Are short-sellers lured by analysts' consensus?*

Harold Contreras†
University of Chile

Francisco Marcet‡
University of Chile

January 15, 2023

Abstract

This study explores short selling patterns under different earnings surprises. We show that short sellers trade more depending on the quality of analysts whose EPS forecasts are missed to make profitable trades. We find that short sellers spot key analysts to trade after rather than before the publication of earnings. This result is in line with the view that short sellers are better at interpreting and processing public information instead of taking advantage of private information. In terms of profits, we find that higher shorting activity following the publication of earnings predicts lower future returns unconditionally, but this association is significantly higher in firms that miss key analysts forecasts rather than the analysts' consensus. This means that short sellers purposely look for top-quality analysts' forecasts and trade more when firms miss their benchmarks to profit on their trades.

Preliminary version. Please do not cite without authors' permission

Keywords: Short selling, analysts' forecasts, earnings announcements
JEL Classification: G12, G19, G39

*We would like to thank as well as the conference and seminar participants at the 2021 IFABS Oxford and University of Chile for their helpful comments. We also acknowledge financial support from the School of Economics and Business, University of Chile (Concurso Proyecto Investigación 2021).

†Department of Management Control and Information Systems, School of Economics and Business, University of Chile, Diagonal Paraguay 257, Santiago, Chile, E-mail: `hcontrer@fen.uchile.cl`

‡Department of Business Administration, School of Economics and Business, University of Chile, Diagonal Paraguay 257, Santiago, Chile, E-mail: `fmarceto@fen.uchile.cl`

1 Introduction

Most of the empirical evidence agrees that short sellers are informed participants in the market. This conclusion comes from the observation that short sales predict negative future stock returns, that is, stocks with high short selling tend to underperformed stocks with low short selling (Desai et al., 2002; Asquith et al., 2005; Boehmer et al., 2008a; Diether et al., 2009). Also, short sellers are very active traders around the release of firms' public information, especially earnings announcements. Engelberg et al. (2012) and Boehmer et al. (2020) show that the majority of short selling activity occurs around the publication of earnings either in anticipation of or after the news. However, despite this vast evidence, we still know very little why short-sellers appear to be informed or, more specifically, what is the source of information they use when trading (Boehmer et al., 2020; Reed, 2013).

The literature is split on whether public information could represent profitable opportunities for more informed investors as the short sellers. On the one hand, public news should decrease information asymmetry among investors and then reduce opportunities for arbitrageurs (Korajczyk et al., 1991; Diamond and Verrecchia, 1987). On the other hand, investors could have different interpretation of the same public news (Kandel and Pearson, 1995; Rubinstein, 1993), or there could be relevant cognitive limitations or financial costs of processing public information (Blankespoor et al., 2020) and therefore, this events could represent profitable opportunities to more skilled traders and/or to investors that have the financial means to bear these costs (Brown et al., 2009; Engelberg et al., 2012).

In this paper we aim to contribute to the literature by analyzing whether the source of information advantage of short sellers have could come from a specific channel, that is, their ability to spot better quality analysts. We conjecture that short sellers, *ex ante* the publication of earnings announcements, identify a subset of analysts (key analysts) who attract more attention from less informed investors and trade based on the surprise generated by these analysts' forecasts to profit on their sales. We believe that the interaction between earnings announcements (public news) and analysts' forecasts heterogeneity offer an ideal setting to explore more deeply the source of information short sellers use when trading.

Undoubtedly, earnings benchmarks, such as the consensus analyst forecasts, play an important role in stock markets. There is extensive evidence that market respond not only to the actual earnings announced but also to the surprise based on analysts' consensus. Just recently, the literature started to pay attention on whether investors' go beyond consensus-type information and rely on signal produced by high-quality analysts. Even when it seems intuitive that investors consider the heterogeneity of analysts' to trade, identifying high quality analysts bears financial and cognitive costs, while obtaining the consensus forecast is relatively easy and inexpensive. In line with these ideas, Michaely et al. (2021) show that investors seem to be lured by the consensus at the earnings announcements, that is, they react more strongly to surprises coming from the consensus than to surprises coming from high quality analysts. In contrast, Kirk et al. (2014) show that investors not only respond to the consensus but also to the percentage of individual forecasts met and whether firms' meet or beat high quality analysts.

Taking the heterogeneity of analysts as a potential trigger for short selling, we first hypothesize that if short sellers trade in possession of private information, firms missing key analysts' benchmarks should be highly shorted before the release of quarterly earnings announcements. This would mean that short sellers trading in anticipation of earnings is not by coincidence or mere speculation, but rather on superior information they have over the upcoming earnings. We then hypothesize, in contrast, that if short sellers trade on their ability to better process all available information there is in the market, then there should be a higher shorting activity after earnings announcements on stocks that miss key analysts' forecasts.

We find that short sellers indeed spot key analysts to make profitable trades, but they do so after the release of earnings rather than before. Specifically, testing the timing of short sales we find no evidence that shorting activity is significantly higher before the publication of earnings in firms that miss key analysts forecasts, but we do find that short selling is higher in these firms after earnings announcements as compared to missing the analysts' consensus. This suggests that, short selling is not only associated to negative news but also to certain type of negative news, the ones that comes from better quality analysts.

We then turn to analyze whether short sellers make profits following this trading strategy, and we do find evidence that this is the case. In particular, we find that higher shorting activity following the publication of earnings predicts lower future returns unconditionally, but this association is significantly higher in firms that miss key analysts forecasts rather than the analysts' consensus. This means that, short sellers purposely look for stocks in which key analysts make forecasts and trade more when firms miss their benchmarks to profit on their trades. These results are in line with the view that processing public information is not a costless activity and investors who have the means to do it could take advantage of it.

We define key analysts based on Kirk et al. (2014) and consider 8 characteristics to create a score. The characteristics we employ are the following: brokerage size, forecast frequency, all-star status, experience, number of companies covered, number of industries covered, forecast horizon and prior forecast accuracy.

In order to provide further support to our findings, we use an exogenous change in analyst coverage and test our predictions through a quasi-experimental design. We conjecture that if short sellers spot key analysts to trade, then an exogenous drop in key analysts covering a firm should reduce short sellers profitable opportunities. The identification strategy is in the spirit of previous studies that use an exogenous reductions in analyst coverage due to closures and mergers of brokerage firms (Hong and Kacperczyk, 2010; Kelly and Ljungqvist, 2012). In particular, we rely on an pseudo-exogenous termination of analyst coverage and the classification of analysts at the moment of the coverage termination. We focus on a group of analysts that stopped working in the financial service industry, and we classify those analysts as key or non-key analysts for the firms that they were following before they quit their jobs.

By using this pseudo-exogenous reduction in key analyst coverage we find that, in line with our conjectures, short-seller activity is significantly lower after the lost of a key analyst. Specifically, our results show that for a given firm which a key analyst stopped covering (because she left the industry), there is a significant drop in short selling for that firm when other key analysts' forecasts are missed thereafter. Importantly, this drop in shorting activity for a particular key analyst is relative to other firms in which that analyst was classified as non-key before she left the industry. We also confirm this result is not driven by unobserved analyst characteristics or by the reduction in analyst coverage itself, but rather by the classification of that analyst as key analyst.

We then analyze whether short sellers spot key analysts in a different context. It's natural to think that if short sellers use the quality of analysts to trade, they should apply this trading strategy in another context in which analysts are very active, that is their recommendations. Using our classification of key analysts we analyze the trading activity of short sellers around downgrade recommendations. Using our classification of key vs. non-key analysts we identify downgrade recommendations of individual analysts relative to the consensus. We find that short selling is significantly higher for downgrades made by key analysts than non-key analysts, reinforcing the idea that short sellers spot key analysts to trade.

Finally, we analyze whether short sellers spot key analysts because missing their forecasts produces a short term mispricing (short term information), or whether this negative news means a structural change in the fundamentals of these firms (long term information). Under the first view, short-sellers are arbitrageurs who process public information to identify short-term mispricing. Under the second view, short sellers are good information processors too but not only about the short-term, but also long-term. Our results are consistent with the first view, that is, the strategy short sellers perform by trading on firms that miss key analysts' forecasts is not associated to more negative future performance, indicating that this trading strategy is short-term oriented.

