WHAT DO SHORT SELLERS KNOW?

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ABSTRACT

Using a five-year panel of proprietary NYSE short sale order data, we investigate the sources of short sellers' informational advantage. Heavier shorting is found the week before negative earnings surprises, analyst downgrades, and downward revisions in analyst earnings forecasts. The biggest effects are associated with analyst downgrades. While earnings and analyst event days constitute only 11.6% of days in our sample, they account for over 23% of the overall underperformance of heavily shorted stocks. Earnings and analyst release days are particularly important for individual short sellers; these days account for 43% of the overall underperformance of stocks that are heavily shorted by individuals. The results are not explained by factor timing and they indicate that short sellers are well-informed about upcoming earnings. Moreover, they possess information about fundamentals similar to that used by analysts.

1. Introduction

Financial economists generally consider short sellers to be important contributors to efficient stock prices. Researchers generally point to the uncovering of the Enron fraud and similar events as evidence of the value of short sellers. However, such frauds are fairly rare occurrences, and yet shorting activity is quite widespread, accounting for as much as 40% of trading volume in recent years, even as trading volume has exploded. It seems particularly important to better understand what animates this large component of equity trading.

In contrast to financial economists, non-economists tend to be much more skeptical of the value of short sellers. There are a variety of reasons for this skepticism, some more valid than others. Evidence on the nature of short sellers' information and the sources of their excess returns might help researchers and other observers better understand the contributions of short sellers.

In this paper, we investigate the sources of short sellers' information advantage by combining a five-year panel of proprietary NYSE short sale order data with data on earnings releases and analyst actions. We use these data to investigate and quantify the sources of short sellers' informational advantage. We find heavier shorting activity the week before negative earnings surprises, analyst downgrades, and downward revisions in analyst earnings forecasts, with the biggest effects associated with analyst downgrades. Our main goal is to see how much of short sellers' information advantage can be attributed to this type of fundamental information. In that sense, our exercise is similar to Roll (1988), who seeks to identify the ex post relationship between news and asset price moves.

We find that while earnings and analyst event days constitute only 11.6% of the days in our sample, these days account for over 23% of the overall underperformance of heavily shorted stocks. We also have some information about different groups of short sellers. In particular, we can distinguish between individuals, institutions, and NYSE member firms trading for their own account. It is possible that different groups of short sellers are trading on different types of information. For example, institutions may be trading based on fundamental information, while member firm proprietary trading desks may be trading based on their knowledge of order flow in a stock. Interestingly, we find that earnings and analyst release days are particularly important for individual short sellers; these days account for 43% of the overall underperformance of stocks that are heavily shorted by individuals. The results indicate that short sellers are well-informed about upcoming earnings and possess information about fundamentals similar to that used by analysts.

The rest of the paper is structured as follows. Section 2 discusses related literature. Section 3 discusses the shorting data as well as the First Call earnings and analyst data. All of the results are provided in Section 4, including a number of additional robustness tests. Section 5 discusses and interprets the results, and Section 6 concludes.

2. Related literature

Many papers show that short sales or short positions are informative about future stock price moves (for example, Boehmer, Jones, and Zhang, 2008 and Asquith, Pathak and Ritter, 2005) and that prices incorporate short sellers' information quickly (Boehmer and Wu, 2010). Several other papers have investigated the nature of the information possessed by short sellers. For example, Christophe, Ferri, and Angel (2004) find that negative earnings surprises are preceded by abnormal short selling, though Daske, Richardson, and Tuna (2005) do not find that short sellers anticipate negative earnings shocks. Francis, Venkatachalam, and Zhang (2005) show that short sellers are able to predict downward analyst forecast revisions, while Desai, Krishnamurthy, and Venkataraman (2006) find that short sellers are able to anticipate earnings restatements. Dechow et al. (2001) show that short sellers target stocks with low book-to-market ratios, a possible measure of overvaluation. Engelberg, Reed, and Ringgenberg (2010) use a news database to argue that short sellers earn excess returns by quickly and effectively processing and responding to published news. Fox, Glosten, and Tetlock (2010) measure the negativity of firm news based on a content analysis of the Dow Jones Newswires, and find that on trading days when there is an abnormally high level of short selling, there is a heightened level of negative news about the issuer in the non-trading hours that follow. In any case, most such papers focus on simply demonstrating that a particular kind of fundamental news is anticipated by short sellers. In contrast, we are primarily interested in assessing how much of short sellers' overall information advantage can be attributed to earnings and analyst-related news.

NYSE account types have been used in a handful of other related papers. For example, Kaniel, Saar, and Titman (2008) use NYSE account types to investigate investor sentiment, and

Boehmer and Kelley (2009) use account types to investigate the relationship between the informational efficiency of prices and the amount of institutional trade.

Older papers generally study short interest data, but more recent work focuses on shorting flow. Other authors who study shorting flow data include Christophe, Ferri, and Angel (2004), Daske, Richardson, and Tuna (2005), and Diether, Lee, and Werner (2008), but all these panels are much shorter than ours and do not distinguish among different trader types.

3. Data

The sample consists of all NYSE system order data (SOD) records related to short sales from October 23, 2000 through September 30, 2005. The sample begins on the date that Reg FD becomes effective, ensuring that there is a uniform regulatory environment governing information dissemination by public companies. Using CUSIP numbers and tickers, we cross-match the list of NYSE stocks to CRSP and retain only common stocks (those with a CRSP *shrcd* equal to 10 or 11), which means we exclude securities such as warrants, preferred shares, American Depositary Receipts, closed-end funds, and REITs. This leaves us a daily average of 1,265 NYSE-listed common stocks.

During our sample period, most short selling on the NYSE was subject to the uptick rule, and each day we aggregate all such short sales in each stock. According to Rule 10a-1(a)(1) of the Securities and Exchange Act of 1934, a listed security could only be sold short (a) at a price above the price at which the immediately preceding sale was effected (known as a plus tick), or (b) at a price equal to the last sale price if it is higher than the last different price (known as a zero-plus tick). Short sales were not permitted on minus ticks or zero-minus ticks. A few short sales were exempt from the uptick rule. These include relative-value trades between stocks and convertible securities, arbitrage trades in the same security trading in New York vs. offshore markets, and short sales initiated by broker-dealers at other market centers as a result of bona fide market-making activity. These exempt short sales are marked separately in the system order data, and their share volume amounts to 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.

We measure daily shorting flow as the fraction of volume executed on the NYSE in a given stock on a given day that involves a system short seller. During our sample period shorting via system orders averages about 14% of overall NYSE trading volume (equal-weighted across stocks). Recall that these are lower bounds on the incidence of shorting at the NYSE, since our sample does not include specialist short sales or short sales that are handled by a floor broker.

