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What Do Short Sellers Know?*

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Abstract

Using NYSE short-sale order data, we investigate whether short sellers' informational advantage is related to firm earnings and analyst-related events. With a novel decomposition method, we find that while these fundamental event days constitute only 12% of sample days, they account for over 24% of the overall underperformance of heavily shorted stocks. Importantly, short sellers use both public news and private information to anticipate news regarding earnings and analysts. Shorting's predictive ability remains significant after controlling for information in analyst actions and displays no reversal patterns, indicating that short sellers know more than analysts, and the nature of their information is long term.

JEL classification: G11, G14, G23

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1. Introduction

Although theories disagree on the informativeness of short sales,[1] much empirical evidence suggests that short sellers are informed traders. Stocks with high short selling tend to

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1 For example, Miller (1977) and Diamond and Verrecchia (1987) argue that short sellers contribute to efficient prices, while Goldstein and Guembel (2008) argues that prices can become less informative due to manipulative short selling.

underperform those with low short selling (e.g., Desai *et al.*, 2002; Asquith, Pathak, and Ritter, 2005; Boehmer, Jones, and Zhang, 2008; Diether, Lee, and Werner, 2009). Despite the fact that short selling negatively predicts future stock returns, we lack a better understanding of *what* short sellers know. In this paper, we examine this issue by focusing on the sources of short sellers' information advantage.

We investigate the sources of short sellers' information advantage by combining a 5-year panel of NYSE short sale order data with data on earnings releases and analyst actions, including forecast changes and recommendation changes. We focus on these fundamental events because of their substantial influences on the stock prices, and also their rich information content. Quarterly earnings releases update investors with key metrics of firm performance. Analyst stock recommendation changes and earnings forecast revisions offer vital pieces of information from analysts following their extensive research, and influence investor investment decisions. Market participants clearly value such information and are willing to spend millions of dollars every year on such services from vendors such as Institutional Brokers' Estimate System (I/B/E/S) and Zacks (Ivković and Jegadeesh, 2004). In addition, information disclosed via the fundamental events we focus on has the advantage of being quite uniform, which facilitates meaningful comparisons of short sellers' information advantage across firms and over time.

We first examine to what extent short sellers' overall information advantage can be attributed to fundamental information. The intuition of this analysis resembles that in Roll (1988), who seeks to identify the *ex post* relationship between news and asset price moves. To implement our tests, we introduce a novel quantitative return decomposition method and document several interesting findings. We decompose short sellers' return-predicative information by identifying and separating out days with fundamental events such as earnings and analyst actions. We find that short selling predicts future returns on non-event days as well as on fundamental event days. The incremental effect of shorting's return predictability, captured by the interaction term of shorting and the event day dummy, is statistically significant and economically large on fundamental news event days, suggesting that a large part of short sellers' information is incorporated into prices through these fundamental events. Our return decomposition method reveals that while earnings and analyst action days constitute only 12% of the days in our sample, these days account for over 24% of the overall underperformance of heavily shorted stocks. These results indicate that a significant source of short sellers' return predictability comes from fundamental events.

Second, we examine the dynamic interactions among public news, firm events, and short sellers' return predictability. Using news data from Thomson Reuters (TR) News Analytics, we decompose short selling activity into shorting driven by public news and shorting driven by private information. We find that short sellers respond to more negative public news by increasing short selling activity, consistent with Engelberg, Reed, and Ringgenberg (2012)'s interpretation that short sellers are skilled at processing public information. More importantly, we find that short sellers also possess private information that goes beyond public news for predicting future stock returns. Both higher shorting based on public information and higher shorting based on private information significantly predict negative future stock returns. When we interact shorting driven by public news with firm event dummy, the interaction term is insignificant in predicting future returns, while the interaction term between shorting driven by private information and the firm event dummy is significantly negative, suggesting that private information helps boost short sellers' performance on event days. In particular, trading by short sellers contains predictive information for future returns above and beyond the information in analyst actions, an indication that short sellers have more private information than analysts.

Third, we examine shorts' return predictive power for the next 60 days to see if short sellers possess long-term value relevant information about firm fundamentals. We find that the short-sellers predictive power for future returns don't reverse in the long run, suggesting that short sellers primarily trade on value-relevant information.

Our study contributes to the short selling literature in unique ways. First, although prior empirical work shows that short sellers can predict negative returns, it is not clear what they know. Computing point estimates using firm fundamental news events based on the return decomposition method demonstrate that the information that short sellers have, and the portion occurring on news days, is quantifiable. This methodology can help researchers, investors, and regulators understand short sellers' information and the sources of their excess returns, and can be applied in a variety of other information contexts.

Second, our study improves the understanding of how information is related to short selling. Short sellers' predictive power for future returns can come from three channels: (i) possession of private information, (ii) better processing of fundamental news-related public information, and (iii) better processing of non-fundamental news-related public information. Our paper examines all three sources of information short sellers trade on. We start with firm fundamental events and show that short sellers are informed about these important events. Then we dig further into the dynamics among firm fundamental events, non-fundamental news-related public information, and private information. A closely related study, Engelberg, Reed, and Ringgenberg (2012), finds that a substantial portion of short sellers' trading advantage comes from their ability to process public information. While Engelberg, Reed, and Ringgenberg (2012) is silent on whether short sellers possess private information or not, we explicitly test how short seller's private information, obtained via a decomposition method, helps to improve the return predictability. These unique analyses reveal that what short sellers know is beyond processing public information, and an importance source of information advantage short sellers have is value-relevant private information, which is not as readily available to the market as firms' public announcements. Overall, our study complements Engelberg, Reed, and Ringgenberg (2012)'s findings and provides additional insights on the information advantage that produces the abnormal returns earned by short sellers, and 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 2 discusses the shorting data as well as the First Call earnings and analyst data. The main results are provided in Section 3. Additional robustness tests and discussion are covered in Section 4. Section 5 concludes.

2. Data

2.1 Data on Short Selling

The sample consists of all NYSE system order data (SOD) records related to short sales from October 23, 2000, when Reg FD becomes effective, to April 30, 2005, right before the start of the Reg SHO pilot program suspending the uptick rule.[2] This sample ensures a uniform regulatory environment governing both information dissemination by public

2 A similar dataset is examined in Boehmer, Jones, and Zhang (2008) and Kaniel, Saar, and Titman (2008).

companies and short sales.[3] The shorting data are maintained by the NYSE for compliance purposes; they are not made available to market participants during our sample period. For robustness, we also examine a more recent 2009–10 sample, during which more information is available to market participants.

Using CUSIPs and ticker symbols, we cross-match the list of NYSE stocks to Center for Research in Security Prices (CRSP). We retain only common stocks (those with a CRSP share code equal to 10 or 11) and exclude securities such as warrants, preferred shares, American Depositary Receipts, closed-end funds, and REITs. This yields 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). These are lower bounds on the incidence of shorting at the NYSE, because 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. Table I Panel A provides summary statistics on the relative prevalence of shorting sorted by market capitalization, stock return volatility, and past week return. It is clear that large firms see more short selling activity. Short selling also increases with stock return volatility and past week return, consistent with Diether, Lee, and Werner (2009).

2.2 Data on Earnings and Analyst-Related Events

The First Call historical database from Thomson Financial is the source of earnings and analyst-related events. This is a widely used, comprehensive database of analyst earnings forecasts, stock recommendations, and actual earnings announcements, among other items. Actual earnings per share 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 with analyst earnings estimates.

We focus on three different types of earnings and analyst-related events: earnings announcements, analyst recommendation changes, and analyst forecast revisions. For earnings announcements, the variable is standardized unexpected earnings per share, defined as the announced EPS for the quarter less the corresponding consensus EPS forecast, divided by the standard deviation of EPS from the previous 16 quarters.[4] For buy/sell recommendation changes, we compute 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

3 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 versus 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.

4 We also consider unscaled earnings surprises, as well as scaling earnings surprises by previous quarter end price. Results are qualitatively similar and are reported in Online Appendix Table IA1.

Table I. Summary statistics

The sample consists of all common stocks listed on the NYSE from October 23, 2000 to April 30, 2005. Panel A reports average daily 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 sixteen quarters, recommendation changes are the number of improvement notches on a five-point scale, and analyst forecast changes are the change in the current consensus EPS forecast compared with the previous consensus forecast, in dollars. Other summary statistics are pooled across all indicated events.

Panel A. Average daily shorting activity (in shares)

Sorted by:	Market cap	Stock return volatility	Past week return
Low	22,382	105,596	109,277
Medium	67,959	111,162	102,125
High	252,715	119,830	132,321

Panel B. Events

Events	Prevalence (%)	Mean	Standard deviation	Correlation with previous 5-day shorting	*P*-value
EPS announcement/surprise	1.2	0.098	0.519	−0.015	0.0627
Recommendation change	2.2	−0.078	1.405	−0.063	<0.001
Forecast change	10.6	−0.003	0.037	−0.010	<0.001

scale. For instance, a change from "buy" to "strong buy" would be a change of "+1". For analyst forecast changes, we compute the magnitude as 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 event variable.

Panel B of Table I reports summary statistics of 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. Note 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. 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.

Previous studies, such as Christophe, Ferri, and Angel (2004), find that short sellers can anticipate earnings surprises. To examine whether this pattern also exists in our sample, we report the correlation between the previous 5 days of shorting and earnings surprises and other analyst-related events. If shorts can predict these upcoming events, then the correlations should be negative and significant. The last two columns of Panel B report these correlations. They range from −0.010 to −0.063, with two P-values <0.001, and one P-value at 0.0627. Clearly, in our sample, shorts have predictive power for upcoming earnings and analyst-related events.[5]

2.3 Data on Public News

We obtain proprietary data from TR' News Analytics. This dataset contains prominent public news articles for a broad set of firms starting from 2003. Similar to Dow Jones News Archive data used in Engelberg, Reed, and Ringgenberg (2012) and Tetlock (2010), TR provides key information about each news story, such as the Reuters Instrument Code (RIC), firm name, exchange code, CUSIP and ISIN, time stamp of the news story, the relevance of the news article for the firm, and the "sentiment" conveyed in the article. The "sentiment" scores for an article measure the probabilities of the article being positive, negative, and neutral, respectively, computed using TR' proprietary algorithm.

