

WHAT DO SHORT SELLERS KNOW?

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ABSTRACT

Using proprietary short-sale order data, we investigate the sources of short-sellers' informational advantage. Heavier shorting occurs the week before negative earnings surprises, analyst downgrades, and downward revisions in analyst earnings forecasts. The biggest effects are associated with analyst downgrades. While these event days constitute only 12% of sample days, they account for 24% of the overall underperformance of heavily shorted stocks. The results indicate that short sellers are well-informed about upcoming earnings news and anticipate analyst recommendation changes. Shorting predictability remains significant after controlling for information in analyst actions, suggesting that short sellers know more than analysts about firm fundamentals.

Keywords: short-selling, earnings news, analyst recommendations, analyst forecasts.

I. INTRODUCTION

Before the most recent financial crisis, financial economists generally viewed short sellers as important contributors to efficient stock prices. Earlier theoretical work argues that when shorting is constrained, assets tend to be overvalued (Miller 1977), and it takes longer for negative information to be incorporated into prices (Diamond and Verrecchia 1987). Numerous empirical studies provide strong support for these claims.¹ Meanwhile, journalists and investors could see that short-sellers had uncovered the Enron fraud and other similar events. Regulators eased restrictions on shorting, including the so-called uptick rule, and shorting activity became quite widespread, accounting for as much as 40% of trading volume by the end of 2007, according to Diether et al. (2009).

Attitudes toward short-sellers changed dramatically as the financial crisis took hold. Short-sellers were heavily criticized for active trading right before the fall of Bear Stearns in March 2008.² As the stock prices of other financial firms continued to erode during 2008, regulators and some market participants began to question whether short-sellers might be profiting by driving prices down to an extent that was not justified by value-related information. In fact, at the height of the crisis, the Securities and Exchange Commission became so concerned about possible manipulation by short sellers that it invoked its emergency powers and temporarily banned short sales of financial stocks (SEC Release 34-58592 2008). Even financial economists seemed less sure of short sellers' salutary effects. For example, in a timely theoretical paper, Goldstein and Guembel (2008) argued that opportunistic short sellers can drive share prices down and destroy firm value.

¹ Lamont and Thaler (2003), Mitchell et al. (2002), Bris et al. (2007), Reed (2007), and Boehmer and Wu (2013) to name a few.

² David Cho, "SEC Probes Shorting of Bear's Stock," Washington Post, March 21, 2008.

Are short-sellers informed traders contributing to market efficiency, or are they manipulators? The answer to the question hinges on identifying the information that short-sellers possess. If short-sellers act only on information about firm fundamentals, then it is hard to charge them as manipulators. Previous literature finds that heavier shorting leads to lower returns in the future³ and worsening firm fundamentals.⁴ But it does not answer the essential question of whether or how much of short sellers' ability to generate excess returns comes from information related to firm fundamentals. That is the focus of this article. To be more specific, we investigate and quantify the sources of short sellers' information advantage by combining a five-year panel of proprietary NYSE short sale order data⁵ with data on earnings releases and analyst actions, such as forecast changes and recommendation changes. Our main goal is to see whether and how much of short sellers' overall information advantage can be attributed to this type of fundamental information. In that sense, our exercise is similar to Roll (1988), who seeks to identify the ex post relationship between news and asset price moves. To do this, we introduce a novel return decomposition. The methodology can help researchers, investors, and regulators understand short sellers' information and the sources of their excess returns, and the methodology can also be applied in a variety of other information contexts. We have two main empirical findings. First of all, while earnings and analyst event days constitute only 12% of the days in our sample, these days account for over 24% of the overall underperformance of heavily shorted stocks. This indicates that a significant portion of shorting activity is related to fundamental news. Between different groups of short-sellers, we find that earnings and analyst

³ For example, Boehmer et al. (2008) and Asquith et al. (2005).

⁴ For example, Christophe et al. (2004) find that negative earnings surprises are preceded by abnormal short selling, and Christophe et al. (2010) find that shorting predicts future analyst downgrades. Dechow et al. (2001) document that short sellers take positions in stocks with high P/E and market-to-book ratios, covering their positions as the ratios revert to the mean. Francis et al. (2005) show that short sellers are able to predict downward analyst forecast revisions, Desai et al. (2006) find that short sellers anticipate earnings restatements, and Karpoff and Lou (2010) show that short sellers have advance knowledge of corporate financial misconduct.

⁵ Similar data are used in Kaniel et al. (2008) and Boehmer and Kelley (2009).

action release days are particularly important for individual (retail) short sellers; these days account for 38% of the overall underperformance of stocks that are heavily shorted by individuals. Among the cross section of stocks, shorts have strong predictability for small stocks, possibly because small firms have less transparency and private information might be more valuable.

Our second main finding is on the information dynamics between analysts and short-sellers, which has attracted attention recently. For instance, Irvine et al (2007) conclude that analysts tip their institutional clients before they announce initial stock buy/sell recommendations. Our data on shorting activity and analyst actions allows us to take a closer look at the information possessed by these two groups of market participants. We find that just before earnings news days, trading by short-sellers contains predictive information for future returns above and beyond the information in analyst actions. This finding offers a new perspective that short sellers actually know more than analysts around earnings release days.

There are other studies investigating how information is related to shorting. For instance, in a contemporaneous effort, Engelberg, Reed, and Ringgenberg (2012) (ERR) collect all news articles in the Dow Jones archive and investigate how short-sellers process publicly available information. Their main finding is that short-sellers are more efficient and skilled information processors, and they trade more actively and profitably after news announcements. Unlike ERR, we do not include all news about a firm and instead concentrate on the most fundamental type of news: news related to earnings. We document that short-sellers can significantly anticipate future news related to a company's earnings, which is different from ERR. This indicates that short-sellers are not just skilled information processors but also have an information advantage. Overall, our study provides important additional insights on the nature of the information

advantages that lead to the well-documented abnormal returns earned by short-sellers, and our paper allows novel inferences about how short-sellers contribute to the price discovery process and market efficiency.

The rest of the paper is structured as follows. Section II discusses the shorting data as well as the First Call earnings and analyst data. Main results are provided in Section III. Additional robustness tests and discussion are covered in Section IV. Section V concludes.

II. DATA

Data on short selling

The sample consists of all NYSE system order data (SOD) records related to short sales from October 23, 2000 through April 30, 2005.⁶ Our sample begins on the date that Reg FD becomes effective, ensuring that there is a uniform regulatory environment governing information dissemination by public companies. To ensure a uniform regulatory environment governing short sales, we stop the sample on April 30, 2005, right before the start of the Reg SHO pilot program suspending the uptick rule.⁷ These shorting data are maintained by the NYSE for compliance purposes; they are not made available to market participants during our sample period. In Section IV, we examine a more recent 2009-2010 sample where more

⁶ A similar dataset is examined in Boehmer et al. (2008), except their dataset extends from January 2000 through April 2004.

⁷ During our sample period, most short selling on the NYSE was subject to the uptick rule (Rule 10a-1(a)(1) of the Securities and Exchange Act of 1934), which required short sales to take place (a) at a price above the price at which the immediately preceding sale was effected (known as a plus tick), or (b) at a price equal to the last sale price if it is higher than the last different price (known as a zero-plus tick). Short sales were not permitted on minus ticks or zero-minus ticks. A few short sales were exempt from the uptick rule. These include relative-value trades between stocks and convertible securities, arbitrage trades in the same security trading in New York vs. offshore markets, and short sales initiated by broker-dealers at other market centers as a result of bona fide market-making activity. These exempt short sales are marked separately in the system order data, and they account for only 1.5% of total shorting volume in our sample. We exclude exempt short sale orders because they are less likely to reflect negative fundamental information about the stock.

information is available to market participants about the volume of short selling in each stock. Using CUSIP numbers and tickers, we cross-match the list of NYSE stocks to CRSP and retain only common stocks (those with a CRSP *shrcd* equal to 10 or 11), which means we exclude securities such as warrants, preferred shares, American Depositary Receipts, closed-end funds, and REITs. This leaves us a daily average of 1,265 NYSE-listed common stocks. We measure daily shorting flow as the fraction of volume executed on the NYSE in a given stock on a given day that involves a system short seller. During our sample period shorting via system orders averages about 14% of overall NYSE trading volume (equal-weighted across stocks). Recall that these are lower bounds on the incidence of shorting at the NYSE, since our sample does not include specialist short sales or short sales that are handled by a floor broker. Based on aggregate data released by the NYSE, our data represent about 80% of NYSE shorting activity.

The dataset also identifies the type of account that submitted the short sale order. Account types are coded by the submitting broker-dealer based on a set of regulations issued by the NYSE. We partition the sample into four different types of accounts:

<u>Account Type Designation</u>	<u>Description</u>
Individual	Agency orders that originate from individuals
Institution	Agency orders that do not originate from individuals.
Proprietary	Orders where NYSE members are trading as principal. Excludes all trades by the specialist for his own account.
Other	Residual group including orders from registered options market-makers, inter alia.

