEHIGH_{i,t} \\
& + INDUSTRY\ dummies_{i} + EXCHANGE\ dummies_{i,t} + QUARTER\ dummies_{t} + \varepsilon_{i,t}
\end{aligned}
\tag{12}
$$

The coefficient of interest again is β_3, which measures the differential sensitivity of high short ratio shocks to unexpected earnings shocks. We include the additional interactions of *UEHIGH* with the other control variables because price sensitivity to news might vary by the different characteristics. For instance, the price of a high price-to-earnings stock might have a different sensitivity to earnings news than a low one. Similarly, the price of a large capitalization stock might respond more to news than the price of a small capitalization stock if the investors in large stocks are more likely to be institutions and institutions pay closer attention to news compared to individuals. We also add interactions of *UEHIGH* and *DISAGREEMENT* because highly shorted stocks may simply have more analyst dispersion and the price of high divergence of opinion stocks may react more to news. The logic for institutional ownership and past volatility are similar. For convertible debt, short interest might be driven by hedging trades associated with the purchase of convertible securities (see Asquith, Pathak and Ritter (2005)). Because we want to measure short interest related to speculative trades as precisely as possible, we include a convertible debt by *UEHIGH* interaction.

The results from this estimation are presented in column (3). β_3 is positive and statistically significant (0.33 with a t-statistic of about 2.5). The estimate shows that the sensitivity to *UE* is greater for high short ratio stocks; for these stocks, the *CAR* is 0.33 percentage points higher for having a high *UE*, similar in size to what we obtained in column (2). In contrast to the estimates in column (2), note that we cannot obtain a unique estimate of β_1 in this specification because of all of the other interactions with *UEHIGH*; as a result, we cannot perform the same economic significance calculations as in column (2). Hence, one can think of the estimate in column (3) as providing a robustness check.

In columns 4-6, we re-estimate the specifications in columns 1-3, except that we now include stock fixed effects. The logic of this specification is that we are worried that even with all of our elaborate controls, there might still be fixed differences across stocks for which we have not yet accounted (e.g., some stocks are more in the spotlight in some un-measurable manner and these stocks attract both more shorts and react more to earnings surprises). We obtain similar estimates compared to our previous specification. The coefficient for *UEHIGH* in column (4) is 3.75 instead of 3.46 from column (1). In column (5), the coefficient for the interaction *of UEHIGH* and *HISR* is 0.79, which is somewhat larger than the estimate of 0.55 in column (2). Interacting *UEHIGH* with the other stock characteristics in column (6) does not substantially affect our estimate of β_3. The comforting result here is that adding stock fixed effects strengthens our differential earnings surprise effect by around 40%.

In columns 7-9, rather than including stock fixed effects, we allow for quarterly variation in the industry effects to account for potential time varying trends that might spuriously be generating our findings in columns 1-3. For instance, the spotlight effect might change over time (some stocks are in the spotlight more at certain times). If this spotlight effect is not specific to a stock but is common across all stocks in the same industry, then our quarter by industry effects will control for any spurious relation generated by such a process. Again, the estimates are similar to columns 1-3. In column (7), the coefficient for *UEHIGH* is now 3.50 instead of 3.46 in column (1). In column (8), the coefficient for $UEHIGH \times HISR$ is now 0.53 instead of 0.55. And the coefficient for $UEHIGH \times HISR$ in column (9) is now 0.30 instead of 0.33. All these estimates are again statistically and economically significant.

The findings in Table 2 help confirm the first prediction of our arbitrageur amplification hypothesis. We have taken an "everything but the kitchen sink" approach in this table, including several stock characteristic controls in the regression specification to rule out alternative explanations. However, an even better way to support our story is to test our model's additional implications that do not arise naturally out of an omitted variable bias story; we consider tests of these implications next.

4.2. Sensitivity of turnover to earnings news

Now we test Proposition 2, which states that the sensitivity of volume to earnings announcements should be positively related to the short interest ratio. We want to measure how the sensitivity of changes in short interest and turnover to earnings news varies by whether a stock is actively shorted or not. In our context, we ideally want to observe daily changes in the short interest ratio around our earnings announcements to examine whether unexpected good news is correlated with a decrease in the daily short interest ratio. However, we only have short ratio information at a monthly frequency. So, it is likely that the daily decrease in short interest ratio we want to measure will be swamped by monthly changes in the short interest ratio caused by other factors. Also, theory suggests that after certain hedge funds are forced to abandon their short positions, the profitability of shorting goes up (as witnessed by our results below regarding the profitability of shorting previously highly shorted stocks with good earnings news). Hence, there will be entry of short hedge funds or the establishment of new short positions after the earnings announcement and so we may see little change in the monthly short interest ratio. Indeed, this is the main finding of Diether, Lee and Werner (2009); they show that daily changes in short interest do not show up when aggregated to the monthly level. As such, we turn to daily turnover as a rough proxy for daily changes in short interest.

Our analysis proceeds in a manner similar to that of Table 2. The results for abnormal turnover around earnings announcements are presented in Table 3; it is the equivalent of Table 2 except that the dependent variable is *ABNTURN*, the abnormal (from trading day -1 to +1 around the earnings announcement) turnover of the stock, and *UEHIGH* is replaced by *ABSUEHIGH* the absolute vale of unexpected earnings, which is a dummy variable equal to one if the absolute value of the earnings surprise is in the top 33% of the *ABSUE* distribution for stocks in our sample for that quarter. The reason we use *ABSUEHIGH* instead of *UEHIGH* is that either good or bad earnings news will lead to turnover according to our model. Good news leads to additional transactions due to short covering, while bad news leads to additional short selling on the part of (initially constrained) speculators.