We contribute to the literature in two important ways. First, even when it has been shown that short selling is higher after negative news (negative earnings surprises) and stock returns follow their trades, suggesting that they are informed, there was no evidence on why they appeared to be informed. This is important, as our results are in line with the view that processing public information is costly and that less informed investors appear to put too much focus on aggregates measures. On the first strand, several studies take firm related publicly available information as costlessly source, but in reality it can be highly costly to acquire and understand firms' disclosures.[1] The existence of processing costs, means that firm disclosures are often a form of private information that sophisticated investors could use to their advantage. On the second strand, it is apparent that both investors and academia routinely use information provided by all analysts in a aggregate way, as evident by the importance of the consensus (Michaely et al., 2021). Our results suggest that, even when analysts' forecasts are public information, obtaining and processing information on analyst quality variation requires time, effort and financial costs that only more sophisticated investors, as short sellers, are willing to bear.

Second, while most of the literature on short selling tries to disentangle whether short sellers trade on foreknowledge of future fundamental information (private information), or better interpretation (or better processing skills or means) of publicly available information in a sort of horse race, disentangle this is very difficult and ergo the evidence in this regard is inconclusive. One the one hand, many papers suggests that short sellers use private information and are able to predict future negative news, as they show results of high shorting activity before important corporate events (Khan and Lu, 2013; Kecskés et al., 2013; Christophe et al., 2010; Karpoff and Lou, 2010; Efendi and Swanson, 2009; Christophe et al., 2004). In contrast, Drake et al. (2011), Engelberg et al. (2012) and Blau and Pinegar (2013) find no evidence of abnormal shorting activity prior bad news events, and Engelberg et al. (2012) finds that the majority of short selling activity is concentrated after corporate news events, especially earnings announcements, and interpret this result as short sellers information advantage coming from their ability to better interpret public information. While Blau and Wade (2012) observe abnormal shorting prior to downgrades, but also prior to upgrades and Boehmer et al. (2020) finds evidence that short sellers trade with both private and public information.

We take a step forward and by focusing on whether short sellers use a specific source of publicly available information to trade, namely analysts heterogeneity, we provide further

[1]See Blankespoor et al. (2020) for a recent review on this topic.

evidence to this literature. Our results on short selling trading with key analysts forecasts after rather than before the publication of earnings are in line Engelberg et al. (2012). However, we add to their evidence by showing an specific source of information short sellers use and process to trade, analysts quality.

Finally, even when we are not the first studying short-selling and analysts' benchmarks, to the best of our knowledge we are the first analyzing the importance of analysts' heterogeneity, in particular analysts quality, on short sellers trading strategies. The empirical evidence is mostly focus on aggregate signals such as the consensus or downgrades with mixed results. For instance, Christophe et al. (2010) find abnormal shorting activity prior to analyst (recommendations) downgrades and interpret this as an indication of trading activity given superior information of short-sellers. In contrast, Blau and Wade (2012) observe abnormal shorting prior to downgrades, but they also find higher shorting prior to upgrades. Moreover, they find that the short-selling patterns surrounding both downgrades and upgrades are symmetric, which suggests that short sellers during the pre-recommendation period are not unusually informed about the direction of upcoming recommendation changes. Our study takes a different approach, because we are interested in the heterogeneity of analysts that makes a recommendation or issue a forecast. We do this because we are interested in studying the source of information short sellers use to trade at the earnings announcements.

The remainder of this paper is organized as follows. Section 2 develops the main hypotheses of the paper. Section 3 describes the data and methodology. Section 4 contains the results for the main hypotheses and Section 5 concludes. Finally, variable definitions are found in Appendix A.

2 Hypothesis development

The literature is split regarding the source of information short-sellers use when trading. One stream of the literature suggests that short sellers use private information and are able to predict future negative news. For instance, there is evidence that that short selling is higher before bad earnings announcements (Christophe et al., 2004), financial misconduct (Efendi and Swanson, 2009; Karpoff and Lou, 2010), analyst forecast revision (Christophe et al., 2010), insider sales (Khan and Lu, 2013), analyst downgrades, credit rating downgrades (Henry et al., 2010; Kecskés et al., 2013), mergers, repurchases (Liu and Swanson, 2012) and seasoned equity offerings (Safieddine and Wilhelm Jr, 1996; Henry and Koski, 2010). In contrast, (Drake et al., 2011; Engelberg et al., 2012; Blau and Pinegar, 2013) find no evidence of abnormal shorting activity prior bad news events. In fact, Engelberg et al. (2012) finds that the majority of short selling activity is concentrated after corporate news events, especially earnings announcements, and interpret this result as short sellers information advantage coming from their ability to better interpret public information. While Boehmer et al. (2020) finds evidence that short sellers trade with both private and public information.

We use forecasts issued by different quality of analysts as the mechanism that would help to identify the source of information short sellers use, either private or (better interpretation of) public. It's well established in the literature that market reacts strongly when firms miss or beat analysts forecasts, generating positive or negative surprises. Most of this evidence though, considers only deviations from the consensus (measured by the average or median of all forecasts in a given period of time) as the only piece of information investors use to trade. Just recently, the literature has evoked their attention to how analysts' heterogeneity can influence investor's decision to trade. Kirk et al. (2014) show... Michaely et al. (2021) show market reacts more to the consensus than to the variation of analysts quality.

In line with Michaely et al. (2021), we argue that identifying better quality analysts requires financial and cognitive costs of processing information that is publicly available. It can be highly costly to acquire and interpret firms' disclosures and market information. As Blankespoor et al. (2020) argue, the existence of processing costs and the learning process from firm specific information is an active economic choice for which investors expect a competitive return. Sophisticated investors, as short sellers, could have better skills and financial means to process and analyze this information and use it to their benefit. If this information represents profitable opportunities for short sellers, they will try to exploit it either before or after the release of the earnings announcements.

We first conjecture that if short sellers trade on private information, then they spot key analysts forecasts to trade before the earnings announcements. This is because, even when identifying better quality analysts could be based on public information, the trading decision made at earnings announcement should based on deviations of firm's actual earnings, which are not know before, relative to key analysts predictions. So our first hypothesis is as follows:

H1: Short selling is higher in the days prior the publication of earnings in firms that miss key analysts' forecasts as opposed to miss the consensus for a given quarter.

Then we conjecture that if short sellers are better processing public information, then they should use missing key analysts forecast as an opportunity to sell profitable before stock prices fall completely. Then our second hypothesis is as follows:

H2: Short selling is higher in the days after earnings announcements in firms that miss key analysts' forecasts as opposed to the consensus for a given quarter.

We next move to the profitability of short sales around earnings announcements. The literature is mixed regarding whether the release of fundamental public information could represent profitable opportunities for more informed investors. On the one side, public news should decrease information asymmetry among investors and then reduce opportunities for arbitrageurs (Korajczyk et al., 1991; Diamond and Verrecchia, 1987). This argument should be stronger in the presence of key analysts, since they are supposed to provide better quality signal for investors. If this is the case, short sellers trading after the publication of earnings in firms with key analysts making forecast should have less opportunities to exploit profitable trades. On the other side, another stream of the literature suggests that investors could have different interpretation of the same public news, and therefore, this events could represent profitable opportunities to more skilled traders (Engelberg et al., 2012; Kandel and Pearson, 1995; Rubinstein, 1993).

Considering both views we formulate the following null and alternative hypotheses:

$H3_0$: Short sales in firms that miss key analysts' forecasts are not more profitable than

in firms that miss the consensus.

$H3_a$: Short sales in firms that miss key analysts' forecasts are more profitable than in firms that miss the consensus

3 Data and methodology

Our sample would comprise firm-quarter information for US publicly-listed firms from July 2006 to December 2017. We consider all US common stocks that are traded on the NYSE, NASDAQ or AMEX exchanges.[2] We obtain quarterly earnings announcements from the COMPUSTAT quarterly data file and delete firm-quarters for which no COMPUSTAT data is available. COMPUSTAT is also source of information for earnings per share, book-to-market ratio, market capitalization, total assets and other accounting information.

Data on short selling and equity-lending supply comes from Markit (who acquired Data Explorers). As of today, we have collected the data and we are processing it. Equity-lending information in Markit is collected daily from 125 large custodians and 32 prime brokers in the industry and covers more than 85% of the equity-lending market. A more detailed description of the data is in Saffi and Sigurdsson (2010). We aim to consider the daily number of stocks on loan based on shorting transactions that are initiated on the most recent business day,[3] scaled by the number of shares outstanding. We believe new stocks on loan within one business day better fits our purposes as we want to analyze short sales that are executed in response to earnings announcements.