These shorting flow data are much finer than traditional coarse monthly short interest data, making it possible to investigate changes in shorting activity at shorter horizons. However, it is worth pointing out that we do not observe short covering in our dataset. We can see additions to short interest, but not the subtractions, so we are unable to use our data to impute the level of short interest between the monthly publication dates. Also, we do not observe all of the short sales that take place. We observe all short sale orders that are submitted electronically or otherwise routed through the NYSE SuperDOT system. We do not observe short sales that are manually executed on the NYSE trading floor by a floor broker. Also, we do not observe short sales that take place away from the NYSE. Short sales executed on regional exchanges, in the upstairs market, or offshore are not included in this sample, nor are shorts created synthetically using total return swaps or other derivatives. Based on aggregate data released by the NYSE, it appears that our data represent about 80% of NYSE shorting activity.

Using our data, we can also identify the type of account that submitted the short sale order. We partition the sample into four different types of accounts:

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

We further partition institutional and proprietary short sales depending on whether the order is part of a program trade. A program trade is defined as simultaneously submitted orders to trade

15 or more securities having an aggregate total value of at least $1 million. There is some incentive for institutions to batch their orders to qualify as a program trade, because program trades are often eligible for commission discounts from brokers.

Account types are coded by the submitting broker-dealer based on a set of regulations issued by the NYSE. While they are generally unaudited, these classifications are important to the NYSE and to broker-dealers because they are required for a number of compliance issues. For example, NYSE Rule 80A suspends certain types of index arbitrage program trading on volatile trading days, and account type classifications are important for enforcing this ban. The specialist and traders on the floor do not, however, observe this account type indicator for an incoming system order. In general, these market participants observe only the type, size, and limit price (if applicable) of an order. It is possible for the specialist to research a particular order in real-time and obtain information about the submitting broker. However, this takes a number of keystrokes and requires a certain amount of time, and given the pace of trading on the exchange and our conversations with specialists, we conclude that this additional information is seldom if ever observed before execution.

In contrast, during our sample period the specialist is generally aware that a particular system sell order is a short sale. For compliance with the uptick rule, short sales must be marked, and during our sample period software at the trading post flags every short sale order to help the specialist comply with the uptick rule.

The First Call historical database from Thomson Financial is the source of earnings and analyst-related news. This is a widely used, comprehensive database of analyst earnings forecasts, stock recommendations, and actual earnings announcements, among other items. Actual per share earnings numbers are adjusted to exclude any unusual items that a majority of the contributing analysts deem non-operating or non-recurring, so that the actual numbers can be compared to analyst earnings estimates. We track changes in the consensus estimate for the closest quarter and fiscal year. Forecast revisions are measured using the change in the consensus estimate for the relevant quarter.

We also examine manager earnings guidance, which refers to events where the company or management discusses the firm's earnings before the earnings are actually announced. This can take the form of a point forecast, a range for earnings, or language suggesting that earnings will be above or below analysts' expectations. We use the CIG (Company Issued Guidelines)

Description Code in the First Call database, which indicates whether the manager guidance is a positive or negative earnings surprise.

4. Econometric specifications and results

A. Summary statistics

Table 1 provides some summary statistics on the relative prevalence of shorting by each of the six account types. The majority of NYSE shorting is by institutions doing non-program trading. Depending on the particular cross-sectional subsample being considered, institutional non-program shorting represents 57% to 62% of the total amount of measured shorting activity. The next biggest category is institutional shorting that is a part of a program trade. This activity accounts for between 12% and 16% of overall shorting. Overall, institutions account for about three-quarters of shorting activity.

Shorting by individuals is notably rare, accounting for less than 1.5% of overall shorting volume. This is not peculiar to shorting; overall NYSE order flow exhibits similar patterns (see, for example, Boehmer and Kelley, 2009). Individuals account for only a small amount of overall trading volume, but orders from individuals are particularly rare at the NYSE during our sample period because most brokerage firms either internalize retail orders in active stocks or route these orders to regional exchanges or third-market dealers in return for payment.

B. Shorting and future earnings news

We begin by investigating whether short sellers anticipate earnings surprises and other earnings-and analyst-related news. For different kinds of earnings and analyst events in NYSE stocks, we estimate pooled regressions of the form:

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

where $UE_{i,t}$ is a particular type of earnings-related news for firm *i* on day *t*. We consider five different types of earnings and analyst-related news: earnings announcements, guidance from company management about future earnings, earnings restatements, analyst recommendation changes, and analyst forecast revisions. For earnings announcement news, *UE* is standardized unexpected earnings per share, defined as the announced EPS for the quarter less the corresponding consensus EPS forecast scaled by the standard deviation of earnings estimates for the quarter. For manager guidance, UE = 1 for upward guidance and UE = –1 for downward guidance. For earnings restatements, UE is restated earnings less original earnings per share. For buy/sell recommendation changes, UE is the number of notches of the change, where a recommendation is classified as strong buy, buy, neutral, sell, or strong sell. For analyst forecast changes, UE is the current consensus EPS forecast less the last consensus forecast.

The explanatory variable of interest is $short_{i,t\text{-}5,t\text{-}1}$, which is shorting by the applicable group in stock i during the interval [t-5, t-1] as a fraction of overall trading volume. We focus on the previous week's shorting activity to match the approach in Boehmer, Jones, and Zhang (2008). Results based on shorting during the previous 20 trading days are qualitatively similar. Other control variables include $lnsize_{i,m\text{-}1}$, the previous month's log market capitalization, the book-to-market ratio $BM_{i,m\text{-}1}$ from six months ago, the previous month's daily return volatility $\sigma_{i,m\text{-}1}$, the return over the past six months $ret_{i,m\text{-}6,m\text{-}1}$, and $turnover_{i,m\text{-}1}$, which is last month's trading volume as a fraction of outstanding shares.

We use a regression approach in order to control for various stock and firm characteristics that have been shown to affect expected returns. All explanatory variables except past returns are normalized to have mean zero and unit variance each period. Shorting becomes somewhat more prevalent as our sample period progresses, so this normalization is designed to mitigate the effects of any trend in this or any other explanatory variable that might otherwise affect inference. Normalization also makes it easier to interpret the coefficients.

Table 2 displays the coefficients on the shorting variable. Each entry in the table represents a different regression that substitutes different earnings or analyst measures as the dependent variable, and shorting by various groups as the relevant explanatory variable. The first row addresses earnings announcements, for example. Stocks with negative earnings surprises experience more overall shorting activity over the previous five trading days, with a t-statistic of 2.16. Only institutional non-program shorting is marginally reliably higher the week before a negative earnings surprise; the relationship between shorting and unexpected earnings is not reliably negative for any of the remaining account types (except for the "Other" category, which we treat as a residual group).

In results not reported, shorting activity does not demonstrate any ability to predict either manager guidance or earnings restatements. The latter result is interesting, because other authors have found a relationship between short interest and earnings restatements. The difference could be due to the shorting flow measure used here. It could be that short interest is able to pinpoint shorting by investors employing long-term fundamental analysis, and perhaps it is those investors who are most able to identify firms with very low quality earnings. Said another way, we only look at shorting in the week before an earnings restatement. If the relevant short sellers establish their positions well in advance of these restatements, our statistical tests would not be able to identify any link.