Columns 1-9 of Table 3 are analogous to those in Table 2. Column (1) shows that higher absolute *UE* increases turnover. Having high absolute *UE* increases turnover by about 0.130 percentage points (about 9% of a standard deviation of abnormal turnover). Column (2) shows that this sensitivity is greater for highly shorted stocks. β_3 is positive and statistically different from zero (.075 with a t-statistic of about 3.3). For little shorted stocks, the sensitivity of turnover to ABSUEHIGH is 0.104 percentage points. In contrast, the sensitivity for highly shorted stocks is 0.179 (0.104+0.075) percentage points, which is about 70% bigger than the magnitude for low-short-ratio stocks. Column (3), which adds as controls interactions of *ABSUEHIGH* with other stock characteristics, slightly strengthens the results of column 2.[14]

In columns 4-6, we present the results including stock fixed effects in the regression specification. Column (4) shows that having a high absolute UE measure increases turnover by 0.130 percentage points. Column (5) indicates that for little shorted stocks, having high absolute *UE* raises turnover by 0.090 percentage points. β_3 from column (5) is positive and statistically significant (0.111 with a t-statistic of about 4.3). The economic effect is large; for highly shorted stocks, the sensitivity of turnover to an absolute earnings surprise is about 120% larger than for little shorted stocks, indicating that the relative effect is even larger when we estimate with stock fixed effects. The results using quarter by industry effects (presented in columns 7-9) are similar to columns 1-3. In sum, these results are broadly consistent with the second prediction of our model. This finding suggests that any alternative story for our first finding regarding highly shorted stocks having a greater sensitivity to news must also explain why abnormal turnover in highly shorted stocks is more sensitive to news.

4.3. Subsequent stock returns and earnings news

Perhaps the most distinctive implication of our theory is Proposition 3, which states that the expected return to shorting after a good earnings surprise for a previously highly-shorted stock is higher than for other stocks. We want to measure how returns *after* the earnings announcement date differ between highly shorted stocks and little shorted stocks. In essence, we

[14] These findings control for level differences in turnover between highly shorted stocks and other stocks. Consistent with our model, highly shorted stocks (*HISR*) have higher turnover than other stocks; however, this could also be consistent with other asset pricing models without our effects. So, our findings are independent of these level differences. Rather, we are measuring differences in sensitivities to the size of absolute earnings surprises.

want to verify that if the *CAR* results are due to the short covering mechanism we propose, then we should see returns to shorting being higher after a good earnings announcement. As we explained in the theory section, the only caveat in testing Proposition 3 is that there is a well-documented post-earnings announcement drift in the data; i.e., stocks with good (bad) news continue to drift in the direction of the news after the announcement. This drift is outside the scope of our model.

Our analysis proceeds in a manner similar to that of the specification of Table 2; the results are presented in Table 4. In other words, Table 4 is the equivalent of Table 2 except that the dependent variable is *POSTCAR* (from 2 trading days after to 126 trading days after the announcement) instead of *CAR*. Columns 1-3 show the standard OLS results. Column (1) suggests that having high *UE* raises *POSTCAR* by about 0.65 percentage points; this is consistent with post-earnings announcement drift. Column (2) shows that for little shorted stocks, the effect of having high unexpected earnings raises *POSTCAR* by 1.57 percentage points. However, the effect of having high *UE* for highly shorted stocks is much lower. β_3 is negative and statistically significant (-2.67 percentage points with a t-statistic of about 5.3). So the overall effect of having high *UE* for highly shorted stocks is the sum of 1.57 and -2.67 or -1.10 percentage points. This sum is statistically different from zero with a p-value of 0.01. For highly shorted stocks, having high unexpected earnings actually leads to negative subsequent returns of about minus 110 basis points. In other words, one would want to sell rather than buy these good news stocks. The result in column (3) using more elaborate controls confirms the result in column (2); the coefficient β_3 is smaller at -1.90, but is still statistically significant.

In columns 4-6, we present the results including stock fixed effects in the specification. Column (5) shows that for little shorted stocks, the effect of having high *UE* raises *POSTCAR* by

0.82 percentage points. β_3 is negative and statistically significant (-2.06 percentage points with a t-statistic of about 4.1). So the overall effect of having high *UE* for highly shorted stocks is the sum of 0.82 and -2.06 or -1.24 percentage points. This sum is again statistically different from zero with a p-value of 0.00. The result in column (6) using more elaborate controls confirms the one in column (5); again, the coefficient β_3 is smaller at -1.25, but is still statistically significant.

The results including quarter by industry effects in the regression specification (presented in columns 7-9) are again similar to those presented in columns 1-3 (baseline) and 4-6 (including stock fixed effects). Column (8) shows that for little shorted stocks, the effect of having high *UE* raises *POSTCAR* by 1.65 percentage points. β_3 is negative and statistically significant (-2.52 percentage points with a t-statistic of about 5.1). The overall effect of having high unexpected earnings for highly shorted stocks is -0.87 percentage points. The p-value of the test that the effect is different from zero is 0.04. The results, taken in totality, are consistent with the third prediction of our model.

4.4. Asymmetries

Following the discussion at the end of the section describing the Model, we now examine whether there are different sensitivities to very good versus very bad news for *CAR*, *ABNTURN* and *POSTCAR*. We expect to find that our *POSTCAR* results should come largely from unexpected good news; whereas, the *CAR* and *ABNTURN* results may come from both unexpected good and bad news. We slightly alter our empirical specification to measure these different reactions to news:

$$\begin{aligned} CAR_{i,t} = {} & \alpha + \beta_1 UEHIGH_{i,t} + \beta_2 HISR_{i,t} + \beta_3 UEHIGH_{i,t} \times HISR_{i,t} + \beta_4 UELOW_{i,t} \\ & + \beta_5 UELOW_{i,t} \times HISR_{i,t} + SIZE\ dummies_{i,t} + P/E\ dummies_{i,t} \\ & + DISAGREEMENT\ dummies_{i,t} + CONVDEBT\ dummy_{i,t} + VOLATILITY\ dummies_{i,t} \\ & + INDUSTRY\ dummies_{i,t} + EXCHANGE\ dummies_{i,t} + QUARTER\ dummies_t + \varepsilon_{i,t} \end{aligned} \tag{13}$$

where *UELOW* equals one if a firm's earnings surprise is in the bottom 33% of the earnings surprise distribution for stocks in our sample for that quarter and zero otherwise. All the other variables are defined as above. The relative magnitudes of β_3 and β_5 measure the difference in the response to good and bad news.

The results are presented in Table 5. For brevity, we only show the regression specification estimated with stock fixed effects; the results for the baseline estimates and quarter by industry effects are qualitatively similar. Column (1) shows the estimate of equation (13) with *CAR* as the dependent variable. The coefficient for the interaction of *UEHIGH* and *HISR* is 0.46, similar to before. The coefficient on the interaction of *UELOW* and *HISR* is -0.55 (note that it should be negative because bad news leads to a lower *CAR*). The absolute values of these two coefficients on the two interactions are similar.[15] So there is not much evidence of an asymmetric response to news in *CAR*.