Our analysis would be built around earnings announcements that are together with accounting information and stock returns. We denote the period between two earnings announcements as a quarter and we aggregate all short selling activity, accounting information and stock returns at this quarterly level. Figure 1 shows our setup and timings. For each quarter, we denote the two earnings announcements at the beginning and end of the quarter as EA0 and EA1, respectively. The numbering of earnings announcements

[2] We exclude non-US incorporated firms, or ADR, ETF and REITS.

[3] Markit also have data on the daily number of stocks that are on loan at different start dates, such as at 3, 7 and 30 days.

then goes up from EA1 to the future and down from EA0 to the past. During the period prior to EA0, we capture analysts' forecasts, which are referred to EA0, and then we classify them as coming from a key or non-key analyst. Since we also want to study whether insider trades show stock return predictability after earnings announcements, we will measure abnormal returns in the period after EA0. To do so, we define a trading response period that runs before the earnings announcements, from day -10 and -5 to day 0; and after, from day 0 to day +5 or +10.

Insert Figure 1 about here.

3.1 Key analysts classification

In order to test our main hypotheses, we must identify key analysts. To make this classification, we follow Kirk et al. (2014) and use 8 characteristics of analysts that are more associated to forecast quality, such as: brokerage size, forecast frequency, all-star status, experience, number of companies covered, number of industries covered, forecast horizon and prior forecast accuracy. Then, as in Kirk et al. (2014), we use a regression-weighted composite score to determine the relative importance that each of these characteristics play to explain the market reaction to earnings announcements. Specifically, for each quarter we use pooled observations from the previous eight firm-quarters and run regressions to estimate the weight that each characteristic has to explain the earnings announcement returns. We then calculate the composite score, based on the regression coefficients, for each forecast in our sample using these rolling weights. Thus, for each firm-quarter, a key analyst forecast is the one with the highest score.

We obtain the information of analysts characteristics from three main sources: IBES, CRSP and the *Institutional Investor Magazine*. We classify an analyst as being influential if he or she appears in the *Institutional Investor* ranking. *Brokerage house size* is determined by the number of analysts making forecasts by the brokerage firm. We define analysts' *experience* in terms of the number of years he or she has been issuing forecast for a given firm. *Accuracy* corresponds to the absolute value of analysts' forecasts errors in prior fiscal quarters ($|EPS^{forecast} - EPS_{actual}|$).

Once we categorize the analysts, we calculate the average EPS forecast and create two dummy variables according to the earnings surprise: $Miss\ top_{i,q}$ takes the value of one when firm i in a given quarter q misses key analysts' EPS forecasts, and zero otherwise. $Miss\ concensus_{i,q}$) identify cases when a firm misses the analyst consensus (or market consensus), so it takes the value of one when firm i in a given quarter q misses the analyst consensus, and zero otherwise. The consensus is measured as the mean of all analysts' EPS forecasts for a particular firm-quarter (we require at least one analyst following the firm).

3.2 Baseline regression

To investigate the heterogeneous influence of key and non-key analysts around earnings surprises on short selling, we estimate the following multivariate regressions:

$$(1) \qquad Y_{i,q} = \beta_0 + \beta_1 Miss\ top_{i,q} + \beta_2 Miss\ consensus_{i,q} + \delta' \cdot X_{i,q} + \alpha_i + \gamma_t + \epsilon_i$$

Where $Y_{i,q}$ is one of the following variables: $Relss(-\tau, 0)$ is the average number of stocks on loan based on daily shorting transactions of firm i that are initiated on the day τ and ending at the publication of earnings, scaled by the number of shares outstanding. $Relss(0, +\tau)$ is the average number of stocks on loan based on daily shorting transactions of firm i that are initiated on the day 0 and ending τ days after the publication of earnings, scaled by the number of shares outstanding. As we want to capture shorting activity as near as possible to the earnings announcements, τ would take the value of 5 and 10.

Regarding control variables, referred to as X in the equation above, we include book-to-market ratio, firm size, the magnitude of earnings surprises measured as the rescaled quintile rank of unexpected earnings, called *Rue*, and the (il)liquidity measure proposed by Amihud (2002). Following Dargenidou et al. (2018) and Mendenhall (2004), we define $Rue_{i,t}$ as a variable taking the value of -0.5 when an observation belongs to the bottom quintile rank of earnings surprises, and 0.5 when an observation belongs to the key quintile rank of earnings surprises. The earnings surprise corresponds to the difference between the actual earnings per share and the mean (or median) earnings per share forecasted by analysts for a firm in a given quarter, scaled by the stock price of the firm two days before the earnings announcement (Ayers et al., 2011).

In addition, the Amihud (2002) liquidity measure is computed as the daily ratio of the absolute stock return over the dollar trading volume of the stock. In our analysis we employ the *Abnormal Amihud*, which is the average liquidity level over a specific window of time after the earnings announcement, divided by the average liquidity measure over 252 days before the earnings announcement. Importantly, as Hanselaar et al. (2019) argue, this measure closely follows the intuition of the market depth parameter in the Kyle (1985) model.

In all of our tests, we will include year-quarter (γ_t) and firm (α_i) fixed effects. This is important in our setting as we want to capture the within-firm variation of the dependent variable when a firm misses key analysts' forecasts as compared to cases when a firm meet or beat these benchmarks. We will compute Hubert/White robust standard errors and allow them to cluster within firms. Finally, all the variables are also defined in the Appendix A.

4 Summary statistics

Table 1 displays the distribution of firm-quarters that are classified by key and non-key analysts. Panel A shows the unconditional distribution for each dummy variable. We have 106,789 firm-quarters with analysts' forecasts, in which 49,488 (approximately 46% of those quarters) are firms that miss the analyst consensus of EPS forecasts (*Miss=1*). Note that in 85,058 firm-quarters there is at least one key analysts issuing a forecast and in 39,209, firms have missed their forecasts, which represents approximately 37% of the total.

Insert Table 1 about here.

Firm-quarters in which key and non-key analysts issue forecasts are quite frequent. They coincide in 83,754 quarters (78% of the total). Also, in around 34% of the firm-quarters in our sample (35,802 cases), firms beat both key analysts and non-key analysts. Similarly, in around 39% of the quarters (41,289 quarters), firms meet or beat forecasts by both key and non-key analysts. Quarters in which firms miss key analysts but meet or beat non-key analysts are relatively rare, constituting approximately 3% of the quarters (3,259 cases). And the same applies to firm-quarters in which firms miss non-key analysts but beat key analysts' forecasts (3,404 cases).

In Table 2 we provide summary statistics for the main variables used throughout the analysis. Panel A displays statistics for the whole sample and Panels B and C split the sample into quarters when key analysts are missed and met or beaten.

Insert Table 2 about here.

5 Market reaction to earnings announcements under key and non-key analysts

Our empirical approach relies on the investor reaction when firms miss key earnings forecasts, and in this section we provide a formal test for this assumption. Specifically, we follow Kirk et al. (2014) and test whether key analysts has explanatory power over the market reaction to the earnings news. We estimate the following regression:

$$EAAR_{i,q} = \beta_0 + \beta_1 Miss\ top_{i,q} + \beta_2 Miss\ consensus_{i,q} + \delta' \cdot X_{i,q} + \alpha_i + \gamma_t + \epsilon_i \tag{2}$$

Where the dependent variable is the earnings announcement abnormal returns ($EAAR_{i,q}$), which corresponds to the buy-and-hold abnormal stock returns over 3 days around the last earnings announcement date $(-1, +1)$. abnormal returns are adjusted by the corresponding 5x5 size and book-to-market portfolio as downloaded from the Kenneth French website. All the other variables are defined in the Appendix. We present the result in Table 3

Insert Table 3 about here.

In column (1), we show the basic specification using *Miss consensus* which corresponds to a firm that misses the analyst consensus (*Miss consensus*) and, as expected, we see a negative and significant coefficient. In column (2) we include only *Miss key*, which indicates a firm that misses only key analysts' forecasts and we also get a negative and significant coefficient. More importantly, when added in conjunction in column (3), both *Miss consensus* and *Miss key* remain negative and significant, and drop slightly in magnitude. The results remain almost invariant when we refine the specifications in columns (4)-(6) including firm, quarter-year and industry fixed effects, and when we also cluster standard errors to the firm level. These results confirm an important finding in the literature: investors not only respond to the consensus, but also respond negatively to earnings missing key analysts' forecasts. In other words, *Miss key* provides an additional explanatory power over the earnings returns after controlling for the market consensus.