We further partition institutional and proprietary short sales depending on whether the order is part of a program trade. A program trade is defined as simultaneously submitted orders to trade 15 or more securities having an aggregate total value of at least \$1 million. There is some incentive for institutions to batch their orders to qualify as a program trade, because program trades are often eligible for commission discounts from brokers.

[Insert Table 1]

Table 1 Panel A provides summary statistics on the relative prevalence of shorting by each of the six account types. The majority of NYSE shorting is by institutions doing non-program trading. Depending on the particular cross-sectional subsample being considered, institutional non-program shorting represents 57% to 62% of the total amount of measured shorting activity. The next biggest category is institutional shorting that is a part of a program trade. This activity accounts for between 8.5% and 12.5% of overall shorting. Overall, institutions account for about three-quarters of shorting activity. Shorting by individuals is notably rare, accounting for less than 1.5% of overall shorting volume. This is not peculiar to shorting; overall NYSE order flow exhibits similar patterns (Boehmer and Kelley, 2009). Individuals account for only a small amount of overall trading volume, but orders from individuals are particularly rare at the NYSE during our sample period because most brokerage firms either internalize retail orders in active stocks or route these orders to regional exchanges or third-market dealers in return for payment.

Data on earnings and analyst news events

The First Call historical database from Thomson Financial is the source of earnings and analyst-related news. This is a widely used, comprehensive database of analyst earnings

forecasts, stock recommendations, and actual earnings announcements, among other items. Actual per share earnings numbers are adjusted to exclude any unusual items that a majority of the contributing analysts deem non-operating or non-recurring, so that the actual numbers can be compared to analyst earnings estimates.

We consider three different types of earnings and analyst-related news: earnings announcements, analyst recommendation changes, and analyst forecast revisions. For earnings announcements, the news variable UE is standardized unexpected earnings per share, defined as the announced EPS for the quarter less the corresponding consensus EPS forecast scaled by the standard deviation of EPS from the previous 16 quarters. For buy/sell recommendation changes, UE is the number of notches of the average change, where a recommendation is classified as strong buy, buy, neutral, sell, or strong sell, according to First Call's five-point scale. For instance, a change from "buy" to "strong buy" would be a change of "+1". For analyst forecast changes, UE is the current consensus EPS forecast in dollars (for a fiscal quarter within a year) less the last consensus forecast for the same quarter. We winsorize the top and bottom 0.5% of each news variable.

Panel B of Table 1 reports summary statistics on the earnings and analyst events. Some events are more prevalent than others. While 1.2% of all days in our sample are earnings announcement days, 2.2% and 10.6% of all days are recommendation change days and forecast change days. Altogether, 12.0% of all days are event days in our sample. Notice that the 12.0% is not equal to the sum of 1.2%, 2.2% and 10.6%, as some days have multiple events.

The average earnings surprise is somewhat positive, with a mean of 0.098 and a standard deviation of 0.519, and the mean recommendation change is -0.078 notches with a standard deviation of 1.405 notches, indicating that downgrades are slightly more common than upgrades.

Downward forecast revisions are a bit more likely than upward forecast revisions, with a mean change of -0.3 cents in the consensus EPS and a standard deviation of 3.7 cents.

III. EMPIRICAL SPECIFICATIONS AND MAIN RESULTS

Shorting and future earnings news

We begin by investigating whether short sellers anticipate earnings surprises and other earnings- and analyst-related news. This section serves two purposes. First, before we consider stock returns at all, it is important to establish that short sellers can anticipate news about fundamentals. Second, while a few previous papers address similar questions, such as Christophe et al. (2004), prior work cannot distinguish between different categories of short sellers. Here we can investigate which groups of short-sellers are able to anticipate earnings news and analyst announcements.

For different kinds of earnings and analyst events in NYSE stocks, we estimate pooled regressions of the form:

$$UE_{i,t} = b_0 + b_1 short_{i,t-5,t-1} + b_2 \ln size_{i,m-1} + b_3 BM_{i,m-6} + b_4 \sigma_{i,m-1} + b_5 r_{i,m-6,m-t} + b_6 turn_{i,m-1} + e_{i,t}, \quad (1)$$

where $UE_{i,t}$ is a particular type of earnings-related news for firm i on day t , as defined in section 2.B. The explanatory variable of interest is $short_{i,t-5,t-1}$, which is shorting by the applicable group in stock i during the interval $[t-5, t-1]$ as a fraction of overall trading volume. We focus on the previous week's shorting activity to match the approach in Boehmer et al. (2008).⁸ Other control

⁸ Results based on shorting during the previous 20 trading days are qualitatively similar.

variables include $lnsize_{i,m-1}$, the previous month's log market capitalization, the book-to-market ratio $BM_{i,m-1}$ from six months ago, the previous month's daily return volatility $\sigma_{i,m-1}$, the return over the past six months $r_{i,m-6,m-1}$, and $turn_{i,m-1}$, which is last month's turnover (trading volume as a fraction of outstanding shares).

We use a regression approach in order to control for publicly available stock and firm characteristics that might help predict earnings surprises or analyst actions. All explanatory variables except past returns are normalized to have zero mean and unit variance each month. Shorting becomes somewhat more prevalent as our sample period progresses, so this normalization is designed to mitigate the effects of any trend in this or any other explanatory variable that might otherwise affect inference. Normalization also makes it easier to interpret the coefficients. The standard errors for all coefficients are clustered by month.⁹

[Insert Table 2]

Table 2 displays the coefficients on the shorting variable. Each entry in the table represents a different regression that uses a particular earnings or analyst measure as the dependent variable, and shorting by a particular account type as the relevant explanatory variable. The first row addresses earnings announcements, for example. Stocks with negative earnings surprises experience more overall shorting activity over the previous five trading days, with a t-statistic of 2.33. Both individual and institutional non-program shorting are reliably higher the week before a negative earnings surprise; the relationship between shorting and unexpected earnings is not reliably negative for any of the remaining account types.

There is heightened shorting activity in the week before downward analyst recommendation changes (t-stat = 9.17), as well as in the week before downward analyst forecast

⁹ Alternatively, we also estimate equation (1) using Fama-MacBeth over each quarter. The results are very similar and we don't report them.

revisions (t-stat = 2.82). As in the case of earnings announcements, these results are mostly driven by institutional non-program shorting, but both types of analyst actions are preceded by heavy individual shorting as well (t-stats = 2.93 and 4.85 for recommendation changes and forecast revisions, respectively).¹⁰

To summarize, we establish in this section that short-sellers anticipate future earnings and analyst news. Individual short sellers and institutional non-program shorts are the most informed about this type of fundamental news.¹¹

Shorting and future returns on event vs. non-event days

To understand whether shorting's predictability is coming from firm fundamentals, the heart of the paper is a decomposition of the excess returns subsequent to shorting activity into components associated with various types of earnings and analyst news. We begin with a simple benchmark regression similar to the one in Boehmer et al. (2008):

$$r_{i,t,t+k} = b_0 + b_1 short_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{i,t}, \quad (2)$$

where we include the usual control variables and normalize shorting to have zero mean and unit variance on each trading day. The dependent variable, $r_{i,t,t+k}$, is the average daily return¹² over the period $[t, t+k]$, where $k=1, 5, 10$, and 20 days. For example, $r_{i,t,t+1}$ is the average of two daily

¹⁰ First Call also provides data on management earnings guidance and earnings restatements. In results not reported, shorting activity predicts neither manager guidance nor earnings restatements, though this could be a consequence of low power due to the limited number of observations in these categories.

¹¹ In results not reported, we also investigate whether the association between shorting and unexpected earnings depends on analyst dispersion. We find that greater analyst dispersion does not seem to significantly affect the relationship between the earnings surprise and the previous week's shorting activity.

¹² For reported results, we use simple returns. We also conduct robustness checks using Fama-French adjusted returns. All results are quantitatively similar.

returns. We run a regression using all short sales, and then we rerun the benchmark regression using shorting by each account type. This regression measures the overall information content of short sellers. That is, if short sellers are informed, the stocks they short heavily should underperform the stocks they avoid shorting. All estimations in this section are Fama-MacBeth regressions, with one regression estimated per calendar month that includes all days t in that calendar month. Standard errors are computed following Newey and West (1987) with one lag due to the partially overlapping return observations.¹³

[Insert Table 3]

The results are in Table 3. The benchmark regression is denoted as Regression I in each panel, and different panels contain the results for different account types. Panel A reports estimates for all shorts. A cross-sectional increase in weekly shorting of one standard deviation is associated with average daily excess returns over the next two days that are 4.06 basis points lower. The t-statistic is a very large 12.02, and the economic significance is quite strong as well, as 4.06 basis points per day equates to more than 10% per year. Short sales continue to be informative at longer horizons. Over the next 20 trading days, for example, the coefficient is -2.51 basis points, which corresponds to 50 basis points of cumulative return over this interval of approximately one month. In the rest of this section, however, we focus on the short-horizon returns from day t to day $t + 1$, because these returns are the easiest to assign to a particular news bin.