In contrast, there is heightened shorting activity in the week before downward analyst recommendation changes (t-stat = 6.77). There is also heightened shorting in the week before downward analyst forecast revisions (t-stat = 2.68). As in the case of earnings announcements, these results are mostly driven by institutional non-program shorting, but both types of analyst actions are preceded by heavy individual shorting (t-stats = 2.50 and 4.60 for recommendation changes and forecast revisions, respectively).

For earnings announcements, we also investigate whether the association between shorting and unexpected earnings depends on analyst dispersion. Greater dispersion is generally considered an indicator of greater disagreement among investors, and in the presence of shorting constraints, greater disagreement generally leads to greater overpricing.[1] Thus, if there are constraints, more disagreement could lead to a larger price decline for a given amount of additional shorting. The specification that we estimate is:

$$UE_{i,t} = b_0 + (c_0 + c_1 disp_i) short_{i,t-5,t-1} + \gamma X_{it} + e_{i,t}$$

where *disp* is the standard deviation of analyst forecasts just prior to the earnings announcement, and X_{it} is the same set of control variables as before: market cap, return volatility, book-to-market, turnover, and returns over the previous six months. The shorting constraint model implies that $c_1 < 0$, as the relationship between shorting and the earnings surprise should be more negative when there is greater disagreement.

The results are in Table 3, and the coefficient on analyst dispersion is statistically indistinguishable from zero. The results suggest that greater analyst dispersion does not affect the relationship between the earnings surprise and the previous week's shorting activity. But

[1] See, for example, Miller (1977), Harrison and Kreps (1978), Duffie, Garleanu, and Pedersen (2002), and Scheinkman and Xiong (2002).

perhaps this is not such a big surprise after all. Greater analyst dispersion could simply reflect greater uncertainty about what is going to happen, and it might be that even well-informed short sellers are relatively unable to divine the upcoming earnings surprise.

C. Shorting and future returns

The heart of the paper is a decomposition of the excess returns subsequent to shorting activity into components associated with various types of earnings and analyst news. We begin with a simple benchmark regression similar to the one in Boehmer, Jones, and Zhang (2008):

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

where we include the usual control variables and normalize shorting to have mean zero and unit variance on each trading day. We run a regression using all short sales, and then we rerun the benchmark regression using shorting by each account type. This regression measures the overall information content of short sellers. That is, if short sellers are informed, the stocks they short heavily should underperform the stocks they avoid shorting.

The results are in Table 4. The benchmark regression is denoted as Regression I in each panel, and Panel A contains the results for all short sales. A cross-sectional increase in weekly shorting of one standard deviation is associated with average daily excess returns over the next two days that are 3.80 basis points lower. The t-statistic is a very large 9.76, and the economic significance is quite strong as well, as 3.80 basis points per day equates to almost 10% per year without compounding. Short sales continue to be informative at longer horizons. Over the next 20 trading days, for example, the coefficient is -2.48 basis points, which corresponds to 49 basis points of cumulative return over this interval of approximately one month. In the rest of this section, however, we focus on the short-horizon returns from day t to day $t + 1$, because these returns are easiest to assign to a particular news bin.

Shorting by each account type is reliably informed, though some account types seem to be trading on stronger signals on average. For instance, a cross-sectional one-standard deviation increase in individual short sales is associated with average daily returns over the next two days that are just 1.26 basis points lower. It is interesting to note that the information in individual short sales appears to be quite short-lived, as the underperformance of stocks that are heavily shorted by individuals is no longer significant at the 10-day or 20-day horizon. Over the short horizon, non-program shorting by institutions is the most informed, with a corresponding 2-day return number of 3.85 basis points per day. Program shorting by institutions is the least informed, with each standard deviation affecting returns by only 0.94 basis points per day.

Next we decompose the short sellers' private information by identifying and separating out days on which there is earnings or analyst-related information. Specifically, we set an indicator variable d_t equal to one if day t has an earnings announcement, a change in any analyst's buy/sell recommendation, or a change in any analyst's earnings forecast. This happens on 11.6% of the stock-days in our sample. We then estimate the following regression:

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

with a focus on the interacted coefficient c_0, which is the incremental stock return associated with the previous week's shorting activity that is due to earnings news or analyst changes.

As before, we estimate this regression using all short sales as well as short sales initiated by various account types. This is reported as Regression II in Table 4, and Panel A contains the results for all NYSE system short sales. When there is no earnings or analyst-related news, b_1 is the estimate of the effect on returns of a one-standard deviation increase in shorting. This coefficient is 3.36 basis points per day, with a t-statistic of 8.72. On days with earnings or analyst-related news, the effect of shorting is $b_1 + c_0$, and this quantity equals 3.36 + 3.84 = 7.20 basis points per day, which is more than double the coefficient on non-news days. The incremental effect on earnings/analyst news days is also strongly statistically significant, with a t-statistic of 5.45.

These results show that a significant amount of short sellers' information is incorporated into price within a week via an earnings announcement or an analyst report. There is another way to gauge the importance of earnings and analyst news, and that is to decompose the overall underperformance of heavily shorted stocks into two components: earnings news-related and other. To do this, we make use of the fact that 11.6% of the days in the sample have an earnings or analyst announcement. The overall underperformance associated with a one-standard deviation increase in short sales is given by:

11.6% * (3.36 + 3.84) + (1 – 11.6%) * 3.36 = 3.80 basis points per day

The first term reflects the portion of short-sellers' information associated with earnings and analyst announcement days, or in this case 22% of the overall underperformance of heavily shorted stocks.

We can also use the same approach to decompose the information in shorting by specific account types. For example, Panel C reports the results for institutional non-program shorts. On a non-news day, the relevant coefficient is 3.31 basis points per day, and the incremental effect on announcement days is 4.64 basis points, for a total effect of 3.31 + 4.64 = 7.95 basis points per day. Thus, it appears that even more of institutional short-sellers' advantage accrues on days where there is an earnings announcement, an analyst forecast revision, and/or an analyst recommendation change. These days account for 24% of the overall underperformance of heavily shorted stocks.

Shorting by individuals is also noteworthy in this context. These results are in Table 4 Panel B, and they show that individual shorting is particularly informative about returns on earnings and analyst news days. On regular days, an additional standard deviation unit of shorting by individuals is associated with returns that are 0.85 basis points lower. On news days, the corresponding figure is 0.85 + 4.03 = 4.88 basis points. Though these days account for only 12% of the total, these earnings and analyst news days account for 43% of the overall underperformance of stocks that are heavily shorted by individuals.

In contrast, earnings and analyst event days do not seem to be particularly important days for all account types' short selling. Consider non-program proprietary trading by NYSE member firms, for example. As reported in Panel E of Table 4, underperformance on news days is statistically indistinguishable from underperformance on non-news days. Earnings announcements and changes in an analyst's outlook do not appear to be particularly important catalysts for excess returns to shorting by these particular accounts.