Column (2) shows the results with *ABNTURN* as the dependent variable. The coefficient on interaction of *UEHIGH* and *HISR* is 0.078, while the coefficient on interaction of *UELOW* and *HISR* is 0.090. Again, these two coefficients are similar in magnitude. These two results are consistent with the model's assumption that arbitrageurs can short more when their short position becomes more profitable on bad news.

[15] The hypothesis that the absolute values of these two coefficients are equal cannot be rejected statistically.

Finally, column (3) shows the result when the dependent variable is *POSTCAR*. Here, the coefficient for the interaction of *UEHIGH* and *HISR* is -2.21, while the coefficient for the interaction of *UELOW* and *HISR* is -.23. The interaction of *HISR* with *UEHIGH* is negative and statistically significant, indicating that there is large reversion for highly shorted stocks after a positive earnings shock. But the interaction on *HISR* and *UELOW* is close to zero, suggesting there is no reversion after bad news. We can reject the hypothesis that $\beta_3+\beta_5=0$ in column (3) with a p-value of 0.05. Hence, the results in Table 5 support the predictions of the model.

4.5. Alternative explanations

We now consider a number of alternative explanations for these three sets of findings. There are two closely related alternatives that can explain our main finding regarding high short ratio stocks having higher price sensitivity to news. The first is that high short ratio is a proxy for stocks with high divergence of opinion. Hence, earnings news leads to more price discovery. We try to control for this alternative story using explicit proxies for divergence of opinion such as analyst forecast disagreement and other controls such as stock fixed effects. But one might still argue that a high short ratio is itself the best proxy. This alternative, however, does not naturally generate a predicted reversal associated with the price reaction. For high short ratio stocks, good news leads to a bigger price move up and subsequent reversal captured by the fact that shorting profitability after the event date increases with better news. A price discovery story would naturally imply that certain groups were right and certain groups were wrong and the bets are resolved through the earnings news, saying nothing about future returns associated with the news.

A closely related variant of this divergence of opinion story is that funds that short are informed and are betting that there is bad news about the company. That is, high short interest predicts a negative earnings surprise. When the news is good, this means that the informed short-sellers happen to be wrong. As before, price adjusts appropriately but with no implications for *POSTCAR*.

Again, we cannot rule out every alternative explanation of our results, but we feel that our three sets of findings do cut strongly against a number of reasonable alternatives, particularly when one takes into account the stock fixed effects and quarter by industry effects specifications.[16]

4.6. Quasi-experiment 1: NASDAQ versus NYSE

It is worthwhile to think of additional ways to identify our amplification mechanism. We now examine a couple of quasi-experiments. For our first one, we exploit differences in short selling regulations across stock exchanges. SEC reforms after July 2007 removed constraints on short selling on any U.S. exchange, but for a large part of our sample, short selling regulations were more lax for stocks listed on NASDAQ than on the NYSE. Before 1994, there were no short selling regulations for NASDAQ stocks; starting in 1994, NASDAQ introduced some degree of regulation to compete with the NYSE/AMEX for firm listings because companies typically do not like to have their stocks shorted. The two exchanges used somewhat different price tests (NYSE/AMEX used the tick test that is generally thought to be more stringent than the bid test used by NASDAQ). In total, the NASDAQ regulations that were introduced were

[16] Note that our results are not simply due just to a short squeeze since we are looking at sensitivities to unexpected earnings surprises (though issues in locating shares after unexpected good news might contribute to our amplification findings).

substantially weaker than those of the NYSE/AMEX.[17] However, the move to decimalization in early 2001 likely made the tick test a much less binding constraint. To be conservative from an identification perspective, we consider the sample period before 2001 and examine whether our destabilization effects are stronger among NASDAQ stocks than NYSE/AMEX stocks.

To begin with, we expect to find that, all else equal, short interest ratios are substantially higher for NASDAQ stocks during this period. In particular, in unreported results, we examine whether being listed on NASDAQ increases the likelihood that the stock is in the top 33% of the short ratio distribution for stocks in our sample using the following regression:

$$\begin{aligned} HISR_{i,t} = \alpha + \beta_1 NASDAQ_{i,t} &+ SIZE\ dummies_{i,t} + P/E\ dummies_{i,t} \\ &+ DISAGREEMENT\ dummies_{i,t} \\ &+ CONVDEBT\ dummy_{i,t} + VOLATILITY\ dummies_{i,t} \\ &+ INDUSTRY\ dummies_{i} + EXCHANGE\ dummies_{i,t} \\ &+ QUARTER\ dummies_{t} + \varepsilon_{i,t} \end{aligned} \quad . \tag{14}$$

The coefficient of interest is β_1, which measures how being listed on *NASDAQ* affects the probability that the stock is in the top 33% of the short ratio distribution.[18] Consistent with our premise, being a *NASDAQ* stock increases the probability that a stock is in the top 33% of the short ratio distribution by about 7.9 percentage points. The t-statistic of the coefficient is about 6.6.

In Table 6, we then show whether our estimates established in Tables 2-4 are stronger among NASDAQ stocks than NYSE/AMEX stocks. To this end, we adopt the same

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[17] First, NASDAQ exempted its market-makers from short selling regulations. Second, trades originating from Electronic Communications Networks (ECNs) were also exempt. This means that 30% of NASDAQ short sale trades were not even subject to a bid test; whereas, all NYSE/AMEX trades are subject to a tick test (see, e.g., Jickling (2005), O'Hara and Angstadt (2004)).

[18] We have also run this as a probit or logit and obtained similar results.

specifications as in Tables 2-4 (column (2)) except that, as with the previous quasi-experiment, we use a sample that includes all stocks in the top and bottom 33% of the short ratio distribution for stocks in our sample for the quarter and exchange and the top and bottom 33% of the unexpected earnings distribution for stocks in our sample for the quarter and exchange.[19] We also include additional explanatory variables including an indicator for being listed on *NASDAQ*, $UEHIGH \times NASDAQ$, $HISR \times NASDAQ$ and the main variable of interest, $UEHIGH \times HISR \times NASDAQ$.