Shorting by each account type is reliably informed, though some account types seem to be trading on stronger signals on average. For instance, a cross-sectional one-standard deviation increase in individual short sales is associated with average daily returns over the next two days

¹³ We also conduct estimation using pooling regressions, as in the previous section. The results are very similar to what we obtain using Fama-MacBeth regressions.

that are just 1.46 basis points lower. It is interesting to note that the information in individual short sales appears to be quite short-lived, as the underperformance of stocks that are heavily shorted by individuals is no longer significant at the 10-day or 20-day horizon. Over the short horizon, non-program shorting by institutions is the most informed, with a corresponding 2-day return number of 4.34 basis points per day. Program shorting by institutions is the least informed, with each standard deviation of additional shorting affecting returns by only 1.19 basis points per day.

Next we decompose the short sellers' private information by identifying and separating out days on which there is earnings or analyst-related information. Specifically, we set an indicator variable d_t equal to one if day t has an earnings announcement, a change in any analyst's buy/sell recommendation, or a change in any analyst's earnings forecast. This happens on 12.0% of the stock-days in our sample. We then estimate the following monthly Fama-MacBeth regressions:

$$r_{i,t,t+k} = b_0 + (b_1 + c_0 d_t) short_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{i,t}, \quad (3)$$

with a focus on the interacted coefficient c_0 , which is the incremental stock return associated with the previous week's shorting activity that is due to earnings news or analyst changes. We purposely do not model a direct effect of the news variable d . If short sellers could indeed anticipate negative news and trade accordingly, the coefficient of d , rather than the coefficient of the interaction of d with $short$, would capture the associated variation in returns. This would make it difficult to interpret the interaction term, and thus the link between shorting, news, and returns. Moreover, under the null of no news-related effect of short selling on returns, the

regression without direct news effect reduces to equation (2), allowing a proper decomposition of the return effects attributable to short selling.¹⁴

As before, we estimate this regression using all short sales as well as short sales initiated by various account types. This is reported as Regression II in Table 3. When there is no earnings or analyst-related news, b_1 is the estimate of the effect on returns of a one-standard deviation increase in shorting. For shorting by all account types (Panel A), this coefficient is 3.46 basis points per day, with a t-statistic of 10.44. On days with earnings or analyst-related news, the effect of shorting is $b_1 + c_0$, and this quantity equals $3.46 + 4.36 = 7.82$ basis points per day, which is more than double the coefficient on non-news days. The incremental effect on earnings/analyst news days is also strongly statistically significant, with a t-statistic of 5.18.

These results show that a significant amount of short sellers' information is incorporated into price within a week via an earnings announcement or an analyst report. There is another way to gauge the importance of earnings and analyst news, and that is to decompose the overall underperformance of heavily shorted stocks into two components: earnings news-related and other. To do this, we make use of the fact that 12.0% of the days in the sample have an earnings or analyst announcement. The overall underperformance associated with a one-standard deviation increase in short sales is given by:

$$12.0\% * (3.46 + 4.36) + (1 - 12.0\%) * 3.46 = 4.00 \text{ basis points per day}$$

¹⁴ Empirically, adding a direct news effect to the models generally leaves the conclusions about the coefficients of the interaction terms intact.

The first term reflects the portion of short-sellers' information associated with earnings and analyst announcement days, or in this case 24% of the overall underperformance of heavily shorted stocks.

We can also use the same approach to decompose the information in shorting by specific account types. For example, Panel B reports the results for individual shorts. On regular days, an additional standard deviation unit of shorting by individuals is associated with returns that are 1.07 basis points lower. On news days, the corresponding figure is $1.07 + 3.76 = 4.83$ basis points. Though these days account for only 12% of the total, these earnings and analyst news days account for 38% of the overall underperformance of stocks that are heavily shorted by individuals. Thus, individual shorting is particularly informative about returns on earnings and analyst news days.

Shorting by institutional non-program shorts is also noteworthy in this context. These results are in Table 3 Panel C. On a non-news day, the relevant coefficient is 3.71 basis points per day, and the incremental effect on announcement days is 4.76 basis points, for a total effect of $3.71 + 4.75 = 8.46$ basis points per day. Thus, it appears that even more of institutional short-sellers' advantage accrues on days where there is an earnings announcement, an analyst forecast revision, and/or an analyst recommendation change. These days account for 24% of the overall underperformance of heavily shorted stocks. In contrast, earnings and analyst event days do not seem to be particularly important days for some groups of short sellers. Consider program institutional trading by NYSE member firms, for example. As reported in Panel D of Table 3, underperformance on news days is statistically indistinguishable from underperformance on non-news days. Earnings announcements and changes in an analyst's outlook do not appear to be particularly important catalysts for excess returns to shorting by these particular accounts.

Which kind of earnings or analyst news is most closely associated with short sellers' information? As noted above, we have information on three different information releases: earnings announcements, analyst recommendation changes, and analyst forecast revisions. Analyst forecast revisions account for the bulk of the information releases, as they occur on 10.6% of the stock-days in our sample. Earnings announcements occur on 1.2% of the stock-days in our sample, and analyst recommendation changes are found on 2.2% of the stock-days.

To investigate the different types of news, we estimate the following regression:

$$r_{i,t,t+k} = b_0 + (b_1 + c_1 d_{1t} + c_2 d_{2t} + c_3 d_{3t}) short_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{i,t}, \quad (4)$$

where $d_{1t} = 1$ if day t has an earnings announcement and zero otherwise, $d_{2t} = 1$ if on day t any analyst changes her buy/sell recommendation, and $d_{3t} = 1$ if on day t any analyst changes her earnings forecast. These are reported as Regression III in the various panels of Table 3.

Panel A has the results for all short sales. Based on the point estimates, short sales are indeed more informative about future returns on each type of news day. But some of the incremental effects are close to zero or statistically indistinguishable from zero. For instance, one more standard deviation of shorting is associated with only 0.65 basis points of additional daily underperformance ($t = 0.86$) on an analyst forecast revision day, as compared to a day without earnings or analyst news. Note that the underperformance of heavily shorted stocks on analyst forecast revision days is still substantial. It is just not very different from the underperformance on ordinary days (4.22 basis points on forecast revision days vs. 3.57 basis points on non-news days). On days when earnings are announced, an additional standard deviation of shorting during the previous week is associated with a daily underperformance of

$3.57 + 5.29 = 8.86$ basis points. But these days are particularly volatile, and ultimately we are unable to reject the hypothesis that the underperformance on any earnings announcement day differs from that of non-news days ($t = 1.16$).

The biggest return effects are on days with an analyst recommendation change. The relevant coefficient on these days is $3.57 + 13.09 = 16.66$ basis points, which is statistically different ($t = 5.98$) from and over four times as large as the coefficient of 3.57 on non-news days. Of course, analyst recommendation changes are not that prevalent, occurring only about once every 40 trading days on average. Thus, while heavily shorted stocks dramatically underperform on days when an analyst recommendation changes, only about 10% of the overall underperformance accrues on these days. Another 10% of the overall underperformance accrues on days with an analyst forecast revision, and only about 3% of the overall underperformance occurs on earnings announcement days.

These qualitative results are not always the same when we examine shorting by various account types. For example, the marginal effects are significant on all three events days for individual shorting, while for institutional non-program shorting, the marginal effects are significant on recommendation change days but are insignificant on earnings announcement and analyst forecast revision days. It is interesting that the previous week's individual shorting is quite informative about returns on earnings announcement days. An additional standard deviation of shorting by this account type is associated with $1.05 + 13.44 = 14.49$ basis points of average daily underperformance immediately following an earnings announcement.

[Insert Figure 1]

To confirm that the results are stationary throughout the sample period and are not being driven by a small number of outliers, we graph the interaction terms c_1 , c_2 , and c_3 for 2-day

returns $[t, t+1]$ for each month from the Fama-MacBeth regressions in Figure 1. The graphs demonstrate that the results are not driven by outliers, and the results do not appear to diminish or grow larger over time. The regressions indicate that the most reliable incremental relationship between shorting and future returns occurs on analyst recommendation change days, and the graphs bear this out. There are only about 10 months out of 54 where the coefficient on the interaction term has the wrong (positive) sign.

Do short-sellers know more than analysts on news days?