6 Main results

6.1 Timing ability of short sellers

One way to distinguish whether short sellers trade with private vs. public information is to analyze the timing of their trades around the publication of news. There is evidence in the literature that short sellers anticipate bad earnings news, however, this may be due speculation rather than private information. In fact, Engelberg et al. (2012) take a broader approach and consider several type of corporate news and find no evidence of anticipation by short sellers. We argue that analysts heterogeneity offers a good setting to shed light on this question. In this section, we aim to provide evidence testing hypotheses 1 and 2.

Table 4 displays the results on the timing of short selling considering key analysts forecasts. In Panel A we include short selling activity prior the publication of earnings in time windows (-7,-2) and (-12,-2), and Panel B considers shorting activity after the news in windows (0,+5) and (0,+10). For both Panels we first show the results for the basic specification, that is, including the dummy *Miss consensus* alone and then in conjunction with the dummy *Miss key*. The results in Panel A show that while *Miss consensus* is significantly positive, the coefficient for *Miss key analysts* is positive but insignificant. This indicates that even when short sellers show some anticipation to bad news (in line with Christophe et al. (2010)), they do not anticipate the prediction made by key analysts to trade. This result holds for both time windows (-7,-2) and (-12,-2) in Panel A.

Insert Table 4 about here.

Panel B, in contrast, show that both coefficients *Miss consensus* and *Miss key analysts* are significantly positive, and the coefficient for key analysts is larger than for the consensus. This means that both provide explanatory power for shorting activity right after earnings announcements. So, short sellers trade on bad news (which is consistent with Engelberg et al. (2012)), but more importantly, short sellers trade more when key analysts forecasts are missed. This result is in line with our conjecture that short sellers spot key analysts predictions to trade, but after rather than before the publication of earnings.

The results in Table 4 rejects hypothesis 1 in favor of hypothesis 2. This means that, in line with Engelberg et al. (2012), short sellers are better to process public news but we add an extra and a specific channel, which is the fact that short sellers identify forecats made by key analysts to make profitable trades.

6.2 Profitability of short sales

Considering our findings in the previous section, in this one we ask whether short sellers spot key analysts forecasts to make profitable trades, which address hypothesis 3. To answer this question we follow the spirit of Boehmer et al. (2008b) and Engelberg et al. (2012), and in Table 5 we run panel-data regressions of the form:

$$\begin{aligned} Ret_{i;t+1,t+20} = \beta_0 &+ \beta_1 Relss_{i,t} + \beta_2 Miss\ top_{i,t} + \beta_3 Miss\ consensus_{i,t} + \beta_4 Mbe\ top_{i,t} \\ &+ \beta_5 Relss_{i,t} \times Miss\ top_{i,t} + \beta_6 Relss_{i,t} \times Miss\ consensus_{i,t} \\ &+ \beta_7 Relss_{i,t} \times Mbe\ top_{i,t} + \delta' \cdot X_{i,q} + \alpha_i + \gamma_t + \epsilon_i \end{aligned}$$

Where the dependent variable is a 20-day rolling window returns (from t+1 to t+20) for the whole sample period. We use two different measures of returns as dependent variables: buy and hold raw and market adjusted returns. For the latter, we use the value weighted portfolio from CRSP to perform the adjustment. As independent variables we include our dummies of interest (*Miss key* and *Miss consensus*), *Mbe key* to consider the case of good news and their interaction with short selling activity.

We can see in columns (1), (3) and (5) that the coefficient for short interest is negative and statistically significant indicating that short selling predicts negative future returns, and confirming that short sellers are informed traders. Also, the three dummies measuring negative and positive news are statistically significant with the expected sign.

Insert Table 5 about here.

When looking at the interaction terms in columns (2), (4) and (6) we see a clear pattern. First, the coefficient for *Miss key* indicating that firm have missed key analyst benchmark is small, negative and statistically significant. However, the coefficient for $Relss \times Miss\ key$ is large and also negative and statistically significant. The results in Panel B show an almost identical pattern. This result gives a clearer picture, the predictive power of short selling after the publication of earnings is almost double when firms miss key analysts forecasts. Importantly, the interaction term with Miss consensus is not statistically significant which reinforces the idea that short sellers spot key analysts to make profitable trades.

7 Short selling and a pseudo-exogenous reduction in key analysts' coverage

One concern is that our main findings might be driven by firms' or analysts' characteristics that may affect short-selling trades specially during the earnings announcements, which we could fail to take into account. Specifically, we rely on the conjecture that short-sellers spot key-analysts and trade when firms miss key analysts' EPS forecasts. However, an omitted variable, such as a worsening of a firm's growth opportunities not captured by the market before the earnings announcement, could drive the results (higher short-seller trades) instead of the role of key analysts.

To alleviate these concerns, we perform a quasi-experimental design and use a difference-in-difference approach to rule out alternative explanations about the role of analysts on the trades of short-sellers. We would expect that an exogenous reduction of key analysts would affect more the trades of short-sellers relative to non-key analysts when firms miss their forecasts. An important assumption, however, is that the reduction of analyst coverage is not related to firm or analyst characteristics.

The identification strategy relies on an pseudo-exogenous termination of analyst coverage and the classification of analysts at the moment of the coverage termination. Specifically, we focus on a group of analysts that stopped working in the financial service industry and we classify those analysts as key or non-key analysts for the firms that they were following before they quit their jobs.

To do so, in I/B/E/S we identify cases in which a set of analysts suddenly stopped their coverage for all firms at the same time (year). In other words, for a given analyst we track all firms that she was following every year and then we identify the moment in which that analyst disappears from I/B/E/S for the rest of the sample period we used in our analysis. By doing that, we can identify the pool of firms under her coverage and the exact moment that she stopped her coverage.

This approach is similar to the quasi-experiment related to closure and merger of brokerage houses employed as an exogenous reduction in analyst coverage (Hong and Kacperczyk (2010), Kelly and Ljungqvist (2012) and (Derrien and Kecskés, 2013)). However, we can not use brokerage house shock for two reasons. First, due to data constraints associated with daily short-selling activity, our sample begins in 2006 and most of the merger and closures event took place before 2006. Second, and more importantly, even if could obtain more closure/merger events for our sample period, we required to have enough variation in terms of key vs. non-key analyst classification to preform our tests, therefore, we would not have enough power because the number of firms involved in the merger/closure event is small.

In our case, we follow the same spirit of the closure/mergers of brokerage houses, but we focus on analysts that stopped their coverage for all the firms they were following before they left the industry. Since we are interested in these cases, we have enough variation across time and within analysts. Also, we can alleviate the concerns that analysts stopped their coverage because of firms' characteristics that may also affect the short-selling activity. Given that the analyst stopped the coverage for all the firms, we believe it is very likely that the decision is unrelated to negative prospects of firms that may also affect the trades of short-sellers.

In this test in particular, we want analyze whether an exogenous reduction in key analyst coverage for a given firm leads to a decrease in short selling when key analysts' forecasts are missed, relative to other firms in which that analyst was classified as non-key before she left the industry. Our conjecture is that a sudden decrease in key analyst coverage hampers short sellers opportunity to trade profitably before and after the publications of earnings. Importantly, we use firms in which the same analyst was classified as non-key as a relevant control group. By doing this, we account for unobserved analyst characteristics, and then the source of variation is the analyst type and not the reduction of the analyst coverage itself.

In Figure 3 we display our identification strategy. Suppose a particular analysts that at some moment in time left the industry and this analyst was covering the following six firms (APPL, MSFT, DELL, GE, TWTR and META). However, this analyst was classified as key only for two of those firms: MSFT and META, then she was non-key for the rest. Thus, in our analysis MSFT and META would form the treatment group, and the remaining firms (APPL, DELL, GE, TWTR) would be the control group. Importantly, we also perform a matching process to improve the control group and keep firms with similar characteristics to the treated firms. We match on calendar year, firm's size and book-to-market.