Which kind of earnings or analyst news is most closely associated with short sellers' information? As noted above, we have information on three different information releases: earnings announcements, analyst recommendation changes, and analyst forecast revisions. Analyst forecast revisions account for the bulk of the information releases, as they occur on 9.9% of the stock-days in our sample. Earnings announcements occur on 1.3% of the stock-days in our sample, and analyst recommendation changes are found on 2.4% of the stock-days. Note that these add up to more than the 11.6% number reported earlier, because occasionally multiple types of information releases occur on the same trading day.

To investigate the different types of news, we estimate pooled regressions of the following form:

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

where d_{1t} = 1 if day t has an earnings announcement and zero otherwise, d_{2t} = 1 iff on day t any analyst changes her buy/sell recommendation, and d_{3t} = 1 iff on day t any analyst changes her earnings forecast. These are reported as Regression III in the various panels of Table 4.

Panel A has the results for all short sales. Based on the point estimates, short sales are indeed more informative about future returns on each type of news day. But some of the incremental effects are close to zero or statistically indistinguishable from zero. For instance, one more standard deviation of shorting is associated with only 0.15 basis points of additional daily underperformance (t = 0.20) on an analyst forecast revision days, as compared to a day without earnings or analyst news. Note that the underperformance of heavily shorted stocks on analyst forecast revision days is still substantial. It is just not very different from the underperformance on ordinary days (3.57 basis points on forecast revision days vs. 3.42 basis points on non-news days). On days when earnings are announced, an additional standard deviation of shorting during the previous week is associated with a daily underperformance of 3.42 + 5.37 = 8.79 basis points. But these days are particularly volatile, and ultimately we are unable to reject the hypothesis that the underperformance on any earnings announcement day differs from that of non-news days (t = 1.45).

The biggest return effects are on days with an analyst recommendation change. The relevant coefficient on these days is 3.42 + 11.74 = 15.16 basis points, which is statistically different (t= 4.76) from and over four times as large as the coefficient of 3.42 on non-news days. Of course, analyst recommendation changes are not that prevalent, occurring only about once every 40 trading days on average. Thus, while heavily shorted stocks dramatically underperform on days when an analyst recommendation changes, only about 10% of the overall underperformance accrues on these days. Another 10% of the overall underperformance accrues on days with an analyst forecast revision, and only about 3% of the overall underperformance occurs on earnings announcement days.

These qualitative results are not always the same when we examine shorting by various account types. For example, the statistical tests result in the same inference for both individual shorting and institutional non-program shorting: the marginal effects are significant on recommendation change days but are insignificant on earnings announcement and analyst forecast revision days. The most notable difference is that the previous week's proprietary program shorting by NYSE members is quite informative about returns on earnings announcement days. An additional standard deviation of shorting by this account type is associated with 1.02 + 8.13 = 9.15 basis points of average daily underperformance immediately following an earnings announcement.

To confirm that the results are stationary throughout the sample period and are not being driven by a small number of outliers, we follow a Fama-MacBeth (1973) approach and estimate this last regression about 60 times, each time using data from a different calendar month. In Figure 1, we graph the interaction terms c_1, c_2, and c_3 for each month. We do this for both 2-day returns [t, t+1] as well as the somewhat longer-term [t, t+20] returns. The graphs demonstrate that the results are not driven by outliers, and the results do not appear to diminish or grow larger over time. The regressions indicate that the most reliable incremental relationship between shorting and future returns occurs on analyst recommendation change days, and the graphs bear this out. For the regressions using two-day returns as the dependent variable, there are only about 10 months where the coefficient on the interaction term has the wrong (positive) sign.

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

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

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

The results are in Table 5, and they indicate that factor timing explains almost none of shorting's cross-sectional return predictability. To see this, we compare model I (similar to the one estimated in Table 4) to model I-FF, which adds interactions between the Fama-French factor sensitivities and shorting. We make a similar comparison between model II, which breaks down the news event by type, and the augmented model II-FF. There is some evidence that factor timing explains part of short sellers' return on non-news days, as indicated by the decline in the b_1 coefficient going from model I to I-FF or from model II to II-FF. But this result applies primarily to the 2-day and 6-day returns, and vanishes for the other horizons. Most importantly, factor timing has essentially no effect on shorting returns on news days - the coefficients on the shorting variable interacted with the various dummies are virtually unchanged from the earlier results. This is true across all holding periods and for all account types. In fact, the coefficients on the interacted betas are almost always insignificantly different from zero, indicating that short sellers are probably not varying their factor loadings in a way that contributes anything to their excess returns. To put it more precisely, we cannot reject the hypothesis that factor timing accounts for none of the relationship between shorting and future returns in the cross-section, and especially not on news days.

While analyst recommendation changes appear to be the most important days for the underperformance of heavily shorted stocks, ultimately we do not know the exact signals being used by short sellers. There are a number of possibilities, and the interpretation of the results differs somewhat across these possibilities. In our view, the most likely explanation is that short sellers have similar fundamental information to the analyst, both groups observe a change in the share price that appears unwarranted, and both groups act in response. If the share price goes up, for example, short sellers short, and analysts reduce their recommendations. Another possibility is that short sellers learn company fundamental information at the same time as the analyst, perhaps from conference calls or meetings with management, and both act accordingly. If material information is not communicated in these private meetings, this kind of information transmission would not run afoul of Reg FD. Or, perhaps short sellers are tipped off that a recommendation change is coming. While most analyst firms have internal policies against such tipping, Irvine, Lipson, and Puckett (2007) point out that the behavior is in a legal gray area, and they find evidence in institutional trades that is consistent with tipping by analysts. One other possibility is that the tipping goes in the opposite direction. Hedge funds or other investors may collect private information or conduct original research or analysis and then share the results with analysts. Analysts then adjust their recommendations or forecasts accordingly, and this affects share prices. A malevolent version of this could arise if the tipper is attempting to manipulate share prices via false information, either with or without the knowledge of the analyst or research firm. While it seems unlikely that this practice is widespread, it may be important in certain instances. For example, Overstock.com filed suit against Rocker Partners (a hedge fund) and Gradient Analytics (a research firm) in 2005 making exactly this accusation, and Rocker settled the suit in 2009 for a reported \$5 million.[2]

D. Shorting after earnings news and analyst information releases

Short sellers are generally contrarian. For example, Diether, Lee, and Werner (2008) find that shorting activity increases in the days and weeks after positive stock returns. In this subsection, we investigate how short sellers react following earnings announcements and analyst information releases. This may shed light on short sellers' beliefs about the markets' speed of adjustment to new information, and may specifically relate to post earnings announcement drift (PEAD). If short sellers become momentum traders after a certain type of announcement, for example, it suggests that they do not believe that markets have yet fully incorporated that information.