Column (1) reports the results for *CAR*; the coefficient on the triple interaction is about 1.40 with a t-statistic of about 3.3. In other words, the higher sensitivity of *CAR* to earnings shocks for highly shorted stocks compared to other stocks is larger among NASDAQ stocks than NYSE/AMEX stocks. Column (2) reports the results for *ABNTURN*. The coefficient on the triple interaction is small and imprecisely measured, but it has the hypothesized sign. So, there is weak evidence that the sensitivity of abnormal turnover to news for high short interest stocks compared to other stocks is slightly larger among NASDAQ stocks than NYSE/AMEX stocks. Column (3) reports the results for *POSTCAR*. The triple interaction coefficient for *POSTCAR* is -4.93 with a t-statistic of about 2.6; the *POSTCAR* reversal results are indeed larger for NASDAQ stocks than NYSE/AMEX stocks. Again, the results in Table 6 broadly support the implications of our model.

4.7. Quasi-experiment 2: The rise of hedge funds

Our second quasi-experiment builds on the work of Hanson and Sunderam (2008) who show a substantial increase since the early 2000s in short ratios concentrated among small stocks (NYSE deciles 1-5). They argue that this is in large part due to the rise of hedge funds; Hedge

[19] This starker comparison of extreme observations helps a bit with economic significance and statistical precision.

Fund Research reports that assets managed by long-short equity hedge funds, among the most sophisticated arbitrageurs, grew from \$133 billion in 2000 to \$409 billion at the end of 2006. Hanson and Sunderam further report that by some estimates, hedge funds account for 85% of short positions in the US equity market. As a result, the percentage of US equity market capitalization sold short nearly doubled from 1.7% in 2000 to 3.0% in 2007.

Most interestingly to us is that this growth has been concentrated in small stocks. In Figure 1, we verify Hanson and Sunderam's finding by plotting the average short ratio over time for two groups: small stocks, which are defined as all stocks (no matter what exchange they are listed on) with a market capitalization that would put it them in the bottom half of the market capitalization of NYSE stocks, and large stocks, which are defined as stocks with a market capitalization that would put them in the 8^{th} through top decile of the market capitalization of NYSE stocks (no matter what exchange they are listed on). We exclude stocks in NYSE deciles 6-7 since these stocks are in between in the sense that they experienced some moderate growth in short ratios. We see from Figure 1 that the short ratio of large stocks has not increased by much over our sample period. It starts at 1% in 1994 and increases to around 2% in 1998 and since then it has fluctuated between 2% and 3%. In contrast, we see a very steep increase in the short ratio among small stocks starting around 2002 from around 2% in 2000 to a high of 9% in 2007.

If our hypothesis is correct, then we expect to find that the destabilizing effects shown above ought to have increased among small stocks since 2002 relative to large stocks. We find some suggestive evidence that this is indeed the case in Table 7. We estimate an augmented version of our specifications in Tables 2 through 4 separately for small and large stocks, expanding the list of independent variables with an indicator *AFTER2001* (a dummy variable that turns on if the observation is after 2001), $UEHIGH \times AFTER2001$ and

$UEHIGH \times HISR \times AFTER2001$. The coefficient of interest is for the triple interaction of $UEHIGH \times HISR \times AFTER2001$. This coefficient tells us whether our destabilization effects are stronger after 2001 than before. Also, we again use a sample that includes stocks only in the top and bottom 33% of the short ratio distribution for stocks in our sample for the quarter and exchange and the top and bottom 33% of the unexpected earnings distribution for stocks in our sample for the quarter and exchange.

We find that for the most part, the magnitudes of the coefficients on the triple interactions are consistent with our hypothesis, although the precision of the estimates is poor. Column (1) reports the results for *CAR* for small stocks. The coefficient for the triple interaction term $UEHIGH \times HISR \times AFTER2001$ is 0.38 with a t-statistic of about 0.79. In other words, among small stocks, the higher sensitivity of *CAR* to the earnings shock for highly shorted stocks compared to other stocks is somewhat larger after 2001 compared to the earlier period. Column (2) shows the same estimate using the sample of large stocks. The coefficient on the triple interaction is -.48, indicating that the sensitivity of *CAR* to unexpected earnings for highly shorted stocks compared to others is somewhat declining later in the sample. Although these coefficients are imprecise, their magnitudes suggest that the sensitivity of highly shorted small stocks to *UE* is growing over time relative to large stocks, consistent with our story.

Column (3) reports the results for *ABNTURN* for the sample of small stocks. The triple interaction coefficient is 0.109. The similar coefficient for large stocks reported in column (4) is 0.139. This suggests that the sensitivity of turnover to earnings shocks for highly shorted stocks compared to other stocks is growing slightly more after 2001 for large stocks compared to small stocks. Although this is not consistent with our story, the difference in the magnitudes of the coefficients is very small and not statistically significant.

Column (5) reports the results for *POSTCAR* for the small stock sample. The triple interaction coefficient is -.33 with a t-stat of about 0.16, suggesting that, among small stocks, the *POSTCAR* reversal result is somewhat stronger after 2001 than before. The similar coefficient for the large stock sample is presented in column (6); it is 0.61, indicating that the increase in sensitivity after 2001, like the *CAR* results, is bigger for the small stock sample than the large stock sample.

These results of this quasi-experiment are roughly consistent with the joint hypothesis that our effects are driven by limits to arbitrage and that such limits bind more strongly for smaller stocks. Interestingly, the increase in the difference of sensitivities of small and large stocks after 2001 is similar in absolute value for the *CAR* and *POSTCAR* estimates. The results are very imprecise, but overall we conclude that the results in Table 7 are broadly supportive of our model.

4.8. Robustness checks and additional analyses

Finally, we have carried out a number of additional robustness checks of our analysis. The results are not presented here; they are available in a web appendix.[20]

5. Conclusion

We develop a simple model based on Shleifer and Vishny (1997) to examine whether arbitrageurs amplify fundamental shocks in the context of short arbitrage in equity markets. The key amplifying mechanism is that the ability of arbitrageurs to hold on to short positions depends on asset values: shorts are often cut following good news about a stock. The extra buying pressure from this short covering temporarily boosts the stock price. As a result, the prices of

[20] The web appendix can be accessed at www.princeton.edu/~hhong.

highly shorted stocks over-shoot (and hence are excessively sensitive to fundamental shocks) but eventually revert back in the long run.