Once the matching process is done, for a window of three years around the analyst shock we run the following regression:

$$\begin{aligned} Relss(0,5)_{i,q} = \beta_0 &+ \beta_1 Miss\ key_{i,q} \times Lost\ Key_i + \beta_2 Lost\ Key_i \\ &+ \beta_3 Miss\ consensus_{i,q} + \delta' \cdot X_{i,q} + \alpha_i + \gamma_{1y} + \gamma_{2q}\epsilon_i \end{aligned}$$

The dependent variable, $Relss(0,+5)_{i,q}$, is the relative number of stocks on loan for firm i in quarter q from day 0 to day +5. *Lost Key* : is a dummy variable that takes the value of one for the quarters three years after that the firm lost a key analyst, and zero otherwise. Our coefficient of interest is β_1, which has a double interaction based on

Miss key and *Lost Key*. As we discussed earlier, our focus is only on firms that suffered a reduction in the analyst coverage. However, the source of variation is coming from the analyst classification: key vs non-key. Hence, we expect that the short-seller activity is lower in firms in which the analyst classified as key left the industry, relative to the firms in which the same analyst classified as non-key.

In Table 7 we present our results. Panel A shows the summary for treated (480) and controls firms (since we keep up to three control firms for each treated firms, we obtain 750 firms) and Wilcoxon tests for size and book-to-market. We find that the treated and control firms are not statically different in distribution based on these two dimensions. Panel B shows our main findings. In column (1) we obtain that interaction term $Miss\ key \times Lost\ Key$ is negative and statistically significant. This result suggests that short-seller activity is lower after the lost of a key analyst. Note that after that key analyst left the industry, she is replaced with a new one for that firm. Hence, we interpret this reduction on short-trading as driven by the lost of that key analyst, and the effect of the new key analyst is less important relative to the older one.

To round up our results, we test whether we find similar results by considering the miss of the consensus and we find that is not the case ($Miss\ consensus \times Lost\ Key$ is not statistically significant). Only the miss of the key analyst matters for the trading activity of short-sellers. In sum, with this test we provide further evidence that the quality of analysts matter for short-sellers and our results are not driven by omitted characteristics of firms and analysts.

8 Key Analysts and Downgrades

Our study focuses on short-trading around earnings announcements. However, if short sellers spot key analysts to trade, they would do so in a different setting as well, for instance, around analyst downgrades. We use our classification of key analysts to check whether the trading activity of short sellers is similar around ((-5,+5) windows) downgrade recommendations. Using our classification of key vs. non-key analysts, we identify downgrade recommendations of individual analysts relative to he consensus. Specifically, we identify cases when analysts (key and non-key analysts) provide a sell recommendation and the consensus in that moment was a buy or hold recommendation. If short-sellers trade based on analysts' quality they would do so in a similar way at earnings announcements than they would do around downgrade recommendations. We compare downgrades of key and non-key analysts versus the average recommendation of analyst consensus to have a similar benchmark than the one at earning announcements.

Following the literature on analyst tipping (Irvine et al., 2007), instead of using the short-selling trades in each day, we calculate the abnormal short-trading activity using the average of daily short-selling trades during 200 days prior the downgrades up to t-5 days before the downgrade as benchmark (which is at firm-level). Then, we calculate the difference between the daily trades and the benchmark.

Figure 2 displays the main pattern of short-selling around analyst downgrades. We can see a higher abnormal trading activity on the announcement day and days after downgrades made by key analysts, relative to downgrades of non-key analysts. Before the downgrades short-seller activity is similar for both key and non-key analysts, and the differences appear when they announce a downgrade recommendation. These results suggests that short sellers also use the quality of analysts to trade after downgrades recommendations, and it gives more support to the idea that short-sellers trade more depending on the type of analysts.

To reinforce this finding we take this result in a regression setting. In particular, we estimate the following regression model:

$$
\begin{aligned}
AbnRelss(t)_i = \beta_0 + \beta_1 Key_{ia} + \sum_{t=-5}^{+5} \gamma_t \times Day(t) + \sum_{t=-5}^{+5} \delta_t \times Key_{ia} \times Day(t) \\
+ \Delta' \cdot X_{i,q} + \alpha_i + \phi_{1y} + \phi_{2q} \epsilon_i
\end{aligned}
$$

The dependent variable, $AbnRelss(t)_i$, is the abnormal relative number of stocks on loan for firm i on day t. Key_{ia} is a dummy variable that takes the value of one when the downgrade recommendation for firm i is made by an analyst a classified as key analyst, and zero otherwise. γ_t captures the average abnormal trading activity on the day t around the downgrade recommendation. Also, we include the interaction term "$Key \times Day(t)$", which represents the abnormal short-selling activity each day when downgrades are made by key analysts relative to non-key analysts. We report these results in Table 6.

Insert Table 6 about here.

In column (1) we test the unconditional specification in which we do not include key analysts dummy and any fixed effects. The results show a higher abnormal trading activity of short-sellers around downgrades. Specifically, in line with previous evidence, there is a higher level of short trades on the recommendation date ($t = 0$) and after. Also, note that short-trades are positive and statistically significant within three days before the recommendation release, which is consistent with the analyst tipping evidence.

In columns (2) and (3) we include key analysts dummy, and firm and time (year and month) fixed effects. First, note that the dummy "Key" is not statistically significant, which suggests that there is no significant difference in the level of short-selling for downgrades made by key versus non-key in the (-5,+5) window. However, when we include the interaction term "$Key \times Day(t)$" in column (4) we find significant differences. Column (4b) shows that "$Key \times Day(t = 0)$" is positive and statistically significant, indicating that short-trades are higher for downgrades made by key analysts relative to non-key analysts at the announcement date.[4] Likewise, this positive difference remains for the +2,+3 and +5 days after the downgrade.

9 Further tests

9.1 Short versus long term information

One question that lies behind the trading patterns we observe for short seller, is whether they spot key analysts because missing their forecasts produces a short term mispricing (short term information), or whether this negative news means a structural change in the fundamentals of these firms (long term information). In other words, whether short sellers identify an arbitrage opportunity based on a market over or under reaction to missing key

[4]For brevity, in two columns (4a and 4b) we display the coefficients of the same regression.

analysts, or whether they have better information about these firms future performance. This question is related recent evidence showing that short sellers exploit both short term and long horizon information.[5]. Our results in Table 5 provides some evidence in line with the short horizon view, however, the returns we consider in that test are too short to make a strong conclusion.

We test this question by analyzing whether short selling activity shortly after the publication of negative news coming from key analysts, is associated with a change in the fundamentals in the same direction. To measure the direction of the long-term information, we use future realizations of earnings innovations following CITAR. First, we define future earnings innovation as $\Delta earn_{k,t,t+q1} = earn_{k,t+q1} - earn_{kt}$ which is the difference between: (1) earnings one quarter ahead $earn_{i,t+q1}$ and the current quarter earnings $earn_{i,t}$ (seasonalized) or (2) next quarter earnings $earn_{i,t+q1}$ and earnings 4 quarters back $earn_{i,t-q3}$ (seasonally adjusted). Then, we estimate the following specification:

$$
\begin{aligned}
\Delta earn_{i,t,t+q1} = \beta_0 &+ \beta_1 Relss_{i,t} + \beta_2 Miss\ top_{i,t} + \beta_3 Miss\ consensus_{i,t} \\
&+ \beta_5 Relss_{i,t} \times Miss\ top_{i,t} + \beta_6 Relss_{i,t} \times Miss\ consensus_{i,t} \\
&+ \delta' \cdot X_{i,q} + \alpha_i + \gamma_t + \epsilon_i
\end{aligned}
$$

The results in Table 8 show that while high shorting activity after earnings announcements is associated to a decrease in earnings (negative coeffient for relss), missing the consensus does not show a clear relation (positive in column 1 and negative in 2). In contrast, the coefficient for missing key analysts' forecast is negative and significant for column 2, showing that this negative news are somehow associated to future negative performance. More importantly, the interaction between missing key analysts forecasts and shorting activity is insignificant for both columns. This means that the strategy short sellers perform by trading on firms that miss key analysts' forecasts is not associated to more negative future performance, indicating that this trading strategy is short-term oriented.

[5] see for example Desai, Krishnamurthy, and Venkataraman (2006) and Boehmer and Wu (2013)

Insert Table 8 about here.

Conclusion

In this paper we explore short selling patterns under different earnings surprises. We show that short sellers trade more depending on the heterogeneity of analysts whose EPS forecasts are missed to make profitable trades. We find that short sellers indeed spot key analysts to make profitable trades, but they do so after the release of earnings rather than before. Specifically, when testing the timing of short sales we find no evidence that shorting activity is significantly higher before the publication of earnings in firms that miss key analysts forecasts, but we do find that short selling is higher in these firms after earnings announcements as compared to missing the analysts' consensus. This suggests that, short selling is not only associated to negative news but also to certain type of negative news, the ones that comes from better quality analysts.