We use CUSIP and ticker to match the news data with our short selling data. We retrieve news that has a relevance score of 0.5 and higher and estimate the net sentiment score of each news article by taking the difference between the probability of being positive and the probability of being negative. The resulting coverage is 1,207 NYSE firms with news coverage for the sample period of January 2003 to April 2005. In total, we have 645,162 stock-day observations, and a typical firm during the 2003–5 sample period has ninety-two news days with a mean (median) net sentiment score of 0.03 (0.02), which indicates slightly more positive sentiment than negative.

3. Empirical Specifications and Main Results

3.1 Decomposition of Shorting's Predictive Power for Future Returns

To examine and quantify whether shorting's predictability comes from firm fundamentals or other information, we start with a decomposition of the excess returns subsequent to shorting activity into components associated with earnings and analyst-related events. We begin with a simple benchmark regression similar to the one in Boehmer, Jones, and Zhang (2008):

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

where the dependent variable, $r_{i,t,t+k}$, is the average daily return over the period $[t, t+k]$ in percent in excess of the risk-free rate, with $k = 1$, 5, 10, and 20 days. For example, $r_{i,t,t+1}$ is the average of two daily returns. The explanatory variable of interest is $\text{short}_{i,t-5,t-1}$, which is shorting 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, Jones, and Zhang (2008).[6] The control variable vector, $X_{i,t-1}$, includes the previous month's log market capitalization $\text{Size}_{i,m-1}$, the book-to-market ratio from 6 months ago $\text{BM}_{i,m-6}$, the previous month's daily return volatility $\sigma_{i,m-1}$ following Ang *et al.* (2006), the return over the past 6 months $r_{i,m-6,m-1}$, and last month's trading volume as a fraction of

5 We provide further regression analysis on earnings surprises in Online Appendix Table IA1, and the results consistently show that shorts have predictive power for upcoming earnings surprises, consistent with Christophe, Ferri, and Angel (2004).

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

outstanding shares turnover$_{i,m-1}$.[7] The shorting variable is normalized to have zero mean and unit variance on each trading day. Shorting becomes somewhat more prevalent as our sample period progresses, so this normalization is designed to mitigate the effects of any trend in this variable that might otherwise affect inference. All control variables, except past returns, are normalized to have zero mean and unit variance each month. Normalization also makes it easier to interpret the results.[8]

We use a regression approach to control for stock and firm characteristics that might help predict returns. All estimations in this section are Fama–MacBeth regressions, with one regression estimated per calendar month that includes all days in that calendar month. Standard errors are computed using monthly time-series of the coefficients, following Newey and West's (1987) approach with one lag due to the partially overlapping return observations.[9] We use the monthly Fama–MacBeth rather than daily Fama–MacBeth because the monthly regression guarantees variation in event dummies each month, whereas a daily Fama–MacBeth may encounter days where there are no events across all firms.

The results are reported in Table II. The benchmark regression is denoted as Regression I. One standard deviation increase in weekly shorting is associated with average daily excess returns over the next 2 days that are 4.06 basis points lower. The t-statistic is very large at 12.02, and the economic significance is quite strong as well, as the annualized excess return is >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 1 month. In the rest of this section, we focus on the short-horizon returns from day t to day $t+1$, because these returns are the cleanest to associate with specific news and analyst-related events.

Next we decompose the short sellers' return-predicative information by identifying and separating out days with earnings or analyst-related events. Specifically, we set an indicator variable Event dummy$_{i,t}$ equal to one if day t has an earnings announcement, a change in any analyst's buy/sell recommendation, and/or a change in any analyst's earnings forecast for firm i. We then expand the benchmark regression (Equation 1) and estimate the following regressions:

$$r_{i,t,t+k} = b_0 + \left(b_1 + c_0\text{Event dummy}_{i,t}\right)\text{short}_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{i,t}, \quad (2)$$

where Event dummy$_{i,t}$ is equal to one if any of the three events occurs on day t for firm i and zero otherwise. We focus on the interaction coefficient c_0, which captures the incremental stock return predictability associated with the previous week's shorting activity that is due to earnings or analyst-related events.

Estimation results from Equation (2) are reported as Regression II in Table II. Without earnings or analyst-related events, a one-standard deviation increase in shorting leads to a 3.46 basis point decrease in the average daily excess return at the 2-day horizon, with a

7 We have also included last week return as an additional control variable. The coefficient on last week return is negative, suggesting evidence of weekly reversal. We also included two more lags of weekly returns. In both tests, our main results remain similar.

8 We also estimate our main specifications using the raw shorting activity measure without standardization. Results are similar and are reported in Online Appendix Table IA2.

9 We also conduct our main specifications using panel regressions with firm- and month-fixed effects and the results are similar to what we obtain from the Fama–MacBeth approach. The results are reported in Online Appendix Table IA3.

Table II. Decomposing shorting's predictive power: event days versus non-event days

This table tests whether short-sellers' ability to predict returns is related to earnings/analyst event days. We estimate five separate regressions for NYSE stocks from October 23, 2000 to April 30, 2005:

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

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

III : $r_{i,t,t+k} = b_0 + (b_1 + c_1 \text{EA dummy}_{i,t} + c_2 \text{REC dummy}_{i,t} + c_3 \text{Forecast dummy}_{i,t}) \text{short}_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{i,t}$.

IV : $r_{i,t,t+k} = b_0 + (b_1 + c_0 \text{Event dummy}_{i,t}) \text{short}_{i,t-5,t-1} + b_2 \text{Event dummy}_{i,t} + \gamma X_{i,t-1} + e_{i,t}$.

V : $r_{i,t,t+k} = b_0 + (b_1 + c_1 \text{EA dummy}_{it} + c_2 \text{REC dummy}_{i,t} + c_3 \text{Forecast dummy}_{i,t}) \text{short}_{i,t-5,t-1} + b_{21} \text{EA dummy}_{i,t} + b_{22} \text{REC dummy}_{i,t} + b_{23} \text{Forecast dummy}_{i,t} + \gamma X_{i,t-1} + e_{i,t}$.

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 risk-free rate. $\text{short}_{i,t-5,t-1}$ is computed as shares shorted scaled by daily volume, normalized to have mean zero and variance one every day. Indicator variables include EA $\text{dummy}_{i,t}$=1 if day *t* has an earnings announcement for firm *i* and zero otherwise, REC $\text{dummy}_{i,t}$=1 if on day *t* any analyst changes her buy/sell recommendation for firm *i* and zero otherwise, Forecast $\text{dummy}_{i,t}$=1 if on day *t* any analyst changes her earnings forecast for firm *i* and zero otherwise, and Event $\text{dummy}_{i,t}$=1 if any of the above three events occur on day *t* for firm *i* and zero otherwise. The control variables, $X_{i,\ t-1}$, include $\text{Size}_{i,m-1}$, the previous month's log market capitalization, the book-to-market ratio $\text{BM}_{i,m-1}$ from 6 months ago, the previous month's daily return volatility $\sigma_{i,m-1}$, the return over the past 6 months $\text{ret}_{i,m-6,m-1}$, and $\text{turnover}_{i,m-1}$, which is last month's trading volume as a fraction of outstanding shares. A separate regression is performed each calendar month, and Newey–West standard errors with one lag are calculated from coefficient time series.

Regression	Variable	$r_{t,\ t+1}$		$r_{t,t+5}$		$r_{t,t+10}$		$r_{t,t+20}$	
		Coefficient	*t*-Statistics	Coefficient	*t*-Statistics	Coefficient	*t*-Statistics	Coefficient	*t*-Statistics
I	Short	–0.0406	–12.02	–0.0326	–11.79	–0.0302	–11.16	–0.0251	–11.04
II	Short	–0.0346	–10.44	–0.0298	–11.62	–0.0287	–11.51	–0.0248	–11.30
II	Short * Event dummy	–0.0436	–5.18	–0.0200	–3.58	–0.0106	–3.43	–0.0011	–0.55
III	Short	–0.0357	–10.46	–0.0302	–11.60	–0.0289	–11.47	–0.0248	–11.32

(continued)

Table II. Continued

Regression	Variable	$r_{t,\,t+1}$		$r_{t,t+5}$		$r_{t,t+10}$		$r_{t,t+20}$	
		Coefficient	*t*-Statistics	Coefficient	*t*-Statistics	Coefficient	*t*-Statistics	Coefficient	*t*-Statistics
III	Short * EA dummy	–0.0529	–1.16	–0.0082	–0.50	0.0008	0.08	–0.0089	–1.49
III	Short * REC dummy	–0.1309	–5.98	–0.0519	–4.40	–0.0235	–3.30	–0.0096	–1.76
III	Short * Forecast dummy	–0.0065	–0.86	–0.0079	–1.57	–0.0056	–1.69	0.0014	0.67
IV	Short	–0.0347	–10.44	–0.0298	–11.60	–0.0287	–11.49	–0.0248	–11.30
IV	Short * Event dummy	–0.0442	–5.21	–0.0206	–3.65	–0.0110	–3.51	–0.0015	–0.77
IV	Event dummy	–0.0011	–0.07	0.0188	1.72	0.0195	2.44	0.0227	4.19
V	Short	–0.0357	–10.46	–0.0301	–11.57	–0.0288	–11.46	–0.0248	–11.31
V	Short * EA dummy	–0.0655	–1.34	–0.0111	–0.64	–0.0021	–0.22	–0.0114	–1.90
V	Short * REC dummy	–0.1303	–5.70	–0.0507	–4.20	–0.0218	–2.93	–0.0086	–1.49
V	Short * Forecast dummy	–0.0081	–1.09	–0.0090	–1.80	–0.0063	–1.89	0.0007	0.35
V	EA dummy	0.1938	2.98	0.1142	3.09	0.0810	3.23	0.0591	3.62
V	REC dummy	–0.2137	–3.95	–0.0451	–2.62	–0.0281	–2.36	–0.0072	–0.92
V	Forecast dummy	0.0061	0.42	0.0129	1.15	0.0174	2.19	0.0196	3.52

t-statistic of –10.44. On days with these events, the effect of shorting is 7.82 (=3.46 + 4.36) basis points of underperformance per day, which is more than double the magnitude on non-event days. The incremental effect on these event days is also strongly statistically significant, with a t-statistic of –5.18. These results reveal that a significant fraction of short sellers' information is incorporated into prices within a week via an earnings announcement or an analyst action.