Consistent with this model, we find that, controlling for a host of other stock characteristics, the price of a highly shorted stock is more sensitive to earnings news than a stock with little short interest. Moreover, using daily share turnover as a proxy for short covering, we show that short interest changes in the predicted direction in response to earnings news. For highly shorted stocks, returns to shorting are actually higher following good earnings news. Finally, these differential sensitivities are more pronounced for NASDAQ stocks, which are easier to short than NYSE stocks, and these effects have become more pronounced over time for small stocks with the rise of hedge funds. These findings are broadly consistent with theories that emphasize the limits of arbitrage in affecting asset price dynamics.

As we suggested in the Introduction, understanding the potentially destabilizing effects of speculators on asset markets is of paramount importance in light of the rise of hedge funds in the last decade and the recent turmoil in financial markets. There are a number of avenues for further research to clarify the various channels through which speculators might destabilize markets. Along the same lines as this paper, if better daily data on short trades becomes available, we can more directly verify the short covering effect around earnings announcements as opposed to simply using share turnover. We can also use options data as opposed to short interest data to measure levered long or short positions in stocks and perform a similar set of analyses as in this paper. Finally, empirical work on the destabilizing potential of quantitative strategies more generally would be very valuable. We plan to pursue these avenues in future research.

Appendix

In this appendix we relax our earlier assumption that speculators put all their resources, F_0, at risk in the stock market immediately, and instead assume that they choose some amount, $D_0 \leq F_0$ to put at risk (the remainder is invested in cash and yields a zero net return). The speculators may want to put some money aside in case the stock becomes an even better short trade after the earnings announcement. To complete the model, we set up the speculators' incentives and solve their optimization problem. We set the problem up in terms of speculators maximizing wealth at the liquidation date. Because speculators are fully invested at time 1, profits from time 0 to 1 are already factored into this maximization. Hence speculators maximize the expectation of $R(D_0) = F_1(D_0)\left(2 - \frac{v}{p_1(D_0)}\right)$ with respect to D_0:

$$\max_{D_0} E[R] = \max_{D_0} \frac{1}{2} F_1(\bar{v})\left(2 - \frac{\bar{v}}{p_1(\bar{v})}\right) + \frac{1}{2} F_1(\underline{v})\left(2 - \frac{\underline{v}}{p_1(\underline{v})}\right) \tag{A1}$$

Taking the first derivative with respect to D_0 above and substituting F_1 from (5) gives us the following FOC:

$$\frac{1}{2}\left(1 - \frac{p_1(\bar{v})}{p_0}\right)\left(2 - \frac{\bar{v}}{p_1(\bar{v})}\right) + \frac{1}{2}\left(1 - \frac{p_1(\underline{v})}{p_0}\right)\left(2 - \frac{\underline{v}}{p_1(\underline{v})}\right) \geq 0 \tag{A2}$$

If the FOC is strictly greater than 0 then $D_0 = F_0$. For $D_0 < F_0$ to be optimal the FOC must be equal to 0. Each term in (A2) represents the incremental gross return following either a positive or a negative fundamental value announcement, accounting for the returns accumulated at both period 1 and period 2. The optimization condition (A2) and the price equations define the equilibrium of this model.

We will make use of the following rearrangement of terms for the earnings-response-coefficient for the proofs below

$$\beta(v) = k\left(1 + \frac{S(v) - S - (F_0 - D_0)}{v - E[v]}\right), \tag{A3}$$

where $k = \left(1 - a\frac{D_0}{p_0}\right)^{-1} \geq 1$ and $k > 1$ for stocks with nonzero initial short ratio $\frac{D_0}{p_0} > 0$. All the propositions below assume that there is not enough capital to bring prices close to fundamental value.

Proof of Proposition 1: Note that the definition for β can be written as

$$\beta(v) = \frac{p_1 - p_0}{v - E[v]} \tag{A4}$$

We will assume that sentiment S and $S(v)$ are raised uniformly for the shorted stock (for which $0 < D_0 < D^*$, where D^* is defined below) over the little shorted stock ($D_0 = 0$) so that $S(v) - S$ does not change.

In order for the proposition to hold, speculators must be subject to capital constraints; i.e., $a > 0$. When $a = 0$, the initial decision regarding D_0 is made independently of the wealth maximization problem of period 1. Hence D_0 will be chosen equal to F_0 to maximize period 1 profits. Along with the fact that $k = \left(1 - a\frac{D_0}{p_0}\right)^{-1} = 1$, this implies that (A3) for $a = 0$ can be simplified to

$$\beta(v) = \left(1 + \frac{S(v) - S}{v - E[v]}\right). \tag{A5}$$

Because $S(v) - S$, and v are the same for the shorted and little shorted stock, all terms in (A5) are equal, and so the betas are equal.

Now return to the case of $a > 0$. First, we demonstrate that the partial derivative of β with respect to D_0 at the point $D_0 = F_0 = 0$ is greater than zero. Hence β is increasing for small D_0. From (A3), β consists of the product of two positive terms, k and $\left(1+\frac{S(v)-S-(F_0-D_0)}{v-E[v]}\right)$. It is straightforward to show that $\frac{\partial k}{\partial D_0} > 0$ at $D_0 = 0$. To prove that $\frac{\partial \beta}{\partial D_0} > 0$, it is only necessary to show that the derivative of the second term is nonnegative. Since the first order condition is continuous in D_0 and is positive for $D_0 = 0$, it must be the case that $D_0 = F_0$ even for small $D_0 > 0$. Hence $\frac{\partial F_0}{\partial D_0} = 1$, and the derivative of the second term is zero.

So far we have shown that β is larger for positive short interest stocks so long as D_0 is small. Since $\frac{\partial k}{\partial D_0}$ is always positive, changes in the sign of $\frac{\partial}{\partial D_0}\beta$ must come from changes in $\frac{\partial F_0}{\partial D_0}$. From the first order condition, we notice that as D_0 and F_0 increase, there will eventually come a point where $\frac{\partial F_0}{\partial D_0} < 1$, and at this point $\frac{\partial}{\partial D_0}\beta$ decreases and may eventually turn negative (we will see momentarily that it must turn negative). From all the equations involved, notice that this is the only possible source of change in the sign of $\frac{\partial}{\partial D_0}\beta$. Finally, consider what happens for very large D_0 and F_0. In such a case, price equals fundamental value and $\beta = 1$. Hence there must exist D^*, and so too F^*, such that the proposition holds whenever initial capital is below F^*.