When analyzing whether this trading strategy is profitable for short sellers, we do find evidence that this is the case. In particular, we find that higher shorting activity following the publication of earnings predicts lower future returns unconditionally, but this association is significantly higher in firms that miss key analysts forecasts rather than the analysts' consensus. This means that, short sellers purposely look for stocks in which key analysts make forecasts and trade more when firms miss their benchmarks to profit on their trades.

Appendix A Variable definitions

Variable	Definition	Source
Abnormal Amihud	Average Amihud liquidity level over a specific window of time after the earnings announcement, divided by the average liquidity measure over 252 days before the earnings announcement. The Amihud (2002) liquidity measure is computed as the daily ratio of the absolute stock return over the dollar trading volume of the stock.	CRSP
B/M ratio	Book value of equity in the previous quarter over the market capitalization 2 days before an earnings announcement	COMPUSTAT
Eaar(-1,+1)	Buy-and-hold abnormal stock returns over 3 days around the last earnings announcement date $(-1,+1)$, estimated as the difference between the observed return and the return corresponding to the 5x5 size and book-to-market portfolio downloaded from the Kenneth French website or the market portfolio return.	CRSP, French's website
Miss	Dummy variable equal to 1 for a firm-quarter that miss the analyst consensus. The analyst consensus is measured as the mean forecasts made for a particular firm's earnings per share (EPS).	IBES
Miss key (non-key)	Dummy variable equal to 1 for a firm-quarter in which a key (non-key) analyst forecast is missed at the earnings announcement.	IBES
$\text{Relss}_{i,t}$	Relative short selling is the number of shares shorted within 1 business day for firm i on date t, scaled by the number of shares outstanding (in basis points)	
$\text{Relss}_{i,t,-\tau,0}$	Relative short selling is the average number of shares shorted within 1 business day for firm i over $(-\tau,0)$ and $(0,+\tau)$ response window ($\tau=\{5,10\}$) around the earnings announcement date t, scaled by the number of shares outstanding (in basis points)	
Past returns (1 year)	The raw stock return over 12 months (265 trading days) ending 2 days before EA_0 adjusted for the corresponding 5x5 size and book-to-market portfolio return downloaded from the Kenneth French website and computed as the buy-and-hold abnormal return.	CRSP, French's website
Post BHAR (τ_1,τ_2)	The raw stock return over 11, 26, 46, 66, 136 and 256 trading days beginning 5 or 10 days after an earnings announcement, adjusted for the corresponding 5x5 size and book-to-market portfolio return as downloaded from the Kenneth French website and computed as the buy-and-hold abnormal return.	CRSP, French's website

continued on next page

continued from previous page

Variable	Definition	Source
Rue	Rescaled quintile rank of standardized earnings surprises. It takes the value of -0.5 when an observation belongs to the bottom quintile rank of earnings surprises, and 0.5 when an observation belongs to the key quintile rank of earnings surprises. The standardized earnings surprise corresponds to the difference between the actual earnings per share and the mean earnings per share forecasted by analysts for a firm in a given quarter. This difference is scaled by the stock price two days before the earnings announcements.	Thomson
Size	Stock price times the number of shares outstanding 2 days before the earnings announcement date, in regressions used in a logarithmic transformation.	COMPUSTAT

References

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets 5*(1), 31–56.

Asquith, P., P. Pathak, and J. Ritter (2005). Short interest, institutional ownership, and stock returns. *Journal of Financial Economics 78*, 243–276.

Ayers, B. C., O. Z. Li, and P. E. Yeung (2011). Investor trading and the post-earnings-announcement drift. *The Accounting Review 86*(2), 385–416.

Blankespoor, E., E. deHaan, and I. Marinovic (2020). Disclosure processing costs, investors' information choice, and equity market outcomes: A review. *Journal of Accounting and Economics 70*(2-3), 101344.

Blau, B. M. and J. M. Pinegar (2013). Are short sellers incrementally informed prior to earnings announcements? *Journal of Empirical Finance 21*, 142–155.

Blau, B. M. and C. Wade (2012). Informed or speculative: Short selling analyst recommendations. *Journal of Banking & Finance 36*(1), 14–25.

Boehmer, E., C. Jones, and X. Zhang (2008a). Which shorts are informed? *Journal of Finance 63*, 491–527.

Boehmer, E., C. M. Jones, J. Wu, and X. Zhang (2020). What do short sellers know? *Review of Finance 24*(6), 1203–1235.

Boehmer, E., C. M. Jones, and X. Zhang (2008b). Which shorts are informed? *The Journal of Finance 63*(2), 491–527.

Brown, S., S. A. Hillegeist, and K. Lo (2009). The effectofearningssurprisesoninformationasymmetry. *Journal of Accounting and Economics 47*, 208–225.

Christophe, S. E., M. G. Ferri, and J. J. Angel (2004). Short-selling prior to earnings announcements. *The Journal of Finance 59*(4), 1845–1876.

Christophe, S. E., M. G. Ferri, and J. Hsieh (2010). Informed trading before analyst downgrades: Evidence from short sellers. *Journal of Financial Economics 95*(1), 85–106.

Dargenidou, C., I. Tonks, and F. Tsoligkas (2018). Insider trading and the post-earnings announcement drift. *Journal of Business Finance & Accounting 45*(3-4), 482–508.

Derrien, F. and A. Kecskés (2013). The real effects of financial shocks: Evidence from exogenous changes in analyst coverage. *The Journal of Finance 68*(4), 1407–1440.

Desai, H., K. Ramesh, S. R. Thiagarajan, and B. V. Balachandran (2002). An investigation of the informational role of short interest in the nasdaq market. *The Journal of Finance 57*(5), 2263–2287.

Diamond, D. W. and R. E. Verrecchia (1987). Constraints on short-selling and asset price adjustment to private information. *Journal of Financial Economics 18*, 277–311.

Diether, K. B., K.-H. Lee, and I. M. Werner (2009). Short-sale strategies and return predictability. *Review of financial Studies 22*, 575–607.

Drake, M. S., L. Rees, and E. P. Swanson (2011). Should investors follow the prophets or the bears? evidence on the use of public information by analysts and short sellers. *The Accounting Review 86*(1), 101–130.

Efendi, J. and E. P. Swanson (2009). Short seller trading in companies with a severe accounting irregularity. *Available at SSRN 1465156*.

Engelberg, J. E., A. V. Reed, and M. C. Ringgenberg (2012). How are shorts informed?: Short sellers, news, and information processing. *Journal of Financial Economics 105*, 260–278.

Hanselaar, R. M., R. M. Stulz, and M. A. Van Dijk (2019). Do firms issue more equity when markets become more liquid? *Journal of Financial Economics 133*(1), 64–82.

Henry, T. R., D. J. Kisgen, and J. Wu (2010). Do equity short sellers anticipate bond rating downgrades. *University of Georgia, Boston College working paper*.

Henry, T. R. and J. L. Koski (2010). Short selling around seasoned equity offerings. *The review of financial studies 23*(12), 4389–4418.

Hong, H. and M. Kacperczyk (2010). Competition and bias. *The Quarterly Journal of Economics 125*(4), 1683–1725.

Irvine, P., M. Lipson, and A. Puckett (2007). Tipping. *The Review of Financial Studies 20*(3), 741–768.

Kandel, E. and N. D. Pearson (1995). Differential interpretation of public signals and trade in speculative markets. *Journal of Political Economy*, 831–872.

Karpoff, J. M. and X. Lou (2010). Short sellers and financial misconduct. *The Journal of Finance 65*(5), 1879–1913.

Kecskés, A., S. A. Mansi, and A. J. Zhang (2013). Are short sellers informed? evidence from the bond market. *The Accounting Review 88*(2), 611–639.

Kelly, B. and A. Ljungqvist (2012). Testing asymmetric-information asset pricing models. *The Review of Financial Studies 25*(5), 1366–1413.

Khan, M. and H. Lu (2013). Do short sellers front-run insider sales? *The Accounting Review 88*(5), 1743–1768.

Kirk, M. P., D. A. Reppenhagen, and J. W. Tucker (2014). Meeting individual analyst expectations. *The Accounting Review 89*(6), 2203–2231.

Korajczyk, R. A., D. J. Lucas, and R. L. McDonald (1991). The effect of information releases on the pricing and timing of equity issues. *Review of Financial Studies 4*, 685–708.