A useful way to gauge the importance of earnings and analyst-related events is to decompose the overall underperformance of heavily shorted stocks into two components: event-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 event. The overall underperformance associated with a one-standard deviation increase in short sales is given by:

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

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

We next examine which kind of fundamental event is most closely associated with short sellers' information. As noted above, we have 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 three different types of events, we estimate the following regression:

$$r_{i,t,t+k} = b_0 + \left(b_1 + c_1 \text{EA dummy}_{i,t} + c_2 \text{REC dummy}_{i,t} + c_3 \text{Forecast dummy}_{i,t}\right) \text{short}_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{i,t}, \tag{3}$$

where EA dummy$_{i,t}$ is equal to one if day t has an earnings announcement for firm i and zero otherwise, REC dummy$_{i,t}$ is equal to one if on day t any analyst changes her buy/sell recommendation for firm i and zero otherwise, Forecast dummy$_{i,t}$ is equal to one if on day t any analyst changes her earnings forecast for firm i and zero otherwise.

Results are reported as Regression III in Table II. Although the majority of the interaction terms have negative signs, indicating that short sales are more informative about future returns on each type of event, some of the incremental effects are close to zero or statistically indistinguishable from zero. For instance, one standard deviation increase in shorting is associated with only 0.65 basis points of additional daily underperformance (t-statistic = −0.86) on an analyst forecast revision day, when compared with a non-event day. 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-event days). On days when earnings are announced, an additional standard deviation of shorting during the previous week is associated with an average daily underperformance of 8.86 (= 3.57 + 5.29) basis points. But these days seem particularly volatile, and we are unable to reject the hypothesis that the underperformance on any earnings announcement day differs from that of non-event days (t-statistic = −1.16).

The biggest return effects are on days with an analyst recommendation change. The average daily underperformance on these days is 16.66 (=3.57 + 13.09) basis points, statistically different (t-statistic = −5.98) from zero and over four times as large as the coefficient of −3.57 on non-event days. Note that analyst recommendation changes are not that frequent, 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.[10]

To ensure that the results are stationary throughout the sample period and are not driven by a small number of outliers, we graph the interaction terms between shorting activity and the event day dummies 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 increase over time. The regression results 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 out of 54 months where the coefficient on the interaction term has the wrong (positive) sign as shown in the middle panel.

An alternative to Regressions II and III is to include the event dummy to control for a possible fixed effect associated with the event. We thus estimate the following two regressions:

$$r_{i,t,t+k} = b_0 + \left(b_1 + c_0 \text{Event dummy}_{i,t}\right)\text{short}_{i,t-5,t-1} + b_2 \text{Event dummy}_{i,t} + \gamma X_{i,t-1} + e_{i,t}, \tag{4}$$

$$\begin{aligned} r_{i,t,t+k} = {} & b_0 + \left(b_1 + c_1 \text{EA dummy}_{it} + c_2 \text{REC dummy}_{i,t} + c_3 \text{Forecast dummy}_{i,t}\right)\text{short}_{i,t-5,t-1} \\ & + b_{21} \text{EA dummy}_{i,t} + b_{22} \text{REC dummy}_{i,t} + b_{23} \text{Forecast dummy}_{i,t} + \gamma X_{i,t-1} + e_{i,t.} \end{aligned} \tag{5}$$

We report the above two specifications as Regressions IV and V in Table II. Comparing Regression IV with Regression II, and Regression V with Regression III, we have two findings. First, the dummies representing event days are significant in some cases, especially in Regression V. Second, the coefficients we are interested in, the interaction terms in Regressions IV and V, are very similar to those in Regressions II and III. The benefit of not including the event day dummies is that the interpretation for the interaction terms is more straightforward, which makes the previous decomposition possible. Since we confirm that the inclusion of the event day dummies does not change the results, we mainly focus on Regressions I–III in the remaining analysis.

When we use short horizons (e.g., 1 day), risk adjustments are not necessary. For longer horizons, however, risk adjustments can become relevant. To make sure that our results are not affected by risk adjustments, we also examine risk-adjusted returns. We first compute firm level betas using the Fama–French three-factor model, estimated over previous-quarter daily returns, then we calculate risk-adjusted returns as the difference between the raw returns and expected returns based on corresponding firm level betas and realized factors. We report results on risk-adjusted returns in Online Appendix Table IA4. Overall, results

10 A similar return decomposition reveals that about 10% of the overall underperformance accrues on days with an analyst forecast revision, and about 3% of the overall underperformance occurs on earnings announcement days. However, return decomposition for earnings announcement and forecasts could be more subject to noise.

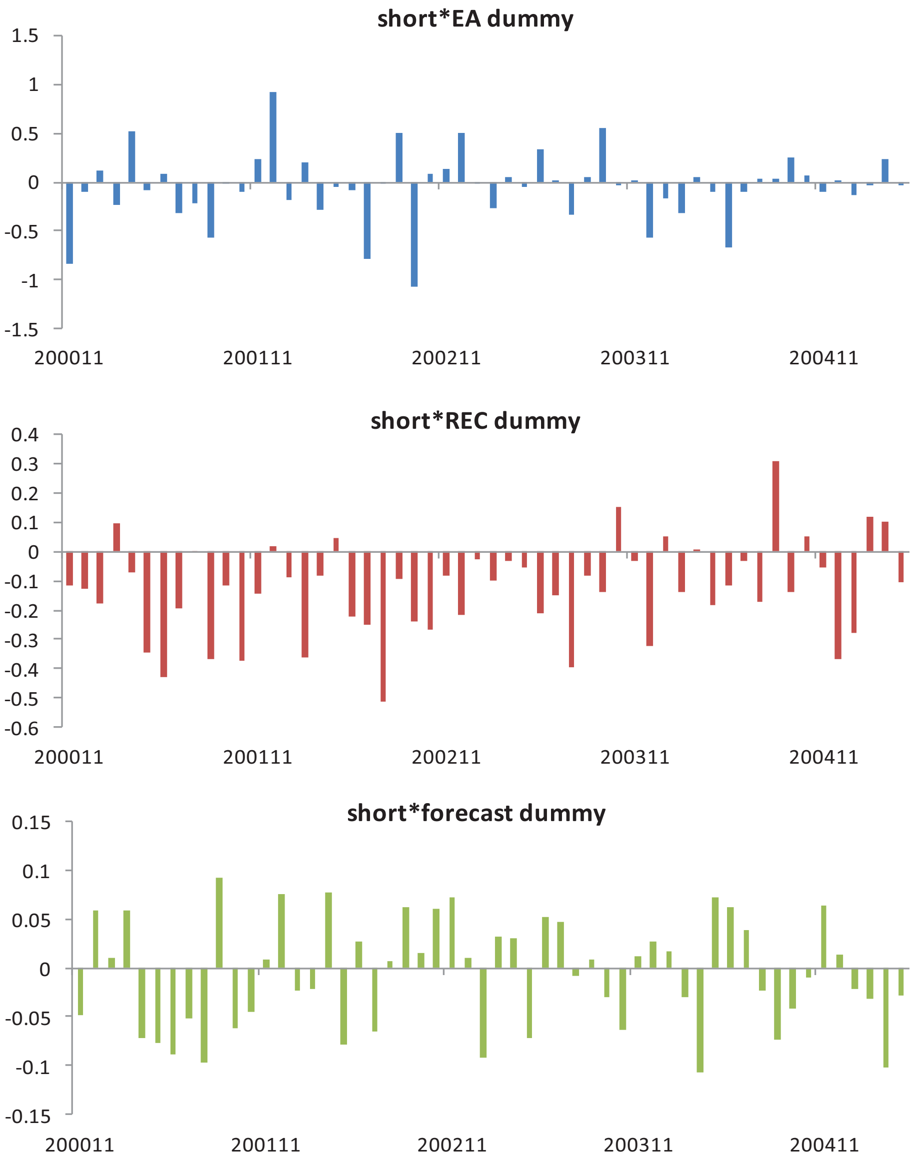

Figure 1. Coefficients over time. The graphs show monthly Fama–MacBeth regression coefficients on the shorting-event interaction term (Table II). We present each event separately (earnings announcements, analyst recommendation changes, and analyst forecast changes). The sample includes NYSE stocks from October 23, 2000 to April 30, 2005.

obtained using risk-adjusted returns are similar to those in Table II. For return horizons up to 20 days, our results are robust to using risk-adjusted return. Therefore, our subsequent discussion on short horizons focuses on raw returns which minimize measurement errors associated with beta estimation. We retain the risk adjustment for our later discussion on longer horizons (up to 60 days).

3.2 What Do Short Sellers Know: Public Information or Private Information?

To help better understand what information short sellers use to enhance their return predictability on earnings and analyst event days, we examine the dynamic interactions among public news, firm events, and short sellers' return predictability. This analysis is partially motivated by Engelberg, Reed, and Ringgenberg (2012) who find that short sellers are skillful at processing public news in such a way that leads to predictable returns. We examine whether public news impacts shorting behavior, and whether and to what extent the return predictability generated from earnings and analyst event days is driven by public and nonpublic news.