Proof of Proposition 2: Intuitively, a positive (negative) earnings shock and resultant increase (decrease) in price cuts into (adds to) the speculator's selling power, implying a lower (higher) short ratio in the following period. A speculator subject to collateral constraints and/or performance based fund flow would also lose (gain) some collateral, inducing him to reduce (expand) his short position further. Now examine this statement algebraically. The initial short ratio is $\frac{D_0}{p_0}$ and the post-announcement short ratio is $\frac{F_1}{p_1}$. Consider the effect of positive news, $v - E[v] > 0$. The change in price, $p_1 - p_0$, is $v + S(v) - F_1 - (E[v] + S - D_0)$. This expression is the sum of the change in fundamental value, $v - E[v]$, and the change in unarbitraged sentiment, $S(v) - F_1 - (S - D_0)$. So long as the positive earnings news does not perversely cause the un-arbitraged sentiment to decrease, both terms are positive and the change in price is proportional to the earnings surprise. Now provided there is not enough capital to bring prices close to fundamental value in the sense of Proposition 1, D_0 is near F_0, and $F_1 < D_0$. Therefore the short ratio changes inversely with the earnings surprise.

To show the statement regarding share turnover, note that the only traders in our model are noise traders and speculators. Hence aggregate share turnover is proportional to the (absolute value of) change in demand of either type of trader. As we've seen above, the speculator's demand is equal to the current short ratio, so turnover is exactly equal to the (absolute) change in short ratio.

Proof of Proposition 3: The expected return to shorting in our model is the ratio of price to fundamental value. Before and after a positive earnings surprise, this ratio is $\frac{p_0}{E[v]}$ and $\frac{p_1(\bar{v})}{\bar{v}}$, respectively. Of course, for $\bar{v} = E[v]$ (i.e. no earnings news), the expected return to shorting does not change. Hence our proposition is equivalent to $\frac{dp_1(\bar{v})}{d\bar{v}} > 1$. Our assumption that sentiment increases proportionally with unexpected earnings news is interpreted as $S'(\bar{v}) > 0$.

From (8), $\frac{dp_1(\bar{v})}{d\bar{v}} = k(1 + S'(v))$. To prove the proposition, note that $k > 1$ for highly shorted stocks.

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Table 1: Summary Statistics

	Mean	25th percentile	Median	75th percentile
	(1)	(2)	(3)	(4)
Short Ratio (% of shares outstanding)	3.44 [4.80]	.60	1.75	4.34
ABNTURN (mean abnormal turnover (%) from trading day -1 to +1)	.00 [1.40]	-.42	-.11	.17
CAR (cumulative abnormal return (%) from trading day -1 to +1)	.11 [8.22]	-3.28	.12	3.73
POSTCAR (cumulative abnormal return from trading day +2 to +126)	-1.61 [31.41]	-16.25	-.93	13.88
Unexpected Earnings (as a % of previous price)	-.10 [1.00]	-.09	.01	.12
Market Capitalization (millions of dollars)	3891 [16,243]	249	639	2018
Price/Earnings (if positive)	39.7 [157.2]	14.0	19.2	29.4
Analyst Disagreement	.17 [.65]	.02	.05	.13
Past Volatility	.12 [.08]	.07	.10	.14
Convertible Debt (millions of dollars)	34.0 [170.1]	0	0	0

This table presents the summary statistics of the sample used in the regression estimations. The sample includes all stocks that are traded either on NYSE/AMEX or NASDAQ from 1994-2007 for which we have short interest, I/B/E/S, CRSP and Compustat data. Standard deviations are in brackets. There are 119,785 observations.

Table 2: OLS Estimates of the Sensitivity of Stock Returns to Unexpected Earnings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Indicator for High Unexpected Earnings (UEHIGH)	3.46 (.06)	3.27 (.07)		3.75 (.07)	3.48 (.07)		3.50 (.06)	3.31 (.07)	
Indicator for High Short Ratio (HISR)	-.09 (.06)	-.27 (.07)	-.17 (.07)	-.16 (.08)	-.41 (.09)	-.31 (.09)	-.09 (.06)	-.27 (.07)	-.17 (.07)
High Unexpected Earnings $\times$ High Short Ratio (UEHIGH $\times$ HISR)		.55 (.12)	.33 (.13)		.79 (.13)	.56 (.14)		.53 (.13)	.30 (.13)
Stock Fixed Effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Quarter $\times$ Industry Effects	No	No	No	No	No	No	Yes	Yes	Yes
R^2	.042	.043	.047	.129	.129	.133	.073	.074	.078

The dependent variable is CAR (cumulative abnormal return (%) from trading day -1 to +1). The independent variables include UEHIGH (indicator that a stock's earnings surprise for the quarter is in the top 33% of the sample distribution that quarter), HISR (a dummy equal to one if the stock is in the top 33% of the sample short ratio distribution for the quarter of the observation and zero otherwise), SIZE (25 dummy variables measuring where a stock's relative market cap is each quarter), P/E (price-to-earnings divided into 25 dummies by quarter and one additional dummy variable for negative earnings stocks), DISAGREEMENT (analyst disagreement divided into 25 dummies calculated each quarter), CONVDEBT (a dummy for the firm having positive convertible debt), VOLATILITY (past volatility divided into 25 dummies calculated each quarter), INDUSTRY dummies (SIC at the 2 digit level), EXCHANGE dummies and QUARTER dummies. In columns (3), (6) and (9), interactions of UEHIGH and all of the other controls except the INDUSTRY, EXCHANGE and QUARTER dummies are included in the specification. The standard errors (in parentheses) are adjusted by allowing for the errors to be correlated across observations of the same stock; i.e. the standard errors are clustered by stock. There are 119,785 observations.