From our previous results, analyst recommendation changes appear to be the most important days for the underperformance of heavily shorted stocks, yet ultimately we do not know the exact signals being used by short sellers. There are a number of possibilities, and the interpretation of the results differs somewhat across these possibilities. One likely explanation is that short sellers and analysts have similar fundamental information, both groups observe a change in the share price that appears unwarranted, and both groups act in response. If the share price goes up too much, for example, short sellers short, and analysts reduce their recommendations. Alternatively, short sellers learn company fundamental information at the same time as analysts, perhaps from conference calls or meetings with management, and both act accordingly. If material information is not communicated in these private meetings, this kind of information transmission would not run afoul of Reg FD. Another possibility is that short sellers are tipped off that a recommendation change is coming. While most analyst firms have internal policies against such tipping, Irvine et al. (2007) point out that tipping exists in a legal gray area, and they find evidence in institutional trades that is consistent with tipping by analysts. Meanwhile, tipping can also go in the opposite direction. Hedge funds or other investors may

collect private information or conduct original research or analysis and then share the results with analysts. Analysts then adjust their recommendations or forecasts accordingly, and this affects share prices. A malevolent version of this could arise if the tipper is attempting to manipulate share prices via false information, either with or without the knowledge of the analyst or research firm. While it seems unlikely that this practice is widespread, it may be important in certain instances. For example, Overstock.com filed suit against Rocker Partners (a hedge fund) and Gradient Analytics (a research firm) in 2005 making exactly this accusation, and Rocker settled the suit in 2009 for a reported \$5 million.¹⁵

To summarize, there are many routes that information flow can take among firms, short-sellers, analysts and investors. It is extremely difficult to pin down the direction of information flow between short-sellers and analysts, given the limited information we have on short-sellers and analysts. But progress is still possible. In this subsection, we examine one straightforward yet powerful question: do short-sellers know something about firm fundamentals that analysts do not? In empirical terms, does shorting provide additional explanatory power for future returns beyond the information contained in the earnings or analyst news alone? If the answer is no, then short-sellers possess only a subset of the information possessed by analysts. However, if the answer is yes, we know that tipping by analysts cannot be the whole story, because short sellers possess some fundamental information that analysts do not.

To investigate this, we estimate the following Fama-MacBeth regressions every month:

$$r_{i,t,t+k} = b_0 + b_1 short_{i,t-5,t-1} + c_1 DUE1_{i,t} + c_2 DUE2_{i,t} + c_3 DUE3_{i,t} + \gamma X_{i,t-1} + e_{i,t}, \quad (5)$$

$$r_{i,t,t+k} = b_0 + (b_1 + e_0 d_i) short_{i,t-5,t-1} + c_1 DUE1_{i,t} + c_2 DUE2_{i,t} + c_3 DUE3_{i,t} + \gamma X_{i,t-1} + e_{i,t}, \quad (6)$$

¹⁵“Rocker Pays \$5 Million to Overstock.com to Settle Lawsuit”, Overstock.com press release, December 8, 2009.

$$r_{i,t,t+k} = b_0 + (b_1 + e_1 d_{1t} + e_2 d_{2t} + e_3 d_{3t}) short_{i,t-5,t-1} + c_1 DUE1_{i,t} + c_2 DUE2_{i,t} + c_3 DUE3_{i,t} + \gamma X_{i,t-1} + e_{i,t} \quad (7)$$

In these regressions, *DUE* variables are the *UE* variables described earlier in the paper interacted with a dummy for the relevant event day. For example, variable $DUE1_{i,t}$ takes the value of the earnings surprise on earnings announcement days, and zero otherwise. Similarly, $DUE2_{i,t}$ and $DUE3_{i,t}$ take the value of the recommendation change and the consensus forecast revision on days when changes happen, and zero otherwise. The dummy variables d_t , d_{1t} , d_{2t} and d_{3t} continue to be defined as in equation (3) and (4). It is worth mentioning that the return variables on the left are from day t to $t+k$ inclusive, while the shorting variable is from day $t-5$ to day $t-1$, and the earnings news variables are for day t . That is, in our setting, the shorting is lagged for predicting future returns, while the earnings news is contemporaneous.

Equation (5) serves as a benchmark regression for the next two regressions, in which we specifically examine whether short-selling before event days can predict returns beyond what is contained in the future earnings surprise or analyst change. In equation (5), if earnings announcements, recommendation changes, and forecast revisions contain relevant information for contemporaneous returns, we would find the coefficients for $DUE1_{i,t}$, $DUE2_{i,t}$, and $DUE3_{i,t}$, respectively, to be significant and positive. For the next two regressions, we add in interactions between shorting and event-day dummies. If the coefficient e_0 in equation (6) or e_1 , e_2 or e_3 in equation (7) is significantly negative, short-selling contains additional information that is relevant for future returns in addition to the information contained in the earnings release or analyst change.

[Insert Table 4]

We report the coefficients in Table 4. In the first regression, as expected, all earnings and analyst news variables are significantly positive, implying that earnings or analyst news is associated with contemporaneous returns in the expected direction. In the second regression, the coefficient e_0 is -0.0260 with a t-statistic of -2.85 for the $[t, t+1]$ interval. This demonstrates that shorting activity in the week before earnings and analyst news days contains additional predictive information about future returns. Shorts must know something about fundamentals beyond what is captured in our earnings and analyst news measures. In the last regression, we separate the three different types of fundamental events, and it turns out that shorting activity mainly provides incremental information about the return effect of a recommendation change (t-stat = -2.37). This indicates in particular that short sellers are trading on information that is finer than just the number of downgrade notches.

To summarize this subsection, we find that shorting contains information about fundamentals beyond that which is embedded in earnings news or analyst releases, as shorting activity has incremental predictive power for future returns even after we control for contemporaneous earnings/analyst news. Put more simply, short sellers know something about fundamentals that analysts do not.

IV. ADDITIONAL RESULTS

In this section, we first examine whether our findings represent stock-specific selectivity vs. aggregate factor risks. Next, we examine whether shorting's predictability varies in the cross section of firms. We also investigate whether the results are any different for analysts from top investment banks. Finally, we provide results for a more recent sample.

Factor timing

While the results up to now have a number of stock and firm characteristics as controls, it may be the case that short sellers are simply loading on one or more common factors at exactly the right time, and this could explain some of the cross-sectional return predictability that we find. To distinguish between returns due to factor timing strategies and returns due to information about fundamentals or temporary mispricings, we add to the model Fama-French factor sensitivities interacted with shorting activity. Specifically, we estimate the following Fama-Macbeth regressions by month:

$$r_{i,t,t+k} = b_0 + (b_1 + c_0 d_t + b_2 \beta_{RM} + b_3 \beta_{HML} + b_4 \beta_{SML}) short_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{i,t}, \quad (8)$$

where the dependent variable is the average daily return¹⁶ for firm *i* over the interval [*t*, *t*+*k*] in percent, the betas are Fama-French factor sensitivities, estimated on daily returns over the previous calendar quarter, and short sales are from all account types. There is also a similar version that breaks out each type of news day separately.

[Insert Table 5]

The results are in Panel A of Table 5. We can directly compare the results with those in model II of Table 3. There is some evidence that factor timing explains part of short sellers' return on non-news days, as the magnitude of the *b*₁ coefficient in model II declines from -0.0346 in Table 3 to -0.0194 in Table 5. But this result applies primarily to the 2-day and 6-day returns and cannot be found at the other horizons. Most importantly, factor timing has essentially

¹⁶ We also use Fama-French adjusted returns, and results are very similar.

no effect on shorting returns on news days – the coefficients on the shorting variable interacted with the various dummies are virtually unchanged from the earlier results. This is true across all holding periods and for all account types. In fact, the coefficients on the interacted betas are almost always insignificantly different from zero, indicating that short sellers are probably not varying their factor loadings in a way that contributes anything to their excess returns. To put it more precisely, we cannot reject the hypothesis that factor timing accounts for none of the relationship between shorting and future returns in the cross-section, and especially not on news days.

Cross-sectional patterns in short sellers' fundamental information advantage

It is possible that short-sellers have a greater information advantage in, and/or target their trading activities towards, certain types of firms. Shorting activities could also have different impacts on firms with different characteristics. For instance, smaller firms have less analyst coverage and have less transparent information environments, so it is possible that careful research of these firms by short-sellers can better anticipate future analyst actions and earnings performance. To investigate this, we group NYSE firms into three size groups – small, medium, and big – with equal numbers of firms in each group based on the previous month's market capitalization. Our goal is to find out whether short-sellers better predict future news and future returns for specific groups of firms, such as smaller firms.

We estimate the following regression:

$$r_{i,t,t+k} = b_0 + \left[\sum_{j=1}^3 (b_j + c_j d_t) d_{i,t}^{GROUPj} \right] short_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{it} , \quad (9)$$

where $d_{i,t}^{GROUPn}$, $n = 1, 2$, or 3 (small, medium or big for market cap), is an indicator with value 1 if firm i at time t belongs to group n , and zero otherwise. In Panel B of Table 5, we only present results for all short sales to save space. Coefficients b_1, b_2, b_3 show that shorting predicts returns best for the smallest firms. Coefficients on the earnings news dummies are monotonic across market-cap groups; shorting activity predicts the returns on earnings and analyst event days better for smaller firms. The overall return predictability pattern implies that short sellers better anticipate negative market reaction to earnings and analyst news in smaller firms. Of course, analysts tend to follow larger firms rather than smaller firms, and thus it is quite plausible that short-sellers would know more about smaller firms' fundamentals than analysts.