To examine the sources of information that short sellers use to trade around firm earnings and analyst-related events, we adopt a two-stage regression analysis. At the first stage, we examine how public news is used by short sellers by projecting short selling on news sentiment and relevant control variables as follows:

$$\text{short}_{i,t-5,t-1} = b_0 + b_1 \text{News Sentiment}_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{i,t}. \tag{6}$$

The variable $\text{News Sentiment}_{i,t-5,t-1}$ is the daily average of contemporaneous net sentiment scores for firm i, which directly captures the direction of information contained in public news coverage.[11] For days without news, the net sentiment score takes the value of zero. Since the news is publicly available, this step naturally decomposes short selling into a public news-related portion, and a residual which captures information short sellers use beyond public news, which we attribute to private information. If short sellers trade on public news about a firm, the coefficient on $\text{News Sentiment}_{i,t-5,t-1}$ should be significant and negative. We estimate Equation (6) using the Fama–MacBeth approach for each calendar month. That is, all coefficients in Equation (6) are estimated each month, and we report the time-series average of these coefficients, with t-statistics based on Newey–West standard errors with one lag.

Results from the first-stage estimation are reported in Panel A of Table III. The coefficient on contemporaneous public news, $\text{News Sentiment}_{i,t-5,t-1}$, is –0.1061 with a t-statistic of –3.40. The significantly negative coefficient indicates that more negative public news is associated with greater short selling activity. Specifically, a 1% decrease in net sentiment score is associated with an increase in shorting of 11%. This result indicates that short sellers process and act on public news, and is consistent with Engelberg, Reed, and Ringgenberg (2012).

At the second stage, based on the estimated coefficients, $\hat{b}_0$, $\hat{b}_1$, and $\hat{\gamma}$, we conduct the following decomposition:

$$\begin{aligned}\text{short}_{i,t-5,t-1} &= \left(\hat{b}_0 + \hat{b}_1 \text{News Sentiment}_{i,t-5,t-1} + \hat{\gamma} X_{i,t-1}\right) + e_{i,t} \\ &= \text{short}^{\text{public news}}_{i,t-5,t-1} + \text{short}^{\text{private info}}_{i,t-5,t-1}.\end{aligned} \tag{7}$$

The variable $\text{short}^{\text{public news}}_{i,t-5,t-1}$ represents shorting activity that is explained by public news and control variables, while the variable $\text{short}^{\text{private info}}_{i,t-5,t-1}$ contains the residual short selling which we attribute to private information. Then we directly examine whether it is the public news-related shorting or the private information-related shorting that drives the

11 Our results are robust to using news from the prior (2) week(s).

predictive power of shorting for future returns, extending the specifications in Equations (2) and (3) into:

$$r_{i,t,t+k} = b_0 + \left(b_1 + c_1 \text{Event dummy}_{i,t}\right) \text{short}_{i,t-5,t-1}^{\text{public news}} + \left(b_2 + c_2 \text{Event dummy}_{i,t}\right) \text{short}_{i,t-5,t-1}^{\text{private info}} + \gamma X_{i,t-1} + e_{i,t} \tag{8}$$

and

$$r_{i,t,t+k} = b_0 + \left(b_1 + c_1 \text{EA dummy}_{i,t} + c_2 \text{REC dummy}_{i,t} + c_3 \text{Forecast dummy}_{i,t}\right) \text{short}_{i,t-5,t-1}^{\text{public news}} + \left(b_2 + c_4 \text{EA dummy}_{i,t} + c_5 \text{REC dummy}_{i,t} + c_6 \text{Forecast dummy}_{i,t}\right) \text{short}_{i,t-5,t-1}^{\text{private info}} + \gamma X_{i,t-1} + e_{i,t}. \tag{9}$$

Both Equations (8) and (9) are estimated using Fama–MacBeth regressions within each month, with t-statistics computed using Newey–West standard errors with one lag.[12] If short sellers return predictability comes from processing public news, we expect $\text{short}_{i,t-5,t-1}^{\text{public news}}$ to be significantly negative. If short sellers use private information to boost their return predictability, we expect $\text{short}_{\text{i},t-5,t-1}^{\text{public news}}$ to be significantly negative.

The estimation results from the second stage regression are reported in Panel B of Table III. We find several interesting results. First, public news-related short selling can reliably predict future returns. For example, results from estimating Equation (8) show that for 2-day returns, the standardized coefficient of $\text{short}_{i,t-5,t-1}^{\text{public news}}$ is –0.113 (t-statistic = –5.46), suggesting that short sellers' predictive power for future returns is partially driven by acting on public news. Second and more interestingly, private information-related short selling can also predict future returns. Specifically, $\text{short}_{i,t-5,t-1}^{\text{private info}}$ has a standardized coefficient of –0.019 (t-statistic = –5.18), indicating that short sellers also trade on information beyond available public news. Comparing these two coefficients reveals that the return predictive power of public news-related shorting is five times larger than that of private info-related short-selling.

Third, the interaction term between $\text{short}_{i,t-5,t-1}^{\text{public news}}$ and Event $\text{dummy}_{i,t}$ in Equation (8) is not significant, while the interaction term between $\text{short}_{i,t-5,t-1}^{\text{private info}}$ and Event $\text{dummy}_{i,t}$ is highly significant. This further suggests that short sellers possess useful private information beyond public news to help them boost return predictability, especially around event days. Interestingly, the interaction term between $\text{short}_{i,t-5,t-1}^{\text{private info}}$ and REC $\text{dummy}_{i,t}$ is highly negative in Equation (9). This result corroborates our main finding in Table II. Furthermore, it reveals that short sellers acquire additional private return-predictive information ahead of stock recommendation changes.

Overall, these results suggest that short sellers are able to process publicly available news and trade on it, consistent with Engelberg, Reed, and Ringgenberg (2012). More importantly, short sellers use additional private information that is correlated with future analyst recommendation changes to boost their performance.[13]

12 We also include the sentiment variable in the second-stage return regression and our results remain the same.

13 We also use the topic code provided by News Analytics to group news into twenty-three categories to see which type of news short sellers can predict and trade on. We examine the return predictability of shorting on each news category by running individual regression for each news

Table III. Sources of the excess return from shorting: events and public news

This table tests whether short-sellers' ability to predict future returns is related to public news. Panel A reports first stage estimation results for the following regression:

$$\text{Short}_{i,t-5,t-1} = b_0 + b_1\text{News Sentiment}_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{i,t}.$$

The dependent variable $\text{Short}_{t\text{-}5,t\text{-}1}$ is computed as shares shorted scaled by daily volume, normalized to have mean zero and variance one every day. News $\text{Sentiment}_{i,t-5,t-1}$ is a net sentiment score averaged across all relevant individual-firm news in the interval by taking the difference between positive and negative sentiment probability, as calculated by TR. The control variables include Size, the previous month's log market capitalization, BM, the book-to-market ratio from 6 months ago, Volatility, the previous month's daily return volatility, PastRet, the return over the past 5 days and Turnover, last month's trading volume as a fraction of outstanding shares.

Panel B reports second stage estimation results for the following regressions:

$$\text{I}: r_{i,t,t+k} = b_0 + (b_1 + c_1\text{Event dummy}_{i,t})\text{Short}^{\text{public news}}_{i,t-5,t-1} + (b_2 + c_2\text{Event dummy}_{i,t})\text{Short}^{\text{private info}}_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{i,t}.$$

$$\text{II}: r_{i,t,t+k} = b_0 + (b_1 + c_1\text{EA dummy}_{i,t} + c_2\text{REC dummy}_{i,t} + c_3\text{ Forecast dummy}_{i,t})\text{Short}^{\text{public news}}_{i,t-5,t-1} + (b_2 + c_4\text{ EA dummy}_{i,t} + c_5\text{REC dummy}_{i,t} + c_6\text{Forecast dummy}_{i,t})\text{Short}^{\text{private info}}_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{i,t}.$$

The 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 risk-free rate. Indicator variables include EA $\text{dummy}_{i,t}$=1 if day t has an earnings announcement for firm i and zero otherwise, REC $\text{dummy}_{i,t}$=1 if on day t any analyst changes her buy/sell recommendation for firm i and zero otherwise, Forecast $\text{dummy}_{i,t}$=1 if on day t any analyst changes her earnings forecast for firm i and zero otherwise, and Event $\text{dummy}_{i,t}$=1 if any of the above three events occur on day t for firm i and zero otherwise. Variable $\text{short}^{\text{public news}}_{i,t-5,t-1}$ is the fitted value from the first stage regression to represent shorting related to public news. Variable $\text{short}^{\text{priviate info}}_{i,t-5,t-1}$ is the residual from the first stage regression to represent shorting related to private information. The control variables are defined in Table II. Our sample covers NYSE stocks from January 2003 to April 2005. A separate regression is performed each calendar month, and Newey–West standard errors with one lag are calculated from coefficients' time-series.

Panel A. First stage regression

Variable	Coefficient	*t*-Statistics
News Sentiment	–0.1061	–3.40
Size	–0.0222	–1.76
BM	–0.0072	–1.33
PastRet	0.1429	18.98
Volatility	–0.2727	–2.41
Turnover	0.2137	27.84
Adj. R^2	0.06	

Table III. Continued

Panel B. Second stage regression

Regression	Variable	$r_{t,\,t+1}$		$r_{t,\,t+5}$		$r_{t,\,t+10}$		$r_{t,\,t+20}$	
		Coefficient	*t*-Statistics	Coefficient	*t*-Statistics	Coefficient	*t*-Statistics	Coefficient	*t*-Statistics
I	$\text{short}_{i,t-5,t-1}^{\text{public news}}$	–0.113	–5.46	–0.129	–5.26	–0.068	–3.72	–0.033	–2.62
I	$\text{short}_{i,t-5,t-1}^{\text{public news}}$ * Event dummy	0.003	0.24	0.009	1.12	0.006	1.17	0.008	2.04
I	$\text{short}_{i,t-5,t-1}^{\text{private info}}$	–0.019	–5.18	–0.012	–3.33	–0.011	–3.77	–0.011	–4.58
I	$\text{short}_{i,t-5,t-1}^{\text{private info}}$ * Event dummy	–0.032	–3.31	–0.016	–3.63	–0.008	–2.01	0.000	0.06
II	$\text{short}_{i,t-5,t-1}^{\text{public news}}$	–0.104	–4.87	–0.121	–4.78	–0.066	–3.80	–0.031	–2.72
II	$\text{short}_{i,t-5,t-1}^{public\ news}$ * EA dummy	0.006	0.11	0.029	1.12	0.026	1.76	0.012	1.29
II	$\text{short}_{i,t-5,t-1}^{\text{public news}}$ * REC dummy	–0.046	–1.86	–0.005	–0.48	–0.002	–0.45	0.001	0.17
II	$\text{short}_{i,t-5,t-1}^{\text{public news}}$ * Forecast dummy	0.014	1.23	0.007	0.91	0.005	0.96	0.007	1.94
II	$\text{short}_{i,t-5,t-1}^{\text{private info}}$	–0.020	–5.16	–0.012	–3.27	–0.011	–3.68	–0.011	–4.56
II	$\text{short}_{i,t-5,t-1}^{\text{private info}}$ * EA dummy	–0.037	–0.89	–0.018	–1.11	–0.017	–2.07	–0.012	–2.01
II	$\text{short}_{i,t-5,t-1}^{\text{private info}}$ * REC dummy	–0.074	–2.70	–0.029	–2.54	–0.019	–2.78	–0.009	–2.15
II	$\text{short}_{i,t-5,t-1}^{\text{private info}}$ * Forecast dummy	–0.014	–1.33	–0.009	–1.82	–0.002	–0.62	0.003	1.25