Regressions in this section are of the form:

$$short_{i,t+1,t+5} = b_0 + b_1 short_{i,t-5,t-1} + c_1 ret_{i,t-7,t-2} + c_2 ret_{i,t-1,t} + \gamma X_{it} + e_{i,t}$$

where event day zero is the earnings announcement or analyst information release date. Most of the control variables have already been discussed previously, and all variables other than stock returns are normalized to have mean zero and unit variance each period. The explanatory variables of interest include shorting over the previous five trading days, the stock return over the

[2]"Rocker Pays \$5 Million to Overstock.com to Settle Lawsuit", Overstock.com press release, December 8, 2009.

interval [t – 7, t – 2], and the stock return over the interval [t – 1, t]. Note that this last stock return is the only variable measured at time t, and its regression coefficient gauges whether short sellers are on average momentum or contrarian investors around the event being studied. A negative coefficient on the [t – 1, t] return means that there is more shorting following a stock price decline, and it indicates that shorts are following a momentum strategy. Given previous results, the more typical result would be a positive coefficient, indicating contrarian trading behavior by short sellers.

Table 7 Panel A is the benchmark specification, estimating the model for all days in the sample. The coefficient on the most recent return is always positive and strongly statistically significant, consistent with contrarian behavior by short sellers. The results are in the same direction and strongly statistically significant for every short seller account type.

The results are slightly different in the week after an earnings announcement. Panel B of Table 7 shows that short sellers are only about half as contrarian on these days, based on the estimated coefficient on the most recent return. Short sellers do not switch over to being momentum traders, but they are no longer as strongly contrarian. The results are consistent with those in Boehmer and Wu (2010), who show that short sellers take advantage of PEAD. As a result, this tilt in trading somewhat undoes the contrarian bias that short sellers normally exhibit.

Similarly, short sellers become somewhat less contrarian after the two analyst-related events: recommendation changes (Panel C) and analyst forecast changes (Panel D). Again, this is consistent with a change in trading patterns by short sellers to take advantage of underreaction to these information events. This tilt in trading makes sense, since Womack (1996) and other previous research demonstrates that the market does indeed incorporate this information only gradually.

Overall, this approach is in the spirit of Mitchell, Pulvino, and Stafford (2002), in that it can help researchers understand how a particular set of sophisticated investors trades in response to well-known event-related expected return patterns.

5. Discussion

The cross-section of shorting predicts the cross-section of future returns, and earnings and analyst-related news accounts for about a quarter of short sellers' overall information advantage. Is this a big number? We think so, especially given that we are in some sense tying our hands by using a short weeklong horizon in this analysis. Readers might instead view the glass as three-quarters empty, since 75% of the underperformance of heavily shorted stocks remains unexplained. In some sense, we sympathize with that view, as our eventual goal (discussed further in the concluding section) is to identify other specific sources of short sellers' information advantage.

Note that our empirical approach partitions by trading day. For example, the entire stock return on the day of an earnings announcement is ascribed to earnings news. There could be other types of news that are in the short sellers' information set and are incorporated into price that same day. If so, underperformance due to that additional information would be attributed erroneously to earnings news. However, our empirical approach is likely to miss a substantial amount of earnings-related information that is being used by short sellers in their trading activity. Earnings-related news can affect stock prices on days other than our event days, in which case our methodology would not assign the stock's underperformance to earnings or analyst-related news.

It is important to emphasize that at the time of our sample, these shorting flow measures were proprietary data collected by the NYSE and were not sold or otherwise shared with any market participant, which means that other traders could not use the regression results here to inform their trading strategies. For this reason, we always refer to our results as indications of the informativeness of shorting. We cannot measure the actual returns to private information possessed by various groups of short sellers, because we do not observe the entire trading history of short-sellers. We would be able to calculate exact excess returns to a class of short sellers only if we knew all of the shorts, all of the covering trades, and the various additional costs associated with a shorting strategy, including commissions and the costs associated with borrowing shares.

Trading venues and large broker-dealers have now started to sell similar data on shorting activity in near real-time. In addition, from 2005 through the middle of 2007, the Securities and Exchange Commission required trading venues to provide intraday data on all executed short sale orders. And starting in late 2009, the Securities and Exchange Commission now requires all trading venues to post overnight a daily summary of shorting activity in each stock. Except for the account type breakdowns, this is exactly the level of aggregation that we use in our analysis in this paper, so once enough time has elapsed to build a panel of reasonable length, it should be possible to replicate and extend this analysis in a more recent sample.

Our results also have modest trading implications. The results suggest that other investors should focus on shorting activity in the week prior to scheduled earnings announcements. That shorting activity could provide some insight into the direction of the earnings surprise and the stock price reaction on that day.

6. Conclusions

In this paper, we consider the trading of short sellers around different types of earnings and analyst-related news. Previous work has found that short sellers are well-informed, and we confirm that heavily shorted stocks substantially underperform lightly shorted stocks over the following week. For example, each standard deviation of additional shorting in the cross-section leads to returns one week later that are almost 10% lower on an annualized basis. When combined with earnings and analyst data, our daily panel of NYSE short sales allows us to examine the sources of these excess returns at various horizons. When we examine returns one day to one week following shorting activity, we find that about a quarter of the underperformance of heavily shorted stocks can be attributed to earnings announcements and analyst-related news releases.

While we have identified the catalysts for about one-quarter of the underperformance of heavily shorted stocks, 75% of the underperformance remains unexplained. In future work, our goal is to improve the fraction of underperformance that we can explain. Earlier work suggests that short sellers trade on the value effect and post earnings-announcement drift, and we intend to assess the importance of these strategies to the overall underperformance of heavily shorted stocks. We also think that short sellers benefit from providing liquidity as contrarian investors, and it would be useful to assess the importance of short-term negative autocorrelation and/or positive cross-autocorrelation to short sellers, along the lines of Lehmann (1990) and Lo and MacKinlay (1991). In particular, the framework of Khandani and Lo (2010) might be useful in assessing the contribution of these kinds of quant strategies to the overall informativeness of short sales.

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Table 1. Summary statistics

The sample consists of all common stocks listed on the NYSE October 2000 to September 2005. 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 return.

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

Table 2. Shorting and future earnings/analyst news

For earnings-related events in NYSE stocks from October 23, 2000 through September 30, 2005, pooled regressions of the form:

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

where $UE_{i,t}$ is the specified type of earnings-related news for firm *i* on day *t*. For earnings announcement news, *UE* is standardized unexpected earnings per share. For manager guidance, *UE* = 1 for upward guidance and *UE* = –1 for downward guidance. For earnings restatements, *UE* is restated earnings less original earnings per share. For buy/sell recommendation changes, *UE* is the number of notches of the change, where a recommendation is classified as strong buy, buy, neutral, sell, or strong sell. For analyst forecast changes, *UE* is the current consensus EPS forecast less the last consensus forecast.