Short-sellers vs. analysts from top investment banks?

As discussed earlier, it may be difficult to determine unambiguously whether short-sellers are tipped by analysts, given the limited information in our datasets. We already find that short sellers have incremental information beyond that contained in analyst recommendation changes. But there is still scope for tipping. This section explores analysts that might be more likely to tip short sellers. In particular, while most brokerage firms employ equity analysts and provide sell-side research during our sample period, investment banks are also involved in underwriting and prime brokerage activities. Investment banks, having more points of contact with hedge funds and other potential short sellers, might have a greater motivation to favor certain subsets of clients by keeping them better informed. Therefore, we investigate whether short sellers better

anticipate forecast revisions and recommendation changes if they come from analysts at large investment banks.

We use the Financial Times League Table from 2010 and 2011 to pick the top ten investment banks, all of which are in the First Call database. Those firms are: Citibank, Credit Suisse, UBS, Barclays, Morgan Stanley, JP Morgan, Goldman Sachs, Bank of America/Merrill Lynch, Deutsche Bank and Bear Stearns. These firms together account for 30-40% of all analyst activity observations in the First Call recommendation and forecast files. We then identify recommendations and forecasts that are issued by analysts at the top investment banks. In addition, following Irvine et al. (2007), we also identify recommendation initiations issued by top investment banks vs. initiations by other brokers. If the top investment banks favor short-sellers by tipping more than other brokers do, we should see short-sellers anticipate analyst activity from the top investment banks better than they predict analysts from other brokers. In addition, given that our data separate short-sellers in subgroups, we can also see whether some particular subgroup of short-sellers receives preferential treatment.

In Table 5 Panel C, we investigate whether short-sellers can anticipate recommendation changes or forecast changes or recommendation initiations differently when they come from top investment banks. The pooled regression is:

$$UE_{i,t} = b_0 + (c_1 dtop_{i,t} + c_2 drest_{i,t}) short_{i,t-5,t-1} + \gamma X_{it} + e_{i,t}, \quad (10)$$

where indicator $dtop_{i,t}$ takes value 1 if there is news issued by a top investment bank analyst and not by other brokers on day t for firm i , and zero otherwise; and indicator $drest_{i,t}$ takes value 1 if there is news issued by other brokers and not by any top investment banks on day t for firm i ,

and zero otherwise. To keep the results from being affected by overlapping information, days are partitioned (with no overlap¹⁷) into “only event from top investment banks”, and “only event from the rest”. If the coefficient c_1 is bigger or more significant than c_2 , then short-sellers are better informed about top investment bank analyst announcements.

There does not seem to be any evidence that top investment banks are more likely to tip. For instance, short sellers anticipate recommendation changes by both groups of analysts more or less equally. The coefficient for top investment banks is 0.0850, while the coefficient for all other brokers is 0.0874, and these are statistically indistinguishable. From results not reported, the same pattern holds for individual short-sellers and institutional short-sellers. For forecast changes, the message is similar. However, in terms of initial recommendation, we do find the coefficients on top investment banks, which is -0.0274 (t-stat=-2.79), to be significantly different from the rest of brokers, which is -0.0087 (t-stat=-1.19). If we read into it, short-sellers seem to know more about initial recommendation issued by top investment banks rather than from the rest. This could be supportive of tipping, as in Irvine et al. (2007), but we also can't exclude the possibility that short-sellers and analysts from top investment banks process the same kinds of information and independently take action in the same direction.¹⁸

More recent evidence

To ensure a consistent informational and regulatory environment for all stocks in our NYSE sample, we end our sample in April 2005 right before the start of the Reg SHO pilot program that suspends the uptick rule and other short sale price tests in 1,000 stocks. The Reg

¹⁷ Overlapping observations account for less than 5% of the sample, and they are deleted to clearly separate the two groups of analysts.

¹⁸ We also conduct tests on return responses to shorting around earnings news, depending on top investment banks and the rest. The results from there are also inconclusive.

SHO pilot program affects a subset of our sample stocks and marks the beginning of two trends: frequent changes in short sale regulation that continue to this day, and the precipitous fall of NYSE market share from about 60% in 2005 to about 20% in 2008. These trends introduce confounding effects and make our sample less representative after 2005. However, the more recent period allows an interesting additional experiment.

Since summer 2009, the SEC has required exchanges to publish daily shorting flows for each stock in real time (during the evening following each trading day). Thus, other traders can now observe and take into account the aggregate actions of short sellers in each stock. If that's done efficiently, we would expect short sellers to have less ability to predict stock returns during the more recent time period, at least at horizons beyond one day. To investigate this change in short-sale data availability, we collect short-selling data from the Nasdaq website. These data specify the daily Nasdaq shorting activity for each Nasdaq-listed stock from August 2009 to July 2010. During this period, there are no other changes in short-sale regulation. This sample ends in July 2010 because Nasdaq stops publishing the daily shorting data on its website at that point.

Panel D of Table 5 reports the results for the new sample. A week's worth of shorting activity still significantly predicts future returns, but with a smaller magnitude in the recent sample (for 2-day returns, a coefficient of -0.0162 for 2009-2010 compared to -0.0406 for 2000-2005). This indicates that short sellers continue to be informed in 2009-2010. Interestingly, stock prices do not immediately adjust to the overnight publication of short-sale data.

A decomposition of short-sellers' private information during this period finds that 17.5% of their information is incorporated into prices on earnings/analyst event days. This is slightly lower than the analogous 24% number calculated for the earlier time period, due in part to fewer earnings/analyst event days in the more recent period (8.6% of the 2009-2010 stock-days have an

earnings or analyst release vs. 12.0% of stock-days for 2000-2005). In contrast to the earlier sample period, short sellers now can predict the returns on earnings announcement days, but no longer can predict returns on recommendation change days. This is inconsistent with tipping by analysts, since earnings surprises should be known in advance only by company management. It also suggests that short sellers gain by using finer information than analysts have, since otherwise they would not be able to predict the deviation of actual earnings from the analyst consensus forecast.¹⁹

V. CONCLUSIONS

In this paper, we consider the trading of short sellers around different types of earnings and analyst-related news. Previous work has found that short sellers are well-informed, and we confirm that heavily shorted stocks substantially underperform lightly shorted stocks over the following week. Combined with earnings and analyst data, our daily panel of NYSE short sales allows us to examine the sources of these excess returns at various horizons. When we examine returns one day to one week following shorting activity from the previous week, we find that about a *quarter* of the underperformance of heavily shorted stocks can be attributed to earnings announcements and analyst-related news releases. The results are quite similar when we look at a more recent sample of Nasdaq short sales.

Is this a big number? We think so, especially given that we are in some sense tying our hands by using a short weeklong horizon in this analysis. Our empirical approach is likely to miss a substantial amount of earnings-related information that is being used by short sellers in their trading activity. Earnings-related news can affect stock prices on days other than our event

¹⁹ In results not reported, shorting activity continues to anticipate future earnings surprises and future recommendation changes, but not analyst forecast revisions.

days, in which case our methodology would not assign the stock's underperformance to earnings or analyst-related news.

Readers might instead view the glass as three-quarters empty, since 75% of the underperformance of heavily shorted stocks remains unexplained. In some sense, we sympathize with that view. While it is not our focus here, one could try to maximize the fraction of explained underperformance by adding in other strategies pursued by short sellers. For example, earlier work suggests that short sellers trade on post earnings-announcement drift and other anomalies, and these strategies probably contribute to the overall underperformance of heavily shorted stocks. Short sellers are also contrarian, and one could also assess the importance of short-term negative autocorrelation and/or positive cross-autocorrelation to short sellers, along the lines of Lehmann (1990) and Lo and MacKinlay (1991). In particular, the framework of Khandani and Lo (2011) might be useful in assessing the contribution of these kinds of quant strategies to the overall informativeness of short sales.

We also provide several interesting findings for information flows between short-sellers and analysts. We show that short sellers' ability to predict future returns is still substantial and significant after we control for information embedded in earnings news and analyst forecast and recommendation changes, indicating that short-sellers are doing much more than simply trading in advance on information gleaned from analysts. We can rule out this extreme version of the tipping hypothesis because short sellers know something that analysts do not. Other tests also point away from a tipping explanation.

Overall, it is clear from our evidence that a substantial fraction of the excess returns accruing to short sellers is based on private information about earnings and fundamentals that later becomes public. Furthermore, short sellers have fundamental information beyond that

possessed by analysts. Together, these results indicate that short sellers make valuable marginal contributions to price discovery in U.S. equities.