3.3 Do Short Sellers Know More than Analysts?

From our previous results, analyst recommendation changes appear to be the most important event days for the underperformance of heavily shorted stocks, and the most profitable event category for short sellers. Analyst recommendations are an end product of extensive research by analysts, and they affect market prices. Analysts play a crucial intermediary role in the financial markets because they recommend a specific course of action that an investor should take. To the extent that analyst recommendations have investment value to investors (e.g., Gleason and Lee, 2003; Asquith, Mikhail, and Au, 2005; Malmendier and Shanthikumar, 2007), it is important to understand whether short sellers know more than analysts.

There are a number of possibilities of why short sellers are more informed than analysts, and the interpretation of the results differs somewhat across these possibilities. One explanation is that short sellers and analysts have similar fundamental information. When either group observes a change in the share price that appears unwarranted, for example, both groups act in response. For example, if they believe that share prices are inflated, then short sellers short and analysts reduce their recommendations. A second explanation is that short sellers and analysts learn company fundamental information at the same time, perhaps from conference calls or meetings with management, and then both act accordingly. If no material information is communicated in these private meetings, this kind of information transmission would not run afoul of Reg FD. Third, analysts may tip off short sellers about impending recommendation changes. While most analyst firms have internal policies against such tipping, Irvine, Lipson, and Puckett (2007) points out that tipping exists in a legal gray area, and they find evidence in institutional trades that is consistent with tipping by analysts. Fourth, tipping can also go in the opposite direction. Hedge funds or other investors may collect private information or conduct original research and analysis and then share the results with analysts. Analysts then adjust their recommendations accordingly, and this affects share prices.[14]

To summarize, there are many routes that information flow can take among firms, short sellers, analysts, and investors. Although it is difficult to pin down the direction of information flow between short sellers and analysts, we tackle this by examining 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 actions alone? If the answer is no, then short sellers have 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 have.

event and only when a news event occurs. We find that short sellers are able to identify the majority of the news events.

14 A malevolent version of this scenario 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. More details are in "Rocker Pays $5 Million to Overstock.com to Settle Lawsuit", Overstock.com press release, December 8, 2009.

To investigate this hypothesis, we estimate the following regressions:

$$r_{i,t,t+k} = b_0 + b_1\text{short}_{i,t-5,t-1} + c_1\text{DUE1}_{i,t} + c_2\text{DUE2}_{i,t} + c_3\text{DUE3}_{i,t} + \gamma X_{i,t-1} + e_{i,t}. \quad (10)$$

$$r_{i,t,t+k} = b_0 + \left(b_1 + e_0\text{Event dummy}_{i,t}\right)\text{short}_{i,t-5,t-1} + c_1\text{DUE1}_{i,t} + c_2\text{DUE2}_{i,t} + c_3\text{DUE3}_{i,t} + \gamma X_{i,t-1} + e_{i,t}. \quad (11)$$

$$r_{i,t,t+k} = b_0 + \left(b_1 + e_1\text{EA dummy}_{i,t} + e_2\text{REC dummy}_{i,t} + e_3\text{Forecast dummy}_{i,t}\right)\text{short}_{i,t-5,t-1} + c_1\text{DUE1}_{i,t} + c_2\text{DUE2}_{i,t} + c_3\text{DUE3}_{i,t} + \gamma X_{i,t-1} + e_{i,t}. \quad (12)$$

In these regressions, DUE takes the value of earnings-related surprises on days when the relevant event occurs, and zero otherwise. For example, variable DUE1 takes the value of the earnings surprise on earnings announcement days, and zero otherwise. Similarly, DUE2 and DUE3 take the value of the recommendation change and the consensus forecast revision on days when changes happen, and zero otherwise. The three dummy variables are defined in the same way as in Equations (2) and (3). The return variables on the left-hand side are measured from day t to $t+k$ inclusive, while the shorting variable is measured from day $t-5$ to day $t-1$, and the earnings and analyst variables are measured on day t. That is, in this setting, we lag shorting to predict future returns, but control for contemporaneous events.

Equation (10) 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 earnings surprises or analyst changes. If earnings announcements, recommendation changes, or forecast revisions contain relevant information for contemporaneous returns, we would find the coefficients for $\text{DUE1}_{i,t}$, $\text{DUE2}_{i,t}$, and $\text{DUE3}_{i,t}$, respectively, to be significant and positive. For the next two regressions, we add interactions between shorting and event-day dummies. If the interaction terms are significantly negative, shorting contains additional return-predicative information beyond the information contained in the earnings or analyst changes. The vector of control variables, $X_{i,t-1,}$ includes $\text{Size}_{i,m-1}$, $\text{BM}_{i,m-6}$ $\sigma_{i,m-1}$, and $\text{turnover}_{i,m-1}$, defined as before. To accommodate the post earnings announcement drift (PEAD), we replace the return over the past 6 months $\text{ret}_{i,m-6,m-1}$, with three past return variables, $\text{ret}_{i,m-1,m}$, $\text{ret}_{i,m-3,m-2}$, and $\text{ret}_{i,m-6,m-4}$.

We report the results in Table IV. In the first regression, all earnings and analyst action variables, DUE1, DUE2, and DUE3, are significantly positive, implying that these events are associated with contemporaneous returns in the expected direction. More importantly, in the second regression, the interaction term of shorting and the event dummy is -0.0257 with a t-statistic of –2.77 for the $[t, t+1]$ interval. This demonstrates that shorting activity in the week before event days contains additional predictive information about future returns. Short sellers know something about fundamentals beyond what is captured in the earnings and analyst measures. In the last regression, we separate the three different types of events, and it turns out that shorting activity mainly provides incremental information about the return effect of analyst recommendation changes (t-statistic = –2.31). This indicates in particular that short sellers are trading on information that is finer than just the magnitude of recommendation changes.

To summarize, we show that shorting contains information about fundamentals beyond what is embedded in earnings announcements and analyst actions, as shorting activity has

Table IV. Do short sellers know more than analysts?

We estimate three separate Fama–MacBeth regressions for NYSE stocks from October 23, 2000 to April 30, 2005:

$$\text{I}: \; r_{i,t,t+k} = b_0 + b_1 \text{short}_{i,t-5,t-1} + c_1\text{DUE1}_{i,t} + c_2\text{DUE2}_{i,t} + c_3\text{DUE3}_{i,t} + \gamma X_{i,t-1} + e_{i,t}.$$
$$\text{II}: \; r_{i,t,t+k} = b_0 + (b_1 + e_0\text{Event dummy}_{i,t})\text{short}_{i,t-5,t-1} + c_1\text{DUE1}_{i,t} + c_2\text{DUE2}_{i,t} + c_3\text{DUE3}_{i,t} + \gamma X_{i,t-1} + e_{i,t}.$$
$$\text{III}: \; r_{i,t,t+k} = b_0 + (b_1 + e_1\text{EA dummy}_{i,t} + e_2\text{REC dummy}_{i,t} + e_3\text{Forecast dummy}_{i,t})\text{short}_{i,t-5,t-1} + c_1\text{DUE1}_{i,t} + c_2\text{DUE2}_{i,t} + c_3\text{DUE3}_{i,t} + \gamma X_{i,t-1} + e_{i,t}.$$

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 risk-free rate. $\text{short}_{t-5,t-1}$ is computed as shares shorted scaled by daily volume, normalized to have mean zero and variance one every day. Indicator variables include EA $\text{dummy}_{i,t}$=1 if day *t* has an earnings announcement for firm *i* and zero otherwise, REC $\text{dummy}_{i,t}$=1 if on day *t* any analyst changes her buy/sell recommendation for firm *i* and zero otherwise, Forecast $\text{dummy}_{i,t}$=1 if on day *t* any analyst changes her earnings forecast for firm *i* and zero otherwise, and Event $\text{dummy}_{i,t}$=1 if any of the above three events occur on day *t* for firm *i* and zero otherwise. The variables $\text{DUE1}_{i,t}$/$\text{DUE2}_{i,t}$/$\text{DUE3}_{i,t}$ are surprises, taking the value of the earnings surprise/recommendation change/forecast revision on event days, and zero otherwise. $X_{i,t-1}$ includes $\text{Size}_{i,m-1}$, $\text{BM}_{i,m-6}$ $\sigma_{i,m-1}$, and $\text{turnover}_{i,m-1}$, defined as before, plus three past return variables to accommodate post-earnings announcement drift (PEAD) or other time-variation in predictability: $\text{ret}_{i,m-1,m}$, $\text{ret}_{i,m-3,m-2}$, and $\text{ret}_{i,m-6,m-4}$. A separate regression is performed each calendar month, and Newey–West standard errors with one lag are calculated from coefficients' time-series.