The explanatory variable of interest is $short_{i,t\text{-}5,t\text{-}1}$, which is shorting by all investors or the applicable group (individual, institutional non-program, etc.) in stock *i* during the interval [*t*-5, *t*-1] as a fraction of overall trading volume. Other control variables include $lnsize_{i,m\text{-}1}$, the previous month's log market capitalization, the book-to-market ratio $BM_{i,m\text{-}1}$ from six months ago, the previous month's daily return volatility $\sigma_{i,m\text{-}1}$, the return over the past six months $ret_{i,m\text{-}6,m\text{-}1}$, and $turnover_{i,m\text{-}1}$, which is last month's trading volume as a fraction of outstanding shares. All explanatory variables except past returns are normalized to have mean zero and unit variance each period.

	all		Indi.		Inst. np		Inst. p		Prop. np		Prop. p		other	
	Coef.	T	Coef.	t	Coef.	t	Coef.	T	Coef.	t	Coef.	t	Coef.	t
Earnings announcements	-0.202	-2.16	0.027	0.41	-0.207	-1.89	-0.131	-1.46	-0.071	-1.41	-0.109	-1.47	0.178	4.39
Recommendation changes	-0.086	-6.77	-0.036	-2.50	-0.100	-7.67	-0.005	-0.53	-0.027	-2.24	-0.024	-2.59	-0.022	-2.26
Analyst forecast revisions	0.000	-2.68	-0.001	-4.60	-0.001	-3.83	0.000	-0.20	0.000	1.51	0.001	3.56	0.000	0.16

Table 3. The effect of analyst dispersion on the relationship between shorting and future earnings news

For earnings events in NYSE stocks from October 23, 2000 through September 30, 2005, pooled regressions of the form:

$$UE_{i,t} = b_0 + (c_0 + c_1 disp_i) short_{i,t-5,t-1} + b_1 \log size_{i,m-1} + b_2 BM_{i,m-6} + b_3 \sigma_{i,m-1} + b_4 ret_{i,m-6,m-t} + b_5 turnover_{i,m-1} + e_{i,t}$$

where *disp* is the dispersion of analyst forecasts, measured as the cross-sectional standard deviation in quarterly EPS estimates at the time of the earnings release. *UE* is standardized unexpected earnings per share. See the Table 2 caption for other variable definitions.

	all		Indi.		Inst. np		Inst. p		Prop. np		Prop. p		other	
	Coef.	t	Coef.	t	Coef.	t	Coef.	t	Coef.	t	Coef.	t	Coef.	t
c0	-0.196	-2.01	0.040	0.52	-0.200	-1.73	-0.130	-1.43	-0.070	-1.39	-0.108	-1.47	0.184	4.29
c1	-0.152	-0.74	-0.366	-0.81	-0.201	-0.82	-0.007	-0.17	-0.029	-0.10	-0.039	-0.15	-0.187	-0.92

Table 4. Sources of the excess return from shorting: fundamental news vs. non-news

Three separate pooled regressions for NYSE stocks from 23 Oct 2000 through 30 Sep 2005:

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

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

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

The dependent variable $r_{i,t,t+k}$ is the average daily return for firm i over the interval [t, $t+k$] in percent in excess of the riskless rate. Indicator variables include $d_{1t} = 1$ if day t has an earnings announcement and zero otherwise, $d_{2t} = 1$ if on day t any analyst changes her buy/sell recommendation, $d_{3t} = 1$ if on day t any analyst changes her earnings forecast, and $d_t = 1$ if any of the above three events occur on day t. Table 2 describes the other explanatory variables, including the vector of control variables $X_{i,t-1}$. Standard errors are clustered by calendar quarter.

Panel A. all shorts

Reg		[t, t+1]		[t, t+5]		[t,t+10]		[t,t+20]	
		Coef.	t	Coef.	t	Coef.	t	Coef.	t
I	b_1	-0.0380	-9.76	-0.0312	-10.06	-0.0294	-10.16	-0.0248	-9.65
II	b_1	-0.0336	-8.72	-0.0296	-9.79	-0.0290	-10.07	-0.0249	-9.60
II	c_0	-0.0384	-5.45	-0.0140	-3.34	-0.0036	-1.26	0.0013	0.64
III	b_1	-0.0342	-8.76	-0.0296	-9.75	-0.0291	-10.14	-0.0250	-9.71
III	c_1	-0.0537	-1.45	-0.0250	-1.65	-0.0115	-1.30	-0.0084	-1.66
III	c_2	-0.1174	-4.76	-0.0436	-3.57	-0.0202	-2.92	-0.0075	-1.33
III	c_3	-0.0015	-0.20	-0.0013	-0.32	0.0034	1.03	0.0051	2.85

Panel B. individual shorts

Reg		[t, t+1]		[t, t+5]		[t,t+10]		[t,t+20]	
		Coef.	t	Coef.	t	Coef.	t	Coef.	t
I	b_1	-0.0126	-3.03	-0.0066	-2.05	-0.0033	-1.19	-0.0025	-1.13
II	b_1	-0.0085	-2.51	-0.0044	-1.53	-0.0023	-0.89	-0.0025	-1.11
II	c_0	-0.0403	-2.35	-0.0213	-3.16	-0.0096	-2.24	-0.0003	-0.09
III	b_1	-0.0084	-2.39	-0.0043	-1.52	-0.0023	-0.87	-0.0024	-1.09
III	c_1	-0.0182	-0.57	-0.0084	-0.78	-0.0021	-0.39	-0.0045	-1.35
III	c_2	-0.1193	-3.50	-0.0469	-2.88	-0.0281	-2.46	-0.0188	-2.90
III	c_3	-0.0184	-1.35	-0.0132	-2.46	-0.0052	-1.48	0.0043	1.36

Panel C. institutional non program

Reg		[t, t+1]		[t, t+5]		[t,t+10]		[t,t+20]	
		Coef.	t	Coef.	t	Coef.	t	Coef.	t
I	b_1	-0.0385	-9.33	-0.0315	-9.30	-0.0285	-8.86	-0.0223	-8.77
II	b_1	-0.0331	-8.06	-0.0294	-8.73	-0.0277	-8.70	-0.0222	-8.64
II	c_0	-0.0464	-4.72	-0.0185	-4.70	-0.0062	-1.74	-0.0010	-0.39
III	b_1	-0.0336	-8.10	-0.0294	-8.79	-0.0279	-8.83	-0.0223	-8.76
III	c_1	-0.0332	-0.72	-0.0215	-1.21	-0.0072	-0.75	-0.0044	-0.82
III	c_2	-0.1561	-4.71	-0.0540	-4.39	-0.0309	-4.17	-0.0121	-1.95
III	c_3	-0.0067	-0.76	-0.0046	-1.11	0.0027	0.68	0.0034	1.28

Panel D. institutional program

Reg		[t, t+1]		[t, t+5]		[t,t+10]		[t,t+20]	
		Coef.	t	Coef.	t	Coef.	t	Coef.	t
I	b_1	-0.0094	-2.14	-0.0076	-2.24	-0.0071	-2.21	-0.0056	-1.98
II	b_1	-0.0081	-1.89	-0.0070	-2.07	-0.0070	-2.14	-0.0059	-2.01
II	c_0	-0.0111	-1.14	-0.0054	-0.93	-0.0009	-0.21	0.0028	1.06
III	b_1	-0.0085	-1.94	-0.0072	-2.10	-0.0070	-2.15	-0.0059	-2.02
III	c_1	-0.0512	-1.62	-0.0188	-1.41	-0.0103	-1.08	-0.0059	-1.14
III	c_2	-0.0581	-1.98	-0.0266	-2.48	-0.0107	-1.55	-0.0017	-0.47
III	c_3	0.0114	1.31	0.0042	0.79	0.0029	0.79	0.0046	1.74