Table 3: OLS Estimates of the Sensitivity of Abnormal Turnover to Unexpected Earnings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High Absolute Unexpected Earnings (ABSUEHIGH)	.130 (.010)	.104 (.009)		.130 (.011)	.090 (.010)		.127 (.010)	.104 (.009)	
Indicator for High Short Ratio (HISR)	.231 (.011)	.206 (.012)	.201 (.012)	.392 (.016)	.355 (.016)	.354 (.016)	.228 (.011)	.206 (.013)	.200 (.012)
High Absolute Unexpected Earnings Decile $\times$ High Short Ratio (ABSUEHIGH $\times$ HISR)		.075 (.023)	.087 (.022)		.111 (.026)	.112 (.026)		.065 (.023)	.081 (.022)
Stock Fixed Effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Quarter $\times$ Industry Effects	No	No	No	No	No	No	Yes	Yes	Yes
R^2	.065	.065	.067	.112	.112	.114	.100	.100	.102

The dependent variable is ABNTURN (mean abnormal turnover (%) from trading day -1 to +1). The independent variables include ABSUEHIGH (indicator that a stock's absolute earnings surprise for the quarter is in the top 33% of the sample distribution that quarter), HISR (a dummy equal to one if the stock is in the top 33% of the sample short ratio distribution for the quarter of the observation and zero otherwise), SIZE (25 dummy variables measuring where a stock's relative market cap is each quarter), P/E (price-to-earnings divided into 25 dummies calculated each quarter and one additional dummy variable for negative earnings stocks), DISAGREEMENT (analyst disagreement divided into 25 dummies calculated each quarter), CONVDEBT (a dummy for the firm having positive convertible debt), VOLATILITY (past volatility divided into 25 dummies calculated each quarter), INDUSTRY dummies (SIC at the 2 digit level), EXCHANGE dummies and QUARTER dummies. In columns (3), (6) and (9), interactions of ABSUEHIGH and all of the other controls except the INDUSTRY, EXCHANGE and QUARTER dummies are included in the specification. The standard errors (in parentheses) are adjusted by allowing for the errors to be correlated across observations of the same stock; i.e. the standard errors are clustered by stock. There are 119,785 observations.

Table 4: OLS Estimates of the Effect of Unexpected Earnings on Subsequent Stock Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Indicator for High Unexpected Earnings (UEHIGH)	.65 (.23)	1.57 (.25)		.11 (.23)	.82 (.25)		.78 (.22)	1.65 (.25)	
Indicator for High Short Ratio (HISR)	-1.37 (.28)	-.51 (.31)	-.77 (.31)	-2.44 (.35)	-1.78 (.38)	-2.05 (.38)	-1.49 (.27)	-.67 (.30)	-.92 (.31)
High Unexpected Earnings $\times$ High Short Ratio (UEHIGH $\times$ HISR)		-2.67 (.50)	-1.90 (.53)		-2.06 (.50)	-1.25 (.52)		-2.52 (.49)	-1.80 (.51)
Stock Fixed Effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Quarter $\times$ Industry Effects	No	No	No	No	No	No	Yes	Yes	Yes
R^2	.020	.022	.024	.216	.214	.218	.123	.123	.125
p-value of test that $\beta_1+\beta_3=0$		0.01			0.00			0.04	

The dependent variable is POSTCAR (cumulative abnormal return (%) from trading day +2 to +126). The independent variables include UEHIGH (indicator that a stock's earnings surprise for the quarter is in the top 33% of the sample distribution that quarter), HISR (a dummy equal to one if the stock is in the top 33% of the sample short ratio distribution for the quarter of the observation and zero otherwise), SIZE (25 dummy variables measuring where a stock's relative market cap is each quarter), P/E (price-to-earnings divided into 25 dummies calculated each quarter and one additional dummy variable for negative earnings stocks), DISAGREEMENT (analyst disagreement divided into 25 dummies calculated each quarter), CONVDEBT (a dummy for the firm having positive convertible debt), VOLATILITY (past volatility divided into 25 dummies calculated quarter), INDUSTRY dummies (SIC at the 2 digit level), EXCHANGE dummies and QUARTER dummies. In columns (3), (6) and (9), interactions of UEHIGH and all of the other controls except the INDUSTRY, EXCHANGE and QUARTER dummies are included in the specification. The standard errors (in parentheses) are adjusted by allowing for the errors to be correlated across observations of the same stock; i.e. the standard errors are clustered by stock. There are 119,785 observations.

Table 5: OLS Estimates of the Differential Effect of High and Low Unexpected Earnings on Returns and Turnover

	CAR	ABNTURN	POSTCAR
	(1)	(2)	(3)
Indicator for High Unexpected Earnings (UEHIGH)	2.33 (.08)	.055 (.009)	.49 (.29)
Indicator for Low Unexpected Earnings (UELOW)	-1.84 (.07)	.093 (.009)	-.53 (.28)
Indicator for High Short Ratio (HISR)	-.07 (.11)	.333 (.028)	-1.62 (.47)
High Unexpected Earnings $\times$ High Short Ratio (UEHIGH $\times$ HISR)	.46 (.14)	.078 (.038)	-2.21 (.57)
Low Unexpected Earnings $\times$ High Short Ratio (UELOW $\times$ HISR)	-.55 (.14)	.090 (.043)	-.23 (.55)
Stock Fixed Effects	Yes	Yes	Yes
R^2	.137	.112	.216

The dependent variable in column (1) is CAR (cumulative abnormal return (%) from trading day -1 to +1). The dependent variable in column (2) is ABNTURN (mean abnormal turnover (%) from trading day -1 to +1). The dependent variable in column (3) is POSTCAR (cumulative abnormal return (%) from trading day +2 to +126). The independent variables include UEHIGH (indicator that a stock's earnings surprise for the quarter is in the top 33% of the sample distribution that quarter), UELOW (indicator that a stock's earnings surprise for the quarter is in the bottom 33% of the sample distribution that quarter), HISR (a dummy equal to one if the stock is in the top 33% of the sample short ratio distribution for the quarter of the observation and zero otherwise), SIZE (25 dummy variables measuring where a stock's relative market cap is each quarter), P/E (price-to-earnings divided into 25 dummies calculated each quarter and one additional dummy variable for negative earnings stocks), DISAGREEMENT (analyst disagreement divided into 25 dummies calculated each quarter), CONVDEBT (a dummy for the firm having positive convertible debt), VOLATILITY (past volatility divided into 25 dummies calculated each quarter), INDUSTRY dummies (SIC at the 2 digit level), EXCHANGE dummies and QUARTER dummies. The standard errors (in parentheses) are adjusted by allowing for the errors to be correlated across observations of the same stock; i.e. the standard errors are clustered by stock. There are 119,785 observations.