REFERENCES

- Ang, A. , R. Hodrick, Y. Xing, and X. Zhang. 2006. The cross-section of volatility and expected returns. *Journal of Finance* 61: 259-299.
- Asquith, P., P. Pathak, and J. R. Ritter. 2005. Short interest, institutional ownership, and stock returns. *Journal of Financial Economics* 78: 243-276.
- Boehmer, E., C. M. Jones, and X. Zhang. 2008. Which shorts are informed? *Journal of Finance* 63: 491-527.
- Boehmer, E., and E. Kelley. 2009. Institutional investors and the informational efficiency of prices. *Review of Financial Studies* 22: 3563-3594.
- Boehmer, E., and J. Wu. 2013. Short selling and the price discovery process. *Review of Financial Studies*, forthcoming.
- Christophe, S. E., M. G. Ferri, and J. J. Angel. 2004. Short-selling prior to earnings announcements. *Journal of Finance* 59: 1845-1876.
- Christophe, S. E., M. G. Ferri, and J. Hsieh. 2010. Informed trading before analyst downgrades: evidence from short sellers. *Journal of Financial Economics* 95: 85-106.
- Dechow, P., A. Hutton, L. Meulbroek, and R. G. Sloan. 2001. Short-sellers, fundamental analysis, and stock returns. *Journal of Financial Economics* 61: 77-106.
- Desai, H., S. Krishnamurthy, and K. Venkataraman. 2006. Do short sellers target firms with poor earnings quality? Evidence from earnings restatements. *Review of Accounting Studies* 11: 71-90.
- Diamond, D. W., and R. E. Verrecchia. 1987. Constraints on short-selling and asset price adjustment to private information. *Journal of Financial Economics* 18: 277-311.
- Diether, K. B., K. Lee, and I. M. Werner. 2009. Short-sale strategies and return predictability.

- Review of Financial Studies* 22(2): 575-607.
- Diether, K. B., I. M. Werner, and K. Lee. 2009. It's SHO time! Short-sale price tests and market quality. *Journal of Finance* 64 (1): 37-73.
- Duffie, D., N. Garleanu, and L. H. Pedersen. 2002. Securities lending, shorting, and pricing. *Journal of Financial Economics* 66: 307-339.
- Engelberg, J., A. V. Reed, and M. Ringgenberg. 2012. How are shorts informed? Short sellers, news, and information processing. *Journal of Financial Economics*: forthcoming.
- Fox, M. B., L. R. Glosten, and P. C. Tetlock. 2010. Short selling and the news: a preliminary report on an empirical study. *New York Law School Review* 54: 645-686.
- Francis, J., M. Venkatachalam, and Y. Zhang. 2005. *Do short sellers convey information about changes in fundamentals or risk?* Working paper, Duke University, George Washington University.
- Harrison, J. M., and D. M. Kreps. 1978. Speculative investor behavior in a stock market with heterogeneous expectations. *Quarterly Journal of Economics*: 323-336.
- Irvine, P., M. Lipson, and A. Puckett. 2007. Tipping. *Review of Financial Studies* 20: 741-768.
- Kaniel, R., G. Saar, and S. Titman. 2008. Individual investor trading and stock returns. *Journal of Finance* 63(1): 273-310.
- Karpoff, Jonathan M. and Lou, Xiaoxia. 2010. Short Sellers and Financial Misconduct. *Journal of Finance* 65, 1879-1913.
- Khandani, A. E., and A. W. Lo. 2007. What happened to the quants in August 2007? *Journal of Investment Management* 5 (4): 29-78.
- Khandani, A. E., and A. W. Lo. 2011. What happened to the quants in August 2007?: evidence from factors and transactions data. *Journal of Financial Markets* 14 (1): 1-46.

- Miller, E. M. 1977. Risk, uncertainty, and divergence of opinion. *Journal of Finance* 32: 1151-1168.
- Mitchell, M., T. Pulvino, and E. Stafford. 2002. Limited arbitrage in equity markets. *Journal of Finance* 57: 551-584.
- Roll, R. 1988. R-squared. *Journal of Finance* 43: 541-566.
- Womack, K. L. 1996. Do Brokerage Analysts' Recommendations Have Investment Value? *Journal of Finance* 51: 137-67.

Table 1. Summary statistics

The sample consists of all common stocks listed on the NYSE from October 23, 2000 through April 30, 2005. Panel A reports shorting activity at the firm level, where stocks are sorted into terciles based on the previous month's market capitalization, the previous month's daily stock return volatility, or the previous week's stock return. Panel B reports summary statistics for First Call earnings/analyst events for our sample. Prevalence is the percentage of stock-days with the indicated event. Earnings surprises are scaled by the standard deviation of earnings per share over the past 16 quarters, recommendation changes are the number of improvement notches on a 5-point scale, and analyst forecast changes are the change in the current consensus EPS forecast compared to the previous consensus forecast, in dollars. Other summary statistics are pooled across all indicated events.

Panel A. Shorting activity

		Daily average shares shorted per stock	Fraction of total shorting volume					
			Individual	Institutional Nonprog.	Institutional Program	Proprietary Nonprog.	Proprietary Program	Other
Market Value of Equity	Small	22,382	1.4%	57.4%	8.5%	14.3%	12.2%	6.3%
	Medium	67,959	1.0%	57.5%	9.2%	15.8%	11.8%	4.7%
	Big	252,715	1.2%	60.2%	12.5%	13.1%	7.7%	5.3%
Stock Return Volatility	Low	105,596	1.0%	58.7%	11.4%	15.5%	8.3%	5.1%
	Medium	111,162	1.1%	58.4%	11.5%	14.7%	9.1%	5.1%
	High	119,830	1.5%	60.3%	12.0%	11.6%	8.9%	5.8%
Past Week Return	Low	109,277	1.3%	61.6%	11.8%	12.1%	7.9%	5.2%
	Medium	102,125	1.0%	59.0%	11.4%	14.8%	8.6%	5.2%
	High	132,321	1.1%	58.1%	11.6%	14.1%	9.8%	5.4%

Panel B. Events

	Prevalence	Mean	Std	Min	Max
EPS announcement/surprise	1.2%	0.098	0.519	-3.988	3.935
Recommendation change	2.2%	-0.078	1.405	-4.000	4.000
Forecast change	10.6%	-0.003	0.037	-1.000	0.957

Table 2. Shorting and future earnings/analyst news

This table provides results on whether short-sellers can predict future earnings-related events. Using NYSE stocks from October 23, 2000 through April 30, 2005, we estimate pooled regressions with standard errors clustered by month. Regressions are specified as follows:

$$UE_{i,t} = b_0 + b_1 short_{i,t-5,t-1} + b_2 \ln size_{i,m-1} + b_3 BM_{i,m-6} + b_4 \sigma_{i,m-1} + b_5 ret_{i,m-6,m-1} + b_6 turnover_{i,m-1} + e_{i,t}$$

Variable $UE_{i,t}$ is the specified type of earnings-related news for firm i on day t . For earnings announcement news, UE is standardized unexpected earnings per share. For recommendation changes, UE is the number of notches of the change, where a recommendation is classified as strong buy, buy, neutral, sell, or strong sell. For analyst forecast changes, UE is the current consensus EPS forecast less the last consensus forecast. The explanatory variable of interest is $short_{i,t-5,t-1}$, which is shorting by all investors or the applicable group (individual, institutional non-program, etc.) in stock i during the interval $[t-5, t-1]$ as a fraction of overall trading volume. Unreported control variables include $\ln size_{i,m-1}$, the previous month's log market capitalization, the book-to-market ratio $BM_{i,m-1}$ from six months ago, the previous month's daily return volatility $\sigma_{i,m-1}$, the return over the past six months $ret_{i,m-6,m-1}$, and $turnover_{i,m-1}$, which is last month's trading volume as a fraction of outstanding shares. All explanatory variables except past returns are normalized to have mean zero and unit variance each period.

	All coef.	t	Indi. coef.	t	Inst. np coef.	t	Inst. p coef.	t	Prop. np coef.	t	Prop. p coef.	t	Other coef.	t
Earnings surprises	-0.0126	-2.33	-0.0158	-3.94	-0.0168	-2.82	-0.0049	-1.08	0.0041	0.76	0.0012	0.30	0.0066	1.86
Recommendation changes	-0.0873	-9.17	-0.0377	-2.93	-0.0919	-8.95	-0.0213	-2.44	-0.0375	-2.97	-0.0301	-2.92	-0.0248	-2.29
Analyst forecast revisions	-0.0004	-2.82	-0.0009	-4.85	-0.0004	-3.16	-0.0003	-1.79	0.0000	0.34	0.0003	2.15	0.0001	0.87

Table 3. Sources of the excess return from shorting: fundamental news vs. non-news days

This table tests whether short-sellers' ability to predict returns is related to earnings/analyst news days. We estimate three separate regressions for NYSE stocks from 23 Oct 2000 to 30 Sep 2005:

$$\text{I: } r_{i,t,t+k} = b_0 + b_1 \text{short}_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{i,t}$$

$$\text{II: } r_{i,t,t+k} = b_0 + (b_1 + c_0 d_t) \text{short}_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{i,t}$$

$$\text{III: } r_{i,t,t+k} = b_0 + (b_1 + c_1 d_{1t} + c_2 d_{2t} + c_3 d_{3t}) \text{short}_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{i,t}$$

The dependent variable $r_{i,t,t+k}$ is the average daily return for firm i over the interval $[t, t+k]$ in percent in excess of the riskless rate. Indicator variables include $d_{1t} = 1$ if day t has an earnings announcement and zero otherwise, $d_{2t} = 1$ if on day t any analyst changes her buy/sell recommendation, $d_{3t} = 1$ if on day t any analyst changes her earnings forecast, and $d_t = 1$ if any of the above three events occur on day t . Table II describes the other explanatory variables, including the vector of control variables $X_{i,t-1}$. A separate regression is performed each calendar month, and Newey-West standard errors with one lag are calculated from coefficient time series.