Panel E. proprietary non program

Reg		[t, t+1]		[t, t+5]		[t,t+10]		[t,t+20]	
		Coef.	t	Coef.	t	Coef.	t	Coef.	t
I	b_1	-0.0183	-5.32	-0.0158	-4.89	-0.0166	-5.12	-0.0164	-5.64
II	b_1	-0.0175	-5.12	-0.0159	-5.06	-0.0168	-5.25	-0.0166	-5.84
II	c_0	-0.0077	-1.00	0.0010	0.18	0.0018	0.52	0.0019	0.67
III	b_1	-0.0181	-5.20	-0.0159	-5.03	-0.0168	-5.25	-0.0165	-5.85
III	c_1	-0.0236	-0.93	-0.0086	-0.64	-0.0048	-0.71	-0.0037	-0.89
III	c_2	0.0256	1.13	0.0062	0.59	0.0094	1.39	0.0055	0.89
III	c_3	-0.0049	-0.59	0.0017	0.32	0.0012	0.31	0.0013	0.51

Panel F. proprietary program

Reg		[t, t+1]		[t, t+5]		[t,t+10]		[t,t+20]	
		Coef.	t	Coef.	t	Coef.	t	Coef.	t
I	b_1	-0.0116	-3.54	-0.0102	-2.92	-0.0104	-3.21	-0.0102	-3.39
II	b_1	-0.0101	-3.35	-0.0096	-2.82	-0.0098	-3.10	-0.0097	-3.37
II	c_0	-0.0157	-1.99	-0.0058	-0.90	-0.0067	-1.50	-0.0046	-1.46
III	b_1	-0.0102	-3.27	-0.0094	-2.71	-0.0097	-3.03	-0.0097	-3.33
III	c_1	-0.0813	-3.22	-0.0290	-2.95	-0.0191	-2.76	-0.0125	-3.57
III	c_2	-0.0083	-0.36	-0.0076	-0.80	-0.0034	-0.53	-0.0062	-1.01
III	c_3	-0.0025	-0.32	-0.0026	-0.38	-0.0050	-1.06	-0.0026	-0.76

Panel G. other

Reg		[t, t+1]		[t, t+5]		[t,t+10]		[t,t+20]	
		Coef.	t	Coef.	t	Coef.	t	Coef.	t
I	b_1	-0.0132	-3.88	-0.0104	-4.57	-0.0104	-4.61	-0.0109	-4.61
II	b_1	-0.0121	-4.29	-0.0095	-4.74	-0.0102	-4.83	-0.0109	-4.69
II	c_0	-0.0100	-0.96	-0.0083	-1.23	-0.0026	-0.52	0.0007	0.19
III	b_1	-0.0129	-4.42	-0.0097	-4.77	-0.0103	-4.94	-0.0110	-4.72
III	c_1	0.0124	0.60	0.0032	0.34	0.0040	0.55	0.0010	0.17
III	c_2	-0.0339	-1.26	-0.0190	-1.93	0.0005	0.06	0.0010	0.22
III	c_3	0.0027	0.25	-0.0034	-0.47	-0.0021	-0.38	0.0008	0.18

Table 5. Factor timing and sources of shorting alphas

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

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

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

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

II-FF: $r_{i,t,t+k} = b_0 + (b_1 + c_1 d_{1t} + c_2 d_{2t} + c_3 d_{3t} + b_2 \beta_{RM} + b_3 \beta_{HML} + b_4 \beta_{SML}) short_{i,t-5,t-1} + \gamma X_{i,t-1} + e_{i,t}$

The dependent variable $r_{i,t,t+k}$ is the average daily Fama-French three-factor alpha for firm *i* over the interval [*t*, *t*+*k*] in percent. Indicator variables include d_{1t} = 1 if day *t* has an earnings announcement and zero otherwise, d_{2t} = 1 if on day *t* any analyst changes her buy/sell recommendation, d_{3t} = 1 if on day *t* any analyst changes her earnings forecast, and d_t = 1 if any of the above three events occur on day *t*. The betas are Fama-French factor sensitivities, estimated on a daily basis over the previous calendar quarter. Table 2 describes the other explanatory variables, including the vector of control variables $X_{i,t-1}$. Short sales are from all account types. A separate regression is performed for data in each calendar month, and Newey-West standard errors with one lag are calculated from the time-series of regression coefficients.

Reg		[t, t+1] Coef.	t	[t, t+5] Coef.	t	[t,t+10] Coef.	t	[t,t+20] Coef.	t
I	b_1	-0.0347	-10.37	-0.0300	-11.29	-0.0289	-11.33	-0.0247	-11.19
I	c_0	-0.0450	-5.72	-0.0199	-4.07	-0.0095	-3.14	-0.0018	-0.85
I-FF	b_1	-0.0198	-2.63	-0.0221	-3.42	-0.0263	-4.16	-0.0234	-4.67
I-FF	c_0	-0.0443	-5.40	-0.0195	-3.85	-0.0097	-2.99	-0.0025	-1.14
I-FF	b_2	-0.0151	-1.61	-0.0071	-0.92	-0.0007	-0.11	0.0005	0.11
I-FF	b_3	0.0006	0.11	-0.0003	-0.07	-0.0023	-0.64	-0.0033	-1.12
I-FF	b_4	0.0014	0.33	-0.0007	-0.20	-0.0026	-0.84	-0.0013	-0.53
II	b_1	-0.0354	-10.19	-0.0300	-11.15	-0.0289	-11.33	-0.0248	-11.26
II	c_1	-0.0555	-1.24	-0.0196	-0.97	-0.0023	-0.22	-0.0104	-1.86
II	c_2	-0.1222	-5.39	-0.0473	-3.97	-0.0232	-3.21	-0.0101	-2.09
II	c_3	-0.0061	-0.81	-0.0069	-1.49	-0.0025	-0.72	0.0020	0.91
II-FF	b_1	-0.0206	-2.76	-0.0222	-3.43	-0.0264	-4.17	-0.0234	-4.68
II-FF	c_1	-0.0560	-1.26	-0.0203	-1.02	-0.0021	-0.21	-0.0098	-1.80
II-FF	c_2	-0.1200	-5.28	-0.0461	-4.02	-0.0229	-3.33	-0.0103	-2.21
II-FF	c_3	-0.0057	-0.72	-0.0066	-1.36	-0.0027	-0.73	0.0013	0.60
II-FF	b_2	-0.0149	-1.61	-0.0071	-0.92	-0.0007	-0.10	0.0005	0.11
II-FF	b_3	0.0004	0.08	-0.0004	-0.10	-0.0023	-0.65	-0.0033	-1.12
II-FF	b_4	0.0014	0.32	-0.0007	-0.19	-0.0025	-0.83	-0.0013	-0.52