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica: Journal of the Econometric Society*, 1315–1335.

Liu, H. and E. P. Swanson (2012). Silent combat: do managers use share repurchases to trade against short sellers? *Available at SSRN 1986396*.

Mendenhall, R. R. (2004). Arbitrage risk and post-earnings-announcement drift. *The Journal of Business 77*(4), 875–894.

Michaely, R., A. Rubin, D. Segal, and A. Vedrashko (2021). Do differences in analyst quality matter for investors relying on consensus information? *Available at SSRN*.

Reed, A. V. (2013). Short selling. *Annu. Rev. Financ. Econ. 5*(1), 245–258.

Rubinstein, A. (1993). On price recognition and computational complexity in a monopolistic model. *Journal of Political Economy*, 473–484.

Saffi, P. A. and K. Sigurdsson (2010). Price efficiency and short selling. *Review of Financial Studies 24*, 821–852.

Safieddine, A. and W. J. Wilhelm Jr (1996). An empirical investigation of short-selling activity prior to seasoned equity offerings. *The Journal of Finance 51*(2), 729–749.

Table 1: Summary statistics: Missing analysts' benchmarks

This table displays the distribution of firm-quarters between key vs. non-key analysts. We define key (non-key) analysts according to five dimensions: tenure, all-star analyst, accuracy, trading abnormal volume and size of the brokerage house. The variable *Miss* is a dummy variable that takes the value of one if a firm i in a given quarter miss the EPS consensus of all analysts, and zero otherwise. *Miss key* takes the value of one when firm i in a given quarter miss key (non-key) analysts' EPS forecasts, and zero otherwise.

	Miss key		
Miss consensus	0	1	Total
0	32,623	6,137	38,760
1	16,778	18,023	34,801
Total	49,401	24,160	73,561

Table 2: Summary statistics

This table displays summary statistics for the main variables on a firm-quarter level. Panel A shows summary statistics for all firm-quarters in the sample and Panels B and C for quarters where firms miss key and meet or beat key analysts' forecasts, respectively. All variables are defined the Appendix A .

Panel A: All Sample	N	Mean	sd	p25	p50	p75
Relss (0,+5)	73,561	0.208%	0.235%	0.053%	0.126%	0.271%
Relss (0,+10)	73,561	0.196%	0.209%	0.056%	0.124%	0.256%
Relss (-7,-2)	73,558	0.165%	0.203%	0.038%	0.093%	0.207%
Relss (-12,-2)	73,558	0.165%	0.191%	0.043%	0.097%	0.209%
Sue	73,561	0.187%	6.248%	-3.132%	0.007%	3.342%
Eaar(-1,+1)	73,561	-0.659%	4.583%	-0.437%	0.000%	0.303%
Abnormal Amihud	73,561	0.925	0.714	0.507	0.763	1.121
Size (Ln(mcap))	73,561	7.161	1.567	6.061	7.105	8.150
B/M ratio	73,561	0.688	0.754	0.274	0.497	0.844
Past returns (1 year)	73,561	-0.099%	36.753%	-22.578%	-4.187%	16.200%
Analysts' coverage	73,561	1.741	0.708	1.099	1.792	2.303
Analysts' dispersion	73,561	0.048	0.076	0.012	0.024	0.051
Panel B: Miss key=1						
Relss (0,+5)	24,160	0.220%	0.245%	0.054%	0.136%	0.293%
Relss (0,+10)	24,160	0.205%	0.217%	0.056%	0.132%	0.274%
Relss (-7,-2)	24,159	0.169%	0.207%	0.036%	0.092%	0.212%
Relss (-12,-2)	24,159	0.167%	0.194%	0.041%	0.098%	0.214%
Sue	24,160	-2.071%	6.029%	-5.587%	-1.576%	1.156%
Eaar(-1,+1)	24,160	-1.710%	5.966%	-1.053%	-0.286%	0.000%
Abnormal Amihud	24,160	1.002	0.814	0.530	0.803	1.198
Size (Ln(mcap))	24,160	6.920	1.557	5.826	6.882	7.924
B/M ratio	24,160	0.763	0.890	0.283	0.532	0.912
Past returns (1 year)	24,160	-4.870%	36.491%	-27.006%	-8.194%	11.579%
Analysts' coverage	24,160	1.656	0.698	1.099	1.609	2.197
Analysts' dispersion	24,160	0.060	0.087	0.015	0.031	0.064
Panel C: Miss key=0						
Relss (0,+5)	49,401	0.202%	0.229%	0.052%	0.122%	0.260%
Relss (0,+10)	49,401	0.191%	0.205%	0.055%	0.121%	0.247%
Relss (-7,-2)	49,399	0.164%	0.201%	0.038%	0.093%	0.204%
Relss (-12,-2)	49,399	0.164%	0.189%	0.043%	0.097%	0.206%
Sue	49,401	1.291%	6.054%	-1.946%	0.699%	4.479%
Eaar(-1,+1)	49,401	-0.146%	3.615%	-0.173%	0.095%	0.455%
Abnormal Amihud	49,401	0.887	0.656	0.496	0.746	1.085
Size (Ln(mcap))	49,401	7.279	1.558	6.181	7.211	8.264
B/M ratio	49,401	0.651	0.675	0.269	0.482	0.813
Past returns (1 year)	49,401	2.235%	36.656%	-20.292%	-2.202%	18.380%
Analysts' coverage	49,401	1.783	0.708	1.099	1.792	2.303
Analysts' dispersion	49,401	0.043	0.069	0.011	0.021	0.045

Table 3: Regressions on earnings announcement returns missing analyst' forecasts

This table displays specifications on the market reaction to earnings announcements over our main explanatory variables, the dummies for miss key analysts and miss analysts' consensus. The dependent variable is the earnings announcement abnormal returns, Eaar(-1,+1), which is the buy-and-hold abnormal stock return over 3 days around the last earnings announcement date $(-1, +1)$ estimated as the difference between the observed return and the return corresponding to the 5x5 size and book-to-market portfolio as downloaded from the Kenneth French website or the market portfolio return.The main independent variables are: $Missconsensus$, which is a dummy variable that takes the value of one when firm i in a given quarter meets or beats the EPS consensus of all analysts, and zero otherwise. *Miss key* takes the value of one when firm i in a given quarter misses key analysts' EPS forecasts, and zero otherwise. All variables are defined in Appendix A and are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level.

	Dependent variable: Earnings announcement abnormal returns (-1,+1)					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Miss consensus	-0.0065***	-0.0129***	-0.0066***	-0.0075***	-0.0165***	-0.0076***
	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0006)	(0.0007)
Perc miss	-0.0449***		-0.0428***	-0.0469***		-0.0452***
	(0.0009)		(0.0012)	(0.0010)		(0.0013)
Miss key		-0.0279***	-0.0021***		-0.0267***	-0.0017**
		(0.0006)	(0.0008)		(0.0007)	(0.0008)
Sue	0.0582***	0.0599***	0.0582***	0.0767***	0.0782***	0.0767***
	(0.0075)	(0.0076)	(0.0075)	(0.0080)	(0.0080)	(0.0080)
Analysts' coverage	0.0005	0.0013***	0.0005	0.0004	0.0004	0.0004
	(0.0004)	(0.0004)	(0.0004)	(0.0007)	(0.0007)	(0.0007)
Analysts' dispersion	0.0158***	0.0032	0.0156***	0.0140***	0.0062	0.0138***
	(0.0036)	(0.0035)	(0.0036)	(0.0045)	(0.0045)	(0.0045)
Abnormal Amihud	-0.0064***	-0.0069***	-0.0064***	-0.0081***	-0.0084***	-0.0081***
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0005)
Size	-0.0016***	-0.0014***	-0.0016***	-0.0173***	-0.0170***	-0.0173***
	(0.0002)	(0.0002)	(0.0002)	(0.0009)	(0.0009)	(0.0009)
B/M ratio	0.0043***	0.0042***	0.0043***	-0.0001	0.0001	-0.0001
	(0.0004)	(0.0004)	(0.0004)	(0.0006)	(0.0006)	(0.0006)
Past returns (1 year)	-0.0069***	-0.0057***	-0.0068***	-0.0085***	-0.0076***	-0.0085***
	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0008)	(0.0008)
Constant	0.0336***	0.0288***	0.0336***	0.1516***	0.1477***	0.1514***
	(0.0015)	(0.0014)	(0.0015)	(0.0070)	(0.0070)	(0.0070)
Observations	73,561	73,561	73,561	73,561	73,561	73,561
R-squared	0.1056	0.0850	0.1057	0.1790	0.1593	0.1791
Cluster SE	Firm	Firm	Firm	Firm	Firm	Firm
Firm FE	no	no	no	yes	yes	yes
Qrtr-Year FE	no	no	no	yes	yes	yes

Table 4: Regressions on short selling around earnings announcements and analyst' forecasts

This table displays firm and quarter fixed effects regressions on short selling after earnings announcements over our main explanatory variables, the dummies for miss key analysts and miss analysts' consensus. As dependent variable, we measure short selling at different time horizons. First, we measure short selling prior the publication of earnings, from day -12 to day -2, and from day -7 to day -2. Then, measure short selling shortly after the earnings announcements, from day 0 to day +5, and from day 0 to day +10. The main independent variables are: *Missconsensus*, which is a dummy variable that takes the value of one when firm i in a given quarter meets or beats the EPS consensus of all analysts, and zero otherwise. *Miss key* takes the value of one when firm i in a given quarter misses key analysts' EPS forecasts, and zero otherwise. All variables are defined in Appendix A and are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level.