Regression	Variable	$r_{t,t+1}$		$r_{t,t+5}$		$r_{t,t+10}$		$r_{t,t+20}$	
		Coefficient	*t*-Statistics	Coefficient	*t*-Statistics	Coefficient	*t*-Statistics	Coefficient	*t*-Statistics
I	Short	–0.0381	–11.68	–0.0313	–10.73	–0.0291	–10.24	–0.0243	–10.43
I	DUE1	1.0948	9.47	0.3837	9.37	0.2009	7.39	0.0974	5.72
I	DUE2	0.8603	15.54	0.3115	15.17	0.1783	13.80	0.0959	12.77
I	DUE3	5.9110	10.76	2.5995	8.78	1.4265	7.54	0.7712	6.43
II	Short	–0.0343	–10.42	–0.0294	–10.71	–0.0281	–10.63	–0.0243	–10.75
II	Short * Event dummy	–0.0257	–2.77	–0.0130	–2.24	–0.0066	–2.12	0.0011	0.53
II	DUE1	1.0951	9.47	0.3850	9.39	0.2016	7.40	0.0979	5.76
II	DUE2	0.8599	15.53	0.3113	15.15	0.1781	13.80	0.0959	12.78
II	DUE3	5.9048	10.74	2.5957	8.78	1.4254	7.55	0.7715	6.45

(continued)

Table IV. Continued

Regression	Variable	$r_{t,t+1}$		$r_{t,t+5}$		$r_{t,t+10}$		$r_{t,t+20}$	
		Coefficient	*t*-Statistics	Coefficient	*t*-Statistics	Coefficient	*t*-Statistics	Coefficient	*t*-Statistics
III	Short	−0.0351	−10.44	−0.0297	−10.69	−0.0282	−10.62	−0.0243	−10.78
III	Short * EA dummy	−0.0614	−1.32	−0.0097	−0.56	−0.0007	−0.07	−0.0097	−1.61
III	Short * REC dummy	−0.0489	−2.31	−0.0212	−1.82	−0.0056	−0.83	−0.0005	−0.08
III	Short * Forecast dummy	−0.0067	−0.91	−0.0075	−1.52	−0.0054	−1.64	0.0017	0.83
III	DUE1	1.0941	9.19	0.3854	8.89	0.1976	7.02	0.0963	5.50
III	DUE2	0.8592	15.51	0.3110	15.04	0.1781	13.73	0.0960	12.56
III	DUE3	5.9099	10.77	2.6011	8.80	1.4273	7.54	0.7713	6.43

incremental predictive power for future returns even after we control for contemporaneous earnings/analyst measures. To put it simply, short sellers know something about fundamentals that analysts do not. Establishing that short sellers know more than analysts adds an important contribution to the literature. The above findings suggest that short sellers are better suited than analysts for compounding information into prices and for more successfully predicting returns.

3.4 Reversal Patterns of Short-Selling's Predictive Power?

We show in the previous sections that over a short horizon, a substantial portion of short sellers' predictive power is associated with firm fundamentals. In this section, we examine potential reversal patterns in shorts' predictive power. If short sellers have long-term value-relevant information about firm fundamentals, their return predictability should be long lasting, and is unlikely to be followed by return reversals. On the other hand, if the predictive power of shorts around fundamental events arises from potential short-term opportunistic behavior and contains little value-relevant information, the negative predictive power for future returns is likely to be transitory, and the price would reverse quickly.

We implement the reversal test in three steps. Since the reversal pattern can depend on firm size, we first divide our sample firms into three size groups based on previous quarter-end market cap. This allows the reversal pattern to vary by firm size. Second, within each size group, we separate firms into quintiles, with the first (fifth) quintile containing the least (most) shorted 20% firms 5 days before the events. We hold the five portfolios for 60 days after their formation and compute holding period returns for each quintile. If shorts around earnings and analyst-related events have predictive power for future returns, the difference between the most and least shorted quintiles should be negative. If the shorts do not have real information content, we expect to observe a quick and significant reversal of the return difference back to zero after a few days. In contrast, if shorts contain information about firm fundamentals, the return effect should be permanent and we should not see a reversal pattern.

We report the results in Table V and Figure 2. With the return horizon extended to 60 days, we present results based on risk-adjusted returns, computed as raw returns adjusted by the Fama–French three-factor model, where the betas are estimated from previous quarter daily returns. In Panel A of Table V, we group all three events, and we report individual events in Panels B–D.

In Panel A of Table V, the return difference for the small firms over $[t, t+1]$ is –0.162% with a t-statistic of –2.94, which indicates that going long stocks with heavy shorting and going short stocks with light shorting leads to a 2-day return of –0.162%. When we extend the horizon to 10 days, the above long-short strategy has a cumulative return of –1.032% with a t-statistic of –5.37. This cumulative return continues to grow for the next 50 days. For the horizon of $[t, t+60]$, the cumulative return for the long-short strategy becomes −2.516%, with a t-statistic of –3.88. Therefore, for small stocks, we do not see any evidence of a reversal.

In the next two columns, we report the same statistics for medium-sized firms. The cumulative return is –0.067% with a t-statistic of –2.57 for the horizon of $[t, t+1]$, and it continues to grow to –1.639% with a t-statistic of –3.33 for the horizon of $[t, t+60]$. Again, we do not observe any evidence of a reversal. But compared with the smaller firms, the return difference is smaller in magnitude, indicating the predictive power of shorts is stronger and more persistent for the smaller firms than for the medium firms.

Table V. Examining potential return reversals

Based on previous quarter market cap, we first partition firms into three terciles: small, medium, and large. In each of the panels, we present the Fama–French adjusted return (%) difference between firms with the heaviest 20% and the lightest 20% shorting within each size group from days [–5, –1] before the event, where adjusted returns are computed as raw returns adjusted by the Fama–French three-factor model, where the betas are estimated from previous quarter daily returns.

	Small difference	*t*-Statistics	Medium difference	*t*-Statistics	Large difference	*t*-Statistics
Panel A. All events for size groups						
[t, t+1]	–0.162	–2.94	–0.067	–2.57	–0.182	–2.39
[t, t+10]	–1.032	–5.37	–0.222	–1.71	–0.513	–1.72
[t, t+20]	–1.486	–4.76	–0.661	–2.90	–0.592	–1.26
[t, t+30]	–1.751	–4.44	–0.991	–3.33	–0.691	–1.09
[t, t+40]	–2.122	–4.52	–1.443	–3.56	–0.683	–0.81
[t, t+50]	–2.386	–4.48	–1.511	–3.33	–0.650	–0.68
[t, t+60]	–2.516	–3.88	–1.639	–3.33	–0.494	–0.47
Panel B. Earnings announcement for size groups						
[t, t+1]	–0.269	–1.80	–0.230	–1.43	0.034	0.46
[t, t+10]	–1.626	–3.27	–0.698	–2.85	–0.530	–1.53
[t, t+20]	–2.387	–3.95	–1.292	–3.55	–0.361	–0.50
[t, t+30]	–2.429	–3.28	–1.266	–1.62	–1.059	–0.88
[t, t+40]	–2.394	–4.04	–2.124	–3.81	–0.345	–0.32
[t, t+50]	–2.237	–2.80	–2.190	–3.58	–1.314	–1.06
[t, t+60]	–2.536	–2.33	–2.792	–3.81	–0.817	–0.80
Panel C. Recommendation change for size groups						
[t, t+1]	–0.267	–2.20	–0.041	–0.43	–0.389	–3.21
[t, t+10]	–1.077	–3.62	–0.025	–0.09	–1.144	–3.49
[t, t+20]	–1.564	–3.41	–0.270	–0.69	–0.825	–1.90
[t, t+30]	–2.430	–3.83	–0.835	–1.65	–0.643	–0.86
[t, t+40]	–3.300	–4.67	–0.873	–1.37	–0.663	–0.74
[t, t+50]	–3.883	–4.78	–0.822	–1.22	–0.781	–0.73
[t, t+60]	–4.095	–4.17	–0.920	–1.43	–0.900	–0.68
Panel D. Forecast change for size groups						
[t, t+1]	–0.149	–2.62	–0.042	–1.96	–0.173	–2.34
[t, t+10]	–1.011	–5.04	–0.267	–2.00	–0.498	–1.64
[t, t+20]	–1.476	–5.10	–0.715	–3.10	–0.638	–1.29
[t, t+30]	–1.713	–4.35	–0.993	–3.18	–0.752	–1.18
[t, t+40]	–2.009	–4.42	–1.498	–3.54	–0.689	–0.81
[t, t+50]	–2.192	–4.43	–1.629	–3.37	–0.696	–0.72
[t, t+60]	–2.391	–3.93	–1.682	–3.11	–0.580	–0.55

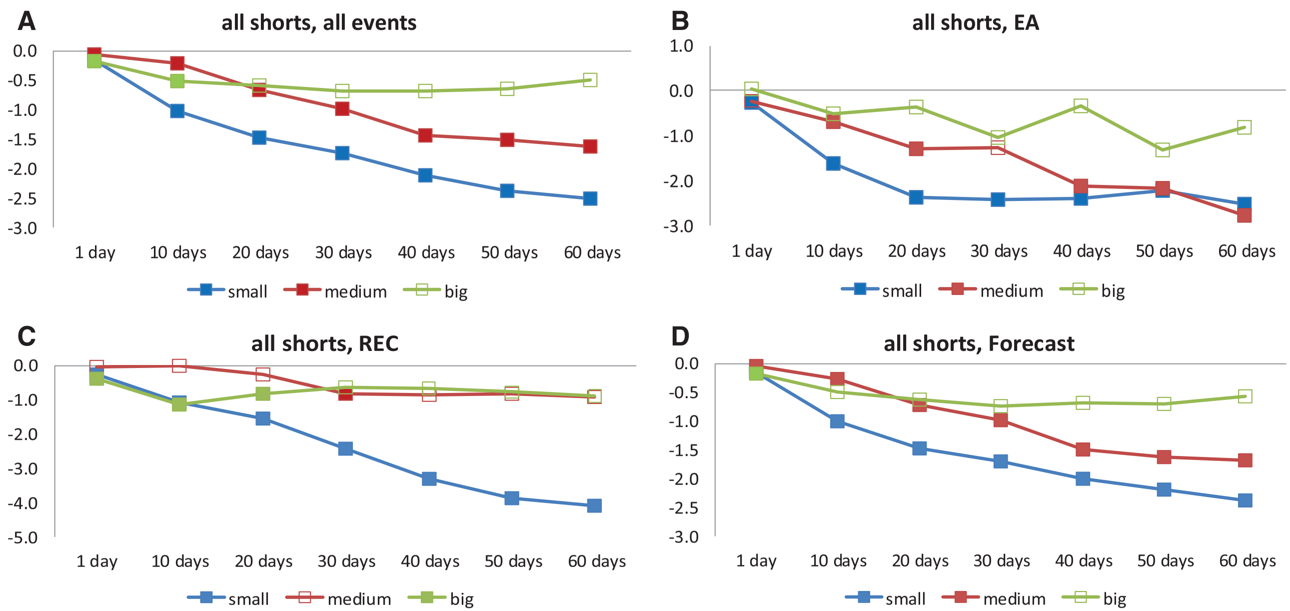

Figure 2. Examining potential return reversals. This figure examines return reversal over [0, +60]. Based on previous quarter market cap, we first separate all firms in three groups: small, medium, and large. In each of the panels, we present the Fama–French adjusted return (%) difference between firms with the heaviest 20% and the lightest 20% shorting from [–5, –1] before the event, within each size group. For each data point, if the return difference is signficant at 10%, we present it with a solid square, and a hollow square othersise.