Table 6: Estimates of the Effect of Unexpected Earnings on Stock Returns, Turnover and Subsequent Stock Returns for NASDAQ versus NYSE Stocks

	CAR	ABNTURN	POSTCAR
	(1)	(2)	(3)
High Unexpected Earnings (UEHIGH or ABSUEHIGH for column 2)	3.04 (.16)	.188 (.021)	3.32 (.70)
Indicator for High Short Ratio(HISR)	.08 (.18)	.009 (.022)	-.44 (.88)
Indicator for NASDAQ stock (NASDAQ)	-.36 (.20)	.034 (.024)	3.00 (.97)
UEHIGH $\times$ HISR	-.18 (.25)	.029 (.032)	-1.64 (1.06)
UEHIGH $\times$ NASDAQ	.80 (.26)	-.069 (.029)	2.26 (1.16)
HISR $\times$ NASDAQ	-.99 (.31)	-.023 (.037)	.18 (1.42)
UEHIGH $\times$ HISR $\times$ NASDAQ	1.40 (.43)	.012 (.052)	-4.93 (1.90)
R^2	.059	.033	.042

The dependent variable is CAR (cumulative abnormal return (%) from trading day -1 to +1) in column (1). The dependent variable is ABNTURN (mean abnormal turnover from trading day -1 to +1) in column (2), and the dependent variable is POSTCAR (cumulative abnormal return from trading day +2 to +126) in column (3). The sample includes all stocks in the top and bottom 33% of the short ratio distribution for the quarter and exchange and the top and bottom 33% of the unexpected earnings distribution for the quarter and exchange. The independent variables include UEHIGH (indicator that a stock's earnings surprise for the quarter is in the top 33% of the sample distribution that quarter), ABSUEHIGH (indicator that a stock's absolute earnings surprise for the quarter is in the top 33% of the sample distribution that quarter), HISR (a dummy equal to one if the stock is in the top 33% of the sample short ratio distribution for the quarter and exchange of the observation and zero otherwise), NASDAQ (a dummy equal to one if the stock is in NASDAQ), SIZE (25 dummy variables measuring where a stock's relative market cap is each quarter), P/E (price-to-earnings divided into 25 dummies calculated each quarter and one additional dummy variable for negative earnings stocks), DISAGREEMENT (analyst disagreement divided into 25 dummies calculated each quarter), IO (institutional ownership divided into 25 dummies calculated each quarter), CONVDEBT (a dummy for the firm having positive convertible debt), VOLATILITY (past volatility divided into 25 dummies calculated each quarter), INDUSTRY dummies (SIC at the 2 digit level) and QUARTER dummies. The standard errors (in parentheses) are adjusted by allowing for the errors to be correlated across observations of the same stock; i.e. the standard errors are clustered by stock. The sample period for these regressions is 1993 through 2000. There are 27,066 observations.

Table 7: Estimates of the Effect of Unexpected Earnings on Stock Returns, Turnover and Subsequent Stock Returns for Small and Large Cap Stocks Before and After 2001

	CAR		ABNTURN		POSTCAR	
	Small	Large	Small	Large	Small	Large
	(1)	(2)	(3)	(4)	(5)	(6)
High Unexpected Earnings (UEHIGH or ABSUEHIGH for columns 3 and 4)	3.74	2.59	.121	.101	6.77	-1.72
	(.20)	(.18)	(.026)	(.023)	(.96)	(.79)
Indicator for High Short Ratio (HISR)	-.85	-.34	-.113	.016	-1.45	-1.11
	(.24)	(.21)	(.044)	(.026)	(1.18)	(.90)
UEHIGH $\times$ HISR	1.38	.64	.125	-.003	-5.44	-.87
	(.33)	(.31)	(.049)	(.044)	(1.59)	(1.33)
UEHIGH $\times$ Indicator for After 2001 (AFTER)	.66	1.26	-.003	.030	-1.87	3.00
	(.30)	(.26)	(.036)	(.036)	(1.28)	(.94)
HISR $\times$ AFTER	-.55	-.08	.363	.533	.69	.08
	(.34)	(.34)	(.072)	(.060)	(1.54)	(1.24)
UEHIGH $\times$ HISR $\times$ AFTER	.38	-.48	.109	.139	-.33	.61
	(.48)	(.48)	(.082)	(.095)	(2.11)	(1.75)
R^2	.075	.066	.067	.126	.036	.024

The dependent variable is CAR (cumulative abnormal return (%) from trading day -1 to +1) in columns (1) and (2). The dependent variable is ABNTURN (mean abnormal turnover (%) from trading day -1 to +1) in columns (3) and (4), and the dependent variable is POSTCAR (cumulative abnormal return (%) from trading day +2 to +126) in columns (5) and (6). The sample includes all stocks in the top and bottom 33% of the short ratio distribution for the quarter and exchange and the top and bottom 33% of the unexpected earnings distribution for the quarter and exchange. Small stocks are firms with a market cap below the 40^{th} percentile and large stocks are firms with market cap above 70^{th} percentile. The independent variables include UEHIGH (the indicator that a stock's earnings surprise for the quarter is in the top 33% of the sample distribution that quarter), ABSUEHIGH (indicator that a stock's absolute earnings surprise for the quarter is in the top 33% of the sample distribution that quarter), HISR (a dummy equal to one if the stock is in the top 33% of the sample short ratio distribution for the quarter and exchange of the observation and zero otherwise), AFTER (a dummy equal to one if the observation is after 2001), SIZE (25 dummy variables measuring where a stock's relative market cap is each quarter), P/E (price-to-earnings divided into 25 dummies calculated quarter and one additional dummy variable for negative earnings stocks), DISAGREEMENT (analyst disagreement divided into 25 dummies calculated each quarter), IO (institutional ownership divided into 25 dummies calculated each quarter), CONVDEBT (a dummy for the firm having positive convertible debt), VOLATILITY (past volatility divided into 25 dummies calculated each quarter), INDUSTRY dummies (SIC at the 2 digit level) EXCHANGE dummies and QUARTER dummies. The standard errors (in parentheses) are adjusted by allowing for the errors to be correlated across observations of the same stock; i.e. the standard errors are clustered by stock. There are 24,781 observations for the small stock models in columns (1), (3) and (5), and 17,274 observations for the large stock models in column (2), (4) and (6).

Figure 1: Plot of Short Interest Ratio Over Time by Firm Size