Table 6. Shorting before and returns following earnings-related news: the effect of analyst dispersion

For earnings announcements of NYSE stocks from October 23, 2000 through September 2005, pooled regressions of the form:

$$ret_{i,t,t+k} = b_0 + (c_0 + c_1 disp_i) short_{i,t-5,t-1} + b_1 \log size_{i,m-1} + b_2 BM_{i,m-6} + b_3 \sigma_{i,m-1} + b_4 ret_{i,m-6,m-t} + b_5 turnover_{i,m-1} + e_{i,t}$$

where *disp* is the dispersion of analyst forecasts, measured as the cross-sectional standard deviation in quarterly EPS estimates at the time of the earnings release. The dependent variable is average daily returns in percent in excess of the riskless rate; all return intervals begin with event day zero. See Table 2 for a description of other explanatory variables.

Panel A. Coefficient c_0

Return interval	all		Indi.		Inst. np		Inst. p		Prop. np		Prop. p		other	
	Coef.	T	Coef.	t	Coef.	t	Coef.	T	Coef.	t	Coef.	t	Coef.	t
[0,+1]	-0.156	-3.86	-0.033	-0.98	-0.148	-2.97	-0.082	-2.23	-0.029	-0.91	-0.080	-2.38	0.021	0.74
[0,+5]	-0.075	-4.32	-0.019	-1.40	-0.080	-4.00	-0.035	-2.29	-0.012	-0.83	-0.029	-1.92	-0.002	-0.15
[0,+10]	-0.048	-4.90	-0.010	-1.22	-0.048	-4.52	-0.020	-1.78	-0.011	-1.40	-0.024	-2.47	-0.006	-0.73
[0,+20]	-0.037	-6.39	-0.005	-1.23	-0.035	-5.21	-0.011	-1.55	-0.013	-2.94	-0.019	-3.05	-0.012	-1.98

Panel B. Coefficient c_1

Return interval	all		Indi.		Inst. np		Inst. p		Prop. np		Prop. p		other	
	Coef.	t	Coef.	t	Coef.	t	Coef.	T	Coef.	t	Coef.	t	Coef.	t
[0,+1]	0.590	2.05	-0.637	-1.04	0.510	1.29	0.250	10.76	-0.647	-1.47	-0.536	-1.23	-0.541	-1.46
[0,+5]	0.102	0.69	-0.314	-1.08	0.054	0.29	0.077	9.16	-0.259	-2.02	-0.205	-1.65	-0.232	-1.53
[0,+10]	0.041	0.39	-0.121	-0.76	0.008	0.06	0.045	7.12	-0.194	-3.39	-0.114	-1.44	-0.085	-0.83
[0,+20]	0.043	0.68	-0.089	-0.91	0.045	0.63	0.027	5.25	-0.133	-3.60	-0.078	-1.32	-0.055	-0.57

Table 7. Earnings news and future shorting

For earnings events in NYSE stocks from October 23, 2000 through September 30, 2005, pooled regressions of the form:

$$short_{i,t+1,t+5} = b_0 + b_1 short_{i,t-5,t-1} + c_1 ret_{i,t-7,t-2} + c_2 ret_{i,t-1,t} + b_4 \ln size_{i,m-1} + b_5 BM_{i,m-6} + b_6 \sigma_{i,m-1} + b_7 ret_{i,m-6,m-t} + b_8 turnover_{i,m-1} + e_{i,t}$$

Event day zero is the earnings announcement or analyst change date. Variable definitions can be found in Table 2.

Panel A. All days

	all Coef.	t	Indi. Coef.	t	Inst. np Coef.	t	Inst. p Coef.	t	Prop. np Coef.	t	Prop. p Coef.	t	other Coef.	t
short[-5,-1]	0.512	76.43	0.280	18.71	0.468	58.23	0.332	39.08	0.498	99.65	0.406	56.39	0.353	18.87
ret[-7,-2]	-0.017	-4.47	0.010	4.28	-0.010	-3.44	0.006	1.94	-0.002	-0.66	-0.005	-0.71	0.017	4.57
ret[-1,0]	0.051	20.50	0.006	5.16	0.035	16.01	0.022	7.63	0.031	19.11	0.042	12.05	0.025	9.79

Panel B. Shorting after earnings announcements

	all Coef.	t	Indi. Coef.	t	Inst. np Coef.	t	Inst. p Coef.	t	Prop. np Coef.	t	Prop. p Coef.	t	other Coef.	t
short[-5,-1]	0.442	52.99	0.203	6.64	0.391	42.93	0.277	15.03	0.414	30.93	0.365	28.59	0.258	15.13
ret[-7,-2]	-0.024	-1.63	0.009	1.02	-0.012	-0.96	0.009	1.28	-0.017	-1.55	0.002	0.16	0.004	0.22
ret[-1,0]	0.026	4.31	0.003	0.76	0.020	4.12	0.006	1.64	0.023	5.03	0.016	2.98	0.017	2.77

Panel C. Shorting after analyst recommendation changes

	all Coef.	t	Indi. Coef.	t	Inst. np Coef.	t	Inst. p Coef.	t	Prop. np Coef.	t	Prop. p Coef.	t	other Coef.	t
short[-5,-1]	0.470	61.90	0.223	11.22	0.436	45.06	0.321	26.82	0.460	35.01	0.383	36.47	0.308	20.33
ret[-7,-2]	-0.014	-2.57	0.009	2.05	-0.004	-0.72	0.002	0.42	-0.004	-0.92	-0.014	-3.08	0.011	3.13
ret[-1,0]	0.025	6.56	0.003	2.23	0.020	6.25	0.007	2.43	0.019	6.73	0.006	1.54	0.021	5.27

Panel D. Shorting after analyst forecast changes

	all Coef.	t	Indi. Coef.	t	Inst. np Coef.	t	Inst. p Coef.	t	Prop. np Coef.	t	Prop. p Coef.	t	other Coef.	t
short[-5,-1]	0.499	77.79	0.244	14.22	0.453	56.56	0.336	35.24	0.481	68.34	0.395	44.85	0.331	30.79
ret[-7,-2]	-0.013	-2.56	0.011	3.66	-0.002	-0.42	0.004	0.92	-0.005	-0.96	-0.005	-0.80	0.012	2.06
ret[-1,0]	0.035	8.82	0.006	4.29	0.027	7.85	0.012	3.40	0.025	11.56	0.019	5.43	0.022	5.94

Figure 1. Coefficient behavior over time.

The graphs show monthly Fama-MacBeth coefficients on the shorting-news day interaction (see Table 5). We present each news event separately (earnings announcements, analyst recommendation changes, and analyst forecast changes) for one day ahead and 20 day ahead forecasts.