Panel A. All shorts

Reg		[t, t+1]		[t, t+5]		[t,t+10]		[t,t+20]	
		Coef.	t	Coef.	t	Coef.	t	Coef.	t
I	b_1	-0.0406	-12.02	-0.0326	-11.79	-0.0302	-11.16	-0.0251	-11.04
II	b_1	-0.0346	-10.44	-0.0298	-11.62	-0.0287	-11.51	-0.0248	-11.30
II	c_0	-0.0436	-5.18	-0.0200	-3.58	-0.0106	-3.43	-0.0011	-0.55
III	b_1	-0.0357	-10.46	-0.0302	-11.60	-0.0289	-11.47	-0.0248	-11.32
III	c_1	-0.0529	-1.16	-0.0082	-0.50	0.0008	0.08	-0.0089	-1.49
III	c_2	-0.1309	-5.98	-0.0519	-4.40	-0.0235	-3.30	-0.0096	-1.76
III	c_3	-0.0065	-0.86	-0.0079	-1.57	-0.0056	-1.69	0.0014	0.67

Panel B. Individual shorts

Reg		[t, t+1]		[t, t+5]		[t,t+10]		[t,t+20]	
		Coef.	t	Coef.	t	Coef.	t	Coef.	t
I	b_1	-0.0146	-3.88	-0.0075	-2.65	-0.0043	-1.76	-0.0043	-1.84
II	b_1	-0.0107	-2.99	-0.0056	-1.98	-0.0032	-1.25	-0.0040	-1.64
II	c_0	-0.0376	-3.74	-0.0195	-3.18	-0.0125	-3.17	-0.0035	-1.16
III	b_1	-0.0105	-2.95	-0.0055	-1.95	-0.0031	-1.23	-0.0040	-1.63
III	c_1	-0.1344	-2.96	-0.0485	-1.70	-0.0039	-0.23	-0.0065	-0.80
III	c_2	-0.1315	-2.71	-0.0423	-2.61	-0.0286	-2.71	-0.0146	-1.98
III	c_3	-0.0193	-2.03	-0.0150	-2.16	-0.0110	-2.23	-0.0023	-0.69

Panel C. Institutional non-program shorts

Reg		[t, t+1]		[t, t+5]		[t,t+10]		[t,t+20]	
		Coef.	t	Coef.	t	Coef.	t	Coef.	t
I	b_1	-0.0434	-12.42	-0.0354	-11.57	-0.0319	-10.13	-0.0250	-10.28
II	b_1	-0.0371	-11.47	-0.0327	-11.44	-0.0305	-10.38	-0.0246	-10.36
II	c_0	-0.0476	-4.71	-0.0202	-3.82	-0.0102	-2.97	-0.0023	-1.11
III	b_1	-0.0379	-11.40	-0.0330	-11.54	-0.0306	-10.45	-0.0246	-10.44
III	c_1	-0.0188	-0.45	-0.0028	-0.19	0.0002	0.02	-0.0057	-0.97
III	c_2	-0.1684	-6.32	-0.0583	-5.49	-0.0316	-4.99	-0.0134	-2.85
III	c_3	-0.0076	-0.91	-0.0069	-1.39	-0.0033	-0.90	0.0009	0.40

Panel D. Institutional program shorts

Reg		[t, t+1]		[t, t+5]		[t,t+10]		[t,t+20]	
		Coef.	t	Coef.	t	Coef.	t	Coef.	t
I	b ₁	-0.0126	-3.42	-0.0096	-3.21	-0.0090	-3.50	-0.0068	-3.21
II	b ₁	-0.0104	-2.61	-0.0085	-2.72	-0.0084	-3.24	-0.0071	-3.33
II	c ₀	-0.0122	-1.34	-0.0069	-1.19	-0.0027	-0.81	0.0030	1.25
III	b ₁	-0.0109	-2.67	-0.0086	-2.74	-0.0084	-3.23	-0.0071	-3.32
III	c ₁	0.0380	0.62	0.0441	1.88	0.0268	1.80	0.0110	1.32
III	c ₂	-0.0652	-2.24	-0.0381	-3.02	-0.0193	-2.01	-0.0096	-1.62
III	c ₃	0.0086	0.87	0.0006	0.10	-0.0004	-0.10	0.0044	1.59

Panel E. Proprietary non-program shorts

Reg		[t, t+1]		[t, t+5]		[t,t+10]		[t,t+20]	
		Coef.	T	Coef.	t	Coef.	t	Coef.	t
I	b ₁	-0.0153	-5.11	-0.0122	-3.93	-0.0127	-4.22	-0.0122	-4.70
II	b ₁	-0.0135	-4.37	-0.0113	-3.63	-0.0122	-3.91	-0.0122	-4.61
II	c ₀	-0.0151	-2.21	-0.0081	-1.60	-0.0053	-1.41	-0.0015	-0.51
III	b ₁	-0.0143	-4.56	-0.0115	-3.66	-0.0123	-3.92	-0.0122	-4.63
III	c ₁	-0.0690	-1.67	-0.0210	-1.13	-0.0155	-1.42	-0.0118	-1.87
III	c ₂	0.0213	0.99	-0.0013	-0.12	0.0077	0.88	0.0054	0.76
III	c ₃	-0.0103	-1.37	-0.0060	-1.17	-0.0059	-1.52	-0.0022	-0.65

Panel F. Proprietary program shorts

Reg		[t, t+1]		[t, t+5]		[t,t+10]		[t,t+20]	
		Coef.	T	Coef.	t	Coef.	t	Coef.	t
I	b ₁	-0.0119	-3.59	-0.0112	-3.42	-0.0111	-3.75	-0.0106	-4.23
II	b ₁	-0.0092	-2.79	-0.0096	-3.10	-0.0099	-3.55	-0.0102	-4.18
II	c ₀	-0.0226	-2.89	-0.0118	-2.21	-0.0098	-2.84	-0.0034	-1.75
III	b ₁	-0.0097	-2.91	-0.0096	-3.09	-0.0099	-3.55	-0.0101	-4.16
III	c ₁	-0.0608	-1.27	-0.0135	-0.68	-0.0023	-0.24	-0.0114	-1.83
III	c ₂	0.0055	0.19	-0.0028	-0.20	0.0045	0.54	0.0005	0.06
III	c ₃	-0.0104	-1.55	-0.0092	-1.95	-0.0095	-2.34	-0.0029	-1.35

Panel G. Other shorts

Reg		[t, t+1]		[t, t+5]		[t,t+10]		[t,t+20]	
		Coef.	T	Coef.	t	Coef.	t	Coef.	t
I	b ₁	-0.0128	-3.46	-0.0086	-3.02	-0.0075	-2.98	-0.0081	-3.60
II	b ₁	-0.0101	-3.20	-0.0066	-2.49	-0.0061	-2.53	-0.0075	-3.34
II	c ₀	-0.0186	-1.92	-0.0144	-2.56	-0.0114	-3.20	-0.0050	-2.05
III	b ₁	-0.0104	-3.19	-0.0067	-2.49	-0.0062	-2.54	-0.0076	-3.33
III	c ₁	0.1513	1.76	0.0611	2.21	0.0247	1.90	0.0040	0.64
III	c ₂	-0.0573	-2.06	-0.0267	-2.58	-0.0084	-1.12	-0.0043	-0.89
III	c ₃	-0.0150	-1.99	-0.0144	-2.82	-0.0136	-4.13	-0.0062	-2.72

Table 4. Do short-sellers know more than analysts?