For big firms, the return difference starts at –0.182% with a t-statistic of –2.39 over the horizon of $[t, t+1]$. When the horizon becomes $[t, t+10]$, the cumulative return difference continues to grow to –0.513%. But it is only marginally significant with a t-statistic of -1.72. For the horizons of $[t, t+20]$ and $[t, t+30]$, the cumulative return difference continues to slowly widen to –0.592% and then –0.691%, respectively, though neither is statistically significant. We observe a very slight and statistically insignificant reversal after 40 days. For horizons of $[t, t+40]$, $[t, t+50]$, and $[t, t+60]$, the cumulative return differences are –0.683%, –0.650%, and –0.494%, respectively. None of these negative return differences is statistically significant. Overall, there is no statistical evidence of a share price reversal in returns up to 60 days.

In Figure 2, we plot the cumulative return differences over the 60 days, which allows us to better visualize these return patterns. When the return difference is significant at 5%, we use a solid square, and a hollow square otherwise. Panel A reports the cumulative returns for all three events. As discussed above, the predictive power of shorts is strongest for smaller firms. But neither small nor medium-sized firms exhibit reversals. For large firms, the return effects are smaller, and there is a slight reversal after 40 days, but these effects are not statistically significant.

Next, we take a closer look at each individual event. Earnings announcement events are depicted in Panel B. For the smallest firms, over horizons of $[t, t+1]$ and $[t, t+60]$, the return differences are –0.269% (t-statistic = –1.80) and –2.536% (t-statistic = –2.33). There is no reversal over this interval. We document a similar pattern for medium-sized firms. For big firms, the return difference starts at a 0.034% for horizon $[t, t+1]$, and it becomes negative at –0.530% over $[t, t+10]$. It stays negative for the next 40 days, but none of the return differences is statistically negative. In contrast to the results in Panel A, for earnings announcements the predictive power of shorts is equally strong and persistent for small- and medium-sized firms. For the large firms, the return pattern is zig-zagging with no statistical significance, again providing no evidence of return reversals.

For recommendation changes in Panel C, the pattern for the smallest firms is very similar to those observed in Panels A and B. The predictive power of shorts is strong and persistent, and there is no reversal. For medium and large firms, the lines become flatter than for smaller firms. This indicates a weak reversal but the effect is not statistically significant.

Finally, for analyst forecast changes in Panel D, the overall results are very similar to those in Panel A. For small and medium firms, we find the predictive power of shorts is strong and persistent, while for large firms, we observe negative returns in the long run but without statistical significance.

To summarize, our examination of return patterns after the trades of short sellers finds no evidence of significant reversals. Especially for small- and medium-sized firms, shorting appears to be mainly motivated by firm fundamental information rather than short-term temporary mispricing. For large firms, the predictive power of shorts becomes weaker over longer horizons, and there is no statistical evidence of reversals.

4. Further Discussion and Robustness Checks

This section provides further discussion and robustness checks. We first examine whether our findings represent stock-specific selectivity or aggregate factor risks. Next, we examine whether shorting's predictability varies in the cross section of firms, or when firm events are extreme. We also investigate whether the results are different for analysts from top investment banks. In addition, we provide results for a more recent sample of Nasdaq short selling from 2009 to 2010. Finally, we examine whether different types of short-sellers have different ability in obtaining information and predicting future returns.

4.1 Factor Timing

While our tests include standard controls for stock and firm characteristics, it may be the case that short sellers are simply loading on one or more common factors at exactly the right time, and that this overlap could explain some of the cross-sectional return predictability. To distinguish between returns due to factor timing strategies and returns due to information about fundamentals, we add Fama–French factor sensitivities to the model and interact them with shorting activity. We estimate monthly Fama–MacBeth regressions as follows:

$$r_{i,t,t+k} = b_0 + \left(b_1 + c_0 \text{Event dummy}_{i,t} \;\; + b_2\beta_{\text{MKT}} + b_2\beta_{\text{SMB}} + b_2\beta_{\text{HML}}\right)\text{short}_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{i,t}, \tag{13}$$

where the dependent variable is the average daily return for firm i over the interval $[t, t+k]$ in percent, and the betas are Fama–French factor sensitivities estimated on daily returns over the previous calendar quarter.

The results are in Panel A of Table VI. We can directly compare the results with those in model II of Table II. There is some evidence that factor timing explains part of short sellers' return on non-event days, as the magnitude of the *b1* coefficient in model II declines from −0.0346 in Table II to –0.0194 here. But this result is present primarily in $[t, t+1]$ and $[t, t+5]$. Most importantly, factor timing has essentially no effect on shorting returns on event days—the coefficients on the shorting variable interacted with the event dummies are not significant and thus do not change the interpretation of our earlier results. This is true across all holding periods and suggests that short sellers do not vary their factor loadings in a systematic way that would affect their excess returns. More precisely, we cannot reject the hypothesis that factor timing does not contribute to the relationship between shorting and future returns in the cross-section, and especially not on event days.

4.2 Cross-Sectional Patterns in Short Sellers' Fundamental Information Advantage

In this subsection, we examine whether short sellers' information advantage varies with firm or event characteristics. In terms of firm characteristics, it is possible that short sellers have a greater information advantage in, and/or target their trading activities toward, 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 a less transparent information environment, so it is possible that careful research of these firms by short sellers is more value relevant than similar research on larger firms. Alternatively, short sellers may have an information advantage with small firms, because analysts generally prefer to cover larger stocks. To investigate these claims, we group 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 types of firms, such as small firms.

Table VI. Additional results

This table reports estimation results for several Fama–MacBeth regressions for NYSE stocks from October 23, 2000 to April 30, 2005. In Panel A, we separate short sellers' stock selectivity from factor loading effects as following:

$$r_{i,t,t+k} = b_0 + \left(\mathrm{b}_1 + c_0 \text{Event dummy}_{i,t} + b_2\beta_{\text{MKT}} + b_2\beta_{\text{SMB}} + b_2\beta_{\text{HML}}\right)\text{short}_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{i,t}.$$

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

$$r_{i,t,t+k} = b_0 + \left[\sum_{J=1}^{3}\left(b_j + c_j \text{Event dummy}_{i,t}\right) d_{it}^{\text{GROUP}j}\right]\text{short}_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{i,t}.$$

In Panel C, we investigate short sellers' ability to predict earnings forecasts and recommendation changes coming from top vs. other investment banks:

$$UE_{i,t} = b_0 + \left(c_1 \text{Top Banks}_{i,t} + c_2 \text{Rest}_{i,t}\right)\text{short}_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{i,t}.$$

In Panel D, we re-estimate the regressions from Table II 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 in excess of the risk-free rate. $\text{short}_{t-5,t-1}$ is computed as shares shorted scaled by daily volume, normalized to have mean zero and variance one every day. Indicator variables include EA $\text{dummy}_{i,t}$=1 if day t has an earnings announcement for firm i and zero otherwise, REC $\text{dummy}_{i,t}$=1 if on day t any analyst changes her buy/sell recommendation for firm i and zero otherwise, Forecast $\text{dummy}_{i,t}$=1 if on day t any analyst changes her earnings forecast for firm i and zero otherwise, and Event $\text{dummy}_{i,t}$=1 if any of the above three events occur on day t for firm i and zero otherwise. The betas $\beta_{\text{RM}}, \beta_{\text{HML}}, \beta_{\text{SML}}$ are Fama–French factor sensitivities, estimated on a daily basis over the previous calendar quarter. Variable $d_{i,t}^{\text{GROUP}j}$ is a size group indicator. Indicator variable Top $\text{Banks}_{i,t}$ ($\text{Rest}_{i,t}$) equals one if on day t any analyst from (not from) a top 10 investment bank provides an update of the specified type. 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 coefficients' time-series.