We estimate three separate Fama-MacBeth regressions for NYSE stocks from 23 Oct 2000 through 30 Sep 2005:

$$\begin{aligned}
 \text{I:} \quad & r_{i,t,t+k} = b_0 + b_1 \text{short}_{i,t-5,t-1} + c_1 \text{DUE1}_{i,t} + c_2 \text{DUE2}_{i,t} + c_3 \text{DUE3}_{i,t} + \gamma X_{i,t-1} + e_{i,t}, \\
 \text{II:} \quad & r_{i,t,t+k} = b_0 + (b_1 + e_0 d_t) \text{short}_{i,t-5,t-1} + c_1 \text{DUE1}_{i,t} + c_2 \text{DUE2}_{i,t} + c_3 \text{DUE3}_{i,t} + \gamma X_{i,t-1} + e_{i,t}, \\
 \text{III:} \quad & r_{i,t,t+k} = b_0 + (b_1 + e_1 d_{1t} + e_2 d_{2t} + e_3 d_{3t}) \text{short}_{i,t-5,t-1} + c_1 \text{DUE1}_{i,t} + c_2 \text{DUE2}_{i,t} + c_3 \text{DUE3}_{i,t} \\
 & + \gamma X_{i,t-1} + e_{i,t}.
 \end{aligned}$$

The dependent variable $r_{i,t,t+k}$ is the average daily return for firm i over the interval $[t, t+k]$ in percent. Indicator variables include $d_{1t} = 1$ if day t has an earnings announcement and zero otherwise, $d_{2t} = 1$ if on day t any analyst changes her buy/sell recommendation, $d_{3t} = 1$ if on day t any analyst changes her earnings forecast, and $d_t = 1$ if any of the above three events occur on day t . The variable $\text{DUE1}_{i,t} / \text{DUE2}_{i,t} / \text{DUE3}_{i,t}$ takes the value of the earnings surprise/recommendation change/forecast revision on event days, and zero otherwise. Table II describes the other explanatory variables, including the vector of control variables $X_{i,t-1}$. Short sales are from all account types. A separate regression is performed each calendar month, and Newey-West standard errors with one lag are calculated from coefficients' time-series.

Reg		[t, t+1]		[t, t+5]		[t, t+10]		[t, t+20]	
		Coef.	t	Coef.	t	Coef.	T	Coef.	T
I	b_1	-0.0385	-11.57	-0.0318	-11.57	-0.0298	-11.02	-0.0248	-10.95
I	c_1	1.0981	9.49	0.3873	9.49	0.2040	7.60	0.0984	5.89
I	c_2	0.8625	15.58	0.3133	15.19	0.1795	13.85	0.0968	13.00
I	c_3	5.9289	10.71	2.5969	8.64	1.4172	7.28	0.7579	6.16
II	b_1	-0.0347	-10.41	-0.0299	-11.62	-0.0287	-11.51	-0.0248	-11.30
II	e_0	-0.0260	-2.85	-0.0135	-2.35	-0.0069	-2.24	0.0008	0.38
II	c_1	1.0982	9.49	0.3885	9.50	0.2046	7.61	0.0989	5.93
II	c_2	0.8621	15.56	0.3131	15.17	0.1793	13.85	0.0969	13.01
II	c_3	5.9231	10.69	2.5932	8.63	1.4162	7.28	0.7583	6.19
III	b_1	-0.0355	-10.43	-0.0301	-11.58	-0.0288	-11.47	-0.0248	-11.32
III	e_1	-0.0613	-1.32	-0.0091	-0.52	-0.0001	-0.01	-0.0093	-1.51
III	e_2	-0.0489	-2.37	-0.0217	-1.88	-0.0060	-0.91	-0.0005	-0.09
III	e_3	-0.0068	-0.93	-0.0079	-1.60	-0.0057	-1.71	0.0013	0.63
III	c_1	1.0970	9.22	0.3887	9.02	0.2005	7.23	0.0972	5.66
III	c_2	0.8614	15.54	0.3127	15.06	0.1794	13.78	0.0969	12.78
III	c_3	5.9288	10.72	2.5989	8.66	1.4182	7.28	0.7581	6.18

Table 5. Additional results

This table reports estimation results for several Fama-MacBeth regressions for NYSE stocks from 23 Oct 2000 through 30 Sep 2005. We only include results estimated using all short sales. In Panel A, we distinguish short sellers' stock selectivity from factor loading effects using the following regression:

$$r_{i,t,t+k} = b_0 + (b_1 + c_0 d_t + b_2 \beta_{RM} + b_3 \beta_{HML} + b_4 \beta_{SMB}) short_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{i,t}$$

In Panel B, we examine shorting's predictability for firms in 3 size terciles:

$$r_{i,t,t+k} = b_0 + \left[\sum_{j=1}^3 (b_j + c_j d_t) d_{i,t}^{GROUPj} \right] short_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{it}$$

In Panel C, we investigate short sellers' ability to predict news coming from top vs. other investment banks:

$$UE_{i,t} = b_0 + (c_1 dtop_{i,t} + c_2 drest_{i,t}) short_{i,t-5,t-1} + \gamma X_{it} + e_{i,t}$$

In Panel D, we re-estimate the regressions from Table III using an August 2009 to July 2010 Nasdaq sample. In these regressions, the dependent variable $r_{i,t,t+k}$ is the average daily return for firm i over the interval $[t, t+k]$ in percent. Indicator variable $d_t = 1$ if day t is an earnings or analyst event day, and zero otherwise. The betas, $\beta_{RM}, \beta_{HML}, \beta_{SML}$, are Fama-French factor sensitivities, estimated on a daily basis over the previous calendar quarter. Variable $d_{i,t}^{GROUPj}$ is a size group indicator. Indicator variable $dtop_{i,t}$ ($drest_{i,t}$) equals one if on day t any analyst from (not from) a top 10 investment bank provides news of the specified type. Table II describes the other explanatory variables, including the vector of control variables $X_{i,t-1}$. Short sales are from all account types. A separate regression is performed each calendar month, and Newey-West standard errors with one lag are calculated from coefficients' time-series.

Panel A. Factor timing

	[t, t+1]		[t, t+5]		[t,t+10]		[t,t+20]	
	Coef.	T	Coef.	t	Coef.	t	Coef.	t
b_1	-0.0194	-2.64	-0.0218	-3.37	-0.0261	-4.13	-0.0235	-4.66
c_0	-0.0436	-4.96	-0.0201	-3.46	-0.0109	-3.24	-0.0017	-0.82
b_2	-0.0155	-1.65	-0.0072	-0.94	-0.0008	-0.11	0.0005	0.10
b_3	0.0007	0.14	-0.0003	-0.08	-0.0023	-0.63	-0.0033	-1.11
b_4	0.0016	0.38	-0.0007	-0.19	-0.0026	-0.83	-0.0013	-0.54

Panel B. Firms of different sizes

	[t, t+1]		[t, t+5]		[t,t+10]		[t,t+20]	
	Coef.	t	Coef.	t	Coef.	t	Coef.	t
b_1 (small)	-0.0583	-7.36	-0.0531	-8.29	-0.0520	-8.09	-0.0438	-7.63
b_2 (med)	-0.0210	-5.85	-0.0209	-6.48	-0.0201	-6.86	-0.0187	-6.96
b_3 (large)	-0.0328	-6.28	-0.0218	-5.67	-0.0202	-6.27	-0.0164	-6.07
c_1 (small)	-0.0654	-2.55	-0.0404	-2.96	-0.0329	-3.04	-0.0116	-2.00
c_2 (med)	-0.0495	-4.53	-0.0156	-2.73	-0.0100	-2.54	-0.0017	-0.62
c_3 (large)	-0.0324	-2.80	-0.0205	-2.77	-0.0070	-1.67	-0.0020	-0.68

Panel C. Top investment banks vs. the rest

	Recommendation change		Forecast change		Initial Recommendation	
	coef.	t	coef.	t	coef.	t
c_1	-0.0850	-5.19	-0.0003	-1.42	-0.0274	-2.79
c_2	-0.0874	-6.16	-0.0005	-1.59	-0.0087	-1.19

Panel D. Recent results from Nasdaq

Reg		[t, t+1]		[t, t+5]		[t,t+10]		[t,t+20]	
		Coef.	t	Coef.	t	Coef.	t	Coef.	t
I	b_1	-0.0162	-2.21	-0.0137	-2.09	-0.0126	-2.44	-0.0099	-2.18
II	b_1	-0.0150	-2.17	-0.0137	-2.08	-0.0127	-2.37	-0.0101	-2.16
II	c_0	-0.0177	-1.27	0.0003	0.04	0.0030	0.67	0.0061	1.18
III	b_1	-0.0143	-2.11	-0.0133	-2.04	-0.0125	-2.36	-0.0100	-2.15
III	c_1	-0.2427	-2.54	-0.1236	-3.42	-0.0733	-3.38	-0.0337	-2.81
III	c_2	0.0066	0.09	-0.0051	-0.20	-0.0158	-1.12	-0.0020	-0.29
III	c_3	-0.0103	-0.55	0.0084	0.90	0.0111	1.52	0.0083	1.46

Figure 1. Coefficient behavior over time.

The graphs show monthly Fama-MacBeth coefficients on the shorting-news day interaction (see Table III). We present each news event separately (earnings announcements, analyst recommendation changes, and analyst forecast changes) for one day ahead.