	$r_{t,\,t+1}$ Coefficient	t-Statistics	$r_{t,\,t+5}$ Coefficient	t-Statistics	$r_{t,\,t+10}$ Coefficient	t-Statistics	$r_{t,\,t+20}$ Coefficient	t-Statistics
Panel A. Factor timing								
Short	–0.0194	–2.64	–0.0218	–3.37	–0.0261	–4.13	–0.0235	–4.66
Short * Event dummy	–0.0436	–4.96	–0.0201	–3.46	–0.0109	–3.24	–0.0017	–0.82
β_{MKT}	–0.0155	–1.65	–0.0072	–0.94	–0.0008	–0.11	0.0005	0.10
β_{SMB}	0.0007	0.14	–0.0003	–0.08	–0.0023	–0.63	–0.0033	–1.11
β_{HML}	0.0016	0.38	–0.0007	–0.19	–0.0026	–0.83	–0.0013	–0.54

(continued)

Table VI. Continued

	$r_{t,\,t+1}$ Coefficient	t-Statistics	$r_{t,\,t+5}$ Coefficient	t-Statistics	$r_{t,\,t+10}$ Coefficient	t-Statistics	$r_{t,\,t+20}$ Coefficient	t-Statistics
Panel B. Firms of different sizes								
Short (small)	−0.0583	−7.36	−0.0531	−8.29	−0.0520	−8.09	−0.0438	−7.63
Short (med)	−0.0210	−5.85	−0.0209	−6.48	−0.0201	−6.86	−0.0187	−6.96
Short (large)	−0.0328	−6.28	−0.0218	−5.67	−0.0202	−6.27	−0.0164	−6.07
Short * Event dummy (small)	−0.0654	−2.55	−0.0404	−2.96	−0.0329	−3.04	−0.0116	−2.00
Short * Event dummy (med)	−0.0495	−4.53	−0.0156	−2.73	−0.0100	−2.54	−0.0017	−0.62
Short * Event dummy (large)	−0.0324	−2.80	−0.0205	−2.77	−0.0070	−1.67	−0.0020	−0.68

Panel C. Top investment banks versus the rest

	Recommendation change		Forecast change		Initial recommendation	
	Coefficient	t-Statistics	Coefficient	t-Statistics	Coefficient	t-Statistics
Short * TopBanks	−0.0850	−5.19	−0.0003	−1.42	−0.0274	−2.79
Short * Rest	−0.0874	−6.16	−0.0005	−1.59	−0.0087	−1.19

Table VI. Continued

Panel D. Recent results from Nasdaq

Regression	Variable	$r_{t,t+1}$		$r_{t,t+5}$		$r_{t,t+10}$		$r_{t,t+20}$	
		Coefficient	*t*-Statistics	Coefficient	*t*-Statistics	Coefficient	*t*-Statistics	Coefficient	*t*-Statistics
I	Short	–0.0162	–2.21	–0.0137	–2.09	–0.0126	–2.44	–0.0099	–2.18
II	Short	–0.0150	–2.17	–0.0137	–2.08	–0.0127	–2.37	–0.0101	–2.16
II	Short * Event dummy	–0.0177	–1.27	0.0003	0.04	0.0030	0.67	0.0061	1.18
III	Short	–0.0143	–2.11	–0.0133	–2.04	–0.0125	–2.36	–0.0100	–2.15
III	Short * EA dummy	–0.2427	–2.54	–0.1236	–3.42	–0.0733	–3.38	–0.0337	–2.81
III	Short * REC dummy	0.0066	0.09	–0.0051	–0.20	–0.0158	–1.12	–0.0020	–0.29
III	Short * Forecast dummy	–0.0103	–0.55	0.0084	0.90	0.0111	1.52	0.0083	1.46

We estimate the following regression:

$$r_{i,t,t+k} = b_0 + \left[\sum\nolimits_{J=1}^{3} \left(b_j + c_j \text{Event dummy}_{i,t}\ \right) d_{it}^{\text{GROUP}j}\right] \text{short}_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{i,t}, \tag{14}$$

where $d_{i,t}^{\text{GROUP}n}$, $n = 1$, 2, or 3 (small, medium, or big for market cap), is an indicator with value of 1 if firm i at time t belongs to group n, and zero otherwise.

In Panel B of Table VI, we present results. From coefficients b_1, b_2, b_3, we learn that shorting predicts returns best for small firms. Shorting activity also predicts returns on event days best for small firms. If analysts indeed prefer to follow larger firms rather than smaller firms, it is quite plausible that short sellers would know more about smaller firms' fundamentals.[15]

4.3 Short Sellers vs. Analysts from Top Investment Banks

An important multifaceted question is whether short sellers or analysts are better informed, whether their information is similar, and whether they can systematically learn from each other. As discussed earlier, this question is difficult to answer because we have no data on analyst (or their clients') trades and also cannot observe the identity of individual short sellers. This means that we cannot determine unambiguously whether short sellers are tipped by analysts or vice versa, and cannot directly compare their respective information sets.

Our earlier tests show that short sellers have incremental information beyond that contained in analyst recommendation changes. But there is still scope for tipping, and we explore this possibility in this section. 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 active traders and short sellers, might have a greater motivation to favor certain 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 10 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

15 We also examine whether shorts' informative advantage differs between positive and negative news days, defined as negative unexpected earnings surprises, recommendation downgrades, or negative revisions of analyst forecasts. We define dummy variables that take the value of one on days with negative events and zero otherwise and add them to the model. If shorts become more or less predictive before negative events compared with positive events, then the coefficients of these dummies should be negative. We find over all four horizons that shorts are predictive in general, whether the event is negative or not. The negative event coefficient is always negative, and is marginally significant for horizons longer than 5 days. This finding suggests that shorts are more predictive before negative events. But when we separate events into different categories, the results become noisy. We still find that shorts have predictive power in general, but only for recommendation changes, short sellers predict negative changes better than positive changes. Overall, the specification using a negative-events dummy decreases the precision of our estimates and we do not tabulate these results.

then identify recommendations and forecasts that are issued by analysts at the top investment banks. In addition, following Irvine, Lipson, and Puckett (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 Panel C of Table VI, we estimate the following pooled model[16]:

$$UE_{i,t} = b_0 + \left(c_1 \text{Top Banks}_{i,t} + c_2 \text{Rest}_{i,t}\right) \text{short}_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{i,t}, \tag{15}$$

where the indicator Top $\text{Banks}_{i,t}$ takes the value of 1 if there is news issued only by a top investment bank analyst but not by other brokers on day t for firm i, and zero otherwise; and indicator $\text{Rest}_{i,t}$ takes the value of 1 if there is news issued by other brokers but not by any of the 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 without overlap into those with "only event(s) from top investment banks," and "only event(s) from the rest."[17] 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. Another possibility for c_1 to be bigger than c_2 is trust. It is possible that top analysts are better trusted by short sellers and thus prices move more following their revisions. Separating tipping from trust is intricate and beyond the scope of the paper, but we would like to acknowledge this possibility.

Panel C reveals no evidence that short sellers trade more profitably on top-bank events. This finding is inconsistent with more tipping by top-bank analysts. 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. For forecast changes, the message is similar. In terms of initial recommendations, however, we do find the coefficient on top investment banks, which is –0.0274 (t-statistic = –2.79), to be significantly different from that of the rest of brokers, which is –0.0087 (t-statistic = –1.19). Based on these results, short sellers seem to know more about initial recommendations issued from top investment banks than from the rest. This could be supportive of tipping, as in Irvine, Lipson, and Puckett (2007), but we also cannot rule out the possibility that short sellers and analysts from top investment banks may process the same information and independently take actions in the same direction.[18]

4.4 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 suspended short sale price tests in 1,000 stocks listed on NYSE and Nasdaq. The Reg 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

16 Because the events are not evenly distributed over trading days, here we adopt a pooled regression rather than Fama–MacBeth regressions.

17 Overlapping observations account for <5% of the sample, and they are deleted to cleanly 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 are also inconclusive.

precipitous fall of NYSE market share from about 60% in 2005 to about 20% in 2008. These trends may introduce confounding effects and may 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 is 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 of 1 day or longer. 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 regulations. This sample ends in July 2010 because Nasdaq stopped publishing the daily shorting data on its website at that point.

Panel D of Table VI 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 2009–10 compared with −0.0406 for 2000–5). This indicates that short sellers continue to be informed in 2009–10. 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 and analyst event days. This is slightly lower than the analogous 24% calculated for the earlier time period, partially due to fewer such event days in the more recent period (8.6% of the 2009–10 stock-days have an earnings or analyst release vs. 12.0% of stock-days for 2000–5). 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.

4.5 Various Types of Short Sellers

Short sellers are not homogeneous and they might trade for different reasons, and obtain information via different channels. Our dataset identifies the type of account that submitted the short sale order, which allows us to study differences among different groups of short sellers. 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: (1) Individual, agency orders that originate from individuals; (2) Institution, agency orders that do not originate from individuals; (3) Proprietary, orders where NYSE members are trading as principal, excluding all trades by the specialist for his own account; and (4) Other, a 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.

We re-estimate the regression specifications in Equations (1)–(3) separately for each trader type and present the results in Online Appendix Table IA5. We find that shorting by each account type is reliably informed, though institutional non-program types seem to be trading on stronger signals on average, largely consistent with the results in Boehmer, Jones, and Zhang (2008). On non-event days, all types of shorts can significantly predict future returns, with institutional non-program trades being the most informative; on event days, institutional non-program short sellers and individual short sellers are better informed than the rest of the short sellers.

5. Conclusion

In this study, we consider the trading of short sellers around fundamental events such as earnings and analyst actions. 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 weeks. Our main objective is to understand the nature of the information that short-sellers use to trade.

We start by identifying how much of the predictive power of short-sellers for future returns are related to fundamental news. Using shorting activity from the previous week, we find that about a *quarter* of the overall underperformance of heavily shorted stocks can be attributed to earnings and analyst-related events. Is this a big number? We think so, especially given that we are in some sense tying our hands by using a short week-long 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 information can affect stock prices on days other than our event days, in which case our methodology would not assign the stock's underperformance to earnings or analyst-related events.

Next, we carefully look into the nature of the information advantage that the short-sellers might possess, and we provide several unique and interesting findings. Between public news and private news, consistent with Engelberg, Reed, and Ringgenberg (2012), we find short sellers are capable of processing publicly available news and trade on it. More importantly, short sellers use additional private information that is orthogonal to public information to boost their performance. Between short-sellers and analysts, we show that short sellers' ability to predict future returns is substantial and significant after we control for information embedded in earnings news and analyst forecast and recommendation changes, indicating that short sellers do much more than simply trading in advance on information gleaned from analysts. In addition, we observe no reversal pattern in short-seller's predictive power for future returns, indicating that the information they possess are more likely to be long-term information.

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 is possessed by analysts. Together, these results indicate that short sellers make valuable marginal contributions to price discovery in US equities that go beyond the efforts of analysts.

Supplementary Material

Supplementary data are available at *Review of Finance* online.

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