	Dependent variable: $Relss(\tau_1, \tau_2,)$							
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Variables	(-7,-2)	(-7,-2)	(-7,-2)	(-7,-2)	(0,+5)	(0,+5)	(0,+5)	(0,+5)
Eaar	-0.0443***	-0.0409***	-0.0434***	-0.0408***	-0.1727***	-0.1436***	-0.1564***	-0.1425***
	(0.0120)	(0.0124)	(0.0122)	(0.0124)	(0.0141)	(0.0145)	(0.0143)	(0.0145)
Sue	-0.0114	-0.0114	-0.0114	-0.0116	-0.0008	-0.0006	-0.0004	-0.0015
	(0.0191)	(0.0191)	(0.0191)	(0.0191)	(0.0209)	(0.0209)	(0.0209)	(0.0209)
Miss consensus	0.0033*	0.0021	0.0030	0.0021	0.0122***	0.0025	0.0072***	0.0024
	(0.0017)	(0.0019)	(0.0018)	(0.0019)	(0.0019)	(0.0022)	(0.0021)	(0.0022)
Perc miss		0.0029				0.0246***		
		(0.0023)				(0.0026)		
Miss key			0.0007	-0.0008			0.0133***	0.0048**
			(0.0016)	(0.0019)			(0.0018)	(0.0021)
Perc miss (excl. key)				0.0049				0.0269***
				(0.0034)				(0.0037)
Analysts' coverage	0.0343***	0.0343***	0.0343***	0.0339***	0.0403***	0.0404***	0.0404***	0.0384***
	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0031)	(0.0031)	(0.0031)	(0.0031)
Analysts' dispersion	0.1193***	0.1186***	0.1192***	0.1183***	0.1410***	0.1351***	0.1393***	0.1342***
	(0.0174)	(0.0174)	(0.0174)	(0.0174)	(0.0198)	(0.0197)	(0.0198)	(0.0197)
Abnormal amihud	-0.0154***	-0.0154***	-0.0154***	-0.0154***	-0.0262***	-0.0263***	-0.0262***	-0.0263***
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Size	0.0109***	0.0109***	0.0109***	0.0110***	0.0166***	0.0170***	0.0167***	0.0171***
	(0.0042)	(0.0042)	(0.0042)	(0.0042)	(0.0047)	(0.0047)	(0.0047)	(0.0047)
B/M ratio	0.0002	0.0002	0.0002	0.0002	-0.0008	-0.0008	-0.0009	-0.0008
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Past returns (1 year)	-0.0160***	-0.0159***	-0.0160***	-0.0159***	-0.0273***	-0.0263***	-0.0269***	-0.0263***
	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0033)	(0.0033)	(0.0033)	(0.0033)
Constant	0.0345	0.0338	0.0344	0.0342	0.0312	0.0248	0.0288	0.0280
	(0.0309)	(0.0309)	(0.0309)	(0.0309)	(0.0348)	(0.0347)	(0.0347)	(0.0347)
Observations	73,558	73,558	73,558	73,558	73,561	73,561	73,561	73,561
R-squared	0.3939	0.3939	0.3939	0.3939	0.4235	0.4244	0.4240	0.4245
Cluster SE	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes
Qrtr-Year FE	yes	yes	yes	yes	yes	yes	yes	yes

Table 5: Post trading returns of short selling.

This table displays panel regressions examining the relation between daily returns, short selling and our main explanatory variables the dummies identifying key analysts forecasts and the consensus. This panel regressions include daily observations for the whole sample period, that is, July 2006 until December 2017. The dependent variables are buy and hold returns at different compounding windows, starting at *t+1* and ending at *t+5*, *t+10* and *t+20*. In Panel A returns are adjusted by the value weighted market portfolio from CRSP, and Panel B includes raw returns. All variables are defined in Appendix A and are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm and date level.

Panel A	Dependent variable: Buy and hold market-adjusted returns					
	(1)	(2)	(3)	(4)	(5)	(6)
Variables		*(t+1, t+5)*			*(t+1, t+10)*	
Relss	-0.084***	-0.073**	-0.073***	-0.207***	-0.200***	-0.189***
	(0.029)	(0.000)	(0.016)	(0.044)	(0.044)	(0.028)
Miss key	-0.008***	-0.006***	-0.005***	-0.009***	-0.007***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Miss consensus	-0.009***	-0.009***	-0.008***	-0.010***	-0.011***	-0.009***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Mbe key	0.011***	0.011***	0.010***	0.012***	0.012***	0.010***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Relss× miss key		-0.911***	-0.805***		-0.955***	-0.876***
		(0.192)	(0.187)		(0.228)	(0.221)
Relss× miss consensus		-0.225	-0.282*		0.236	0.229
		(0.161)	(0.159)		(0.188)	(0.186)
Relss× mbe key		-0.210*	-0.185		-0.301**	-0.264*
		(0.119)	(0.118)		(0.147)	(0.141)
Size	-0.007***	-0.007***	-0.008***	-0.013***	-0.013***	-0.015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Return_{t-1}	-0.015**	-0.015**	-0.014***	-0.017**	-0.017**	-0.017***
	(0.007)	(0.007)	(0.001)	(0.009)	(0.009)	(0.001)
Return_{t-2}	-0.016***	-0.016***	-0.018***	-0.016*	-0.016*	-0.017***
	(0.006)	(0.006)	(0.001)	(0.009)	(0.009)	(0.001)
Perc miss (excl. key)			-0.416***			-0.808***
			(0.012)			(0.023)
Analyst coverage			0.002***			0.003***
			(0.000)			(0.000)
Analysts dispersion			-0.004***			-0.008***
			(0.001)			(0.001)
Constant	1.136***	1.136***	1.157***	1.263***	1.263***	1.303***
	(0.006)	(0.006)	(0.004)	(0.009)	(0.009)	(0.008)
Observations	7,588,850	7,588,850	6,459,060	7,581,302	7,581,302	6,453,025
R-squared	0.010	0.010	0.012	0.019	0.019	0.023
Cluster SE	Firm	Firm	Firm	Firm	Firm	Firm

Table 5 continued from previous page

Panel B	Dependent variable: Buy and hold raw returns					
	(1)	(2)	(3)	(4)	(5)	(6)
Variables		*(t+1, t+5)*			*(t+1, t+10)*	
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Qrtr-year FE	yes	yes	yes	yes	yes	yes

Table 5 continued from previous page

Panel B	Dependent variable: Buy and hold raw returns					
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	*(t+1, t+5)*			*(t+1, t+10)*		
Relss	-0.143***	-0.131**	-0.140***	-0.325***	-0.319***	-0.322***
	(0.052)	(0.052)	(0.018)	(0.078)	(0.000)	(0.031)
Miss key	-0.009***	-0.007***	-0.006***	-0.011***	-0.009***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Miss consensus	-0.010***	-0.010***	-0.009***	-0.012***	-0.013***	-0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mbe key	0.010***	0.011***	0.010***	0.009***	0.009***	0.007***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Relss× miss key		-0.991***	-0.875***		-1.023***	-0.921***
		(0.218)	(0.206)		(0.258)	(0.240)
Relss× miss consensus		-0.197	-0.267		0.322	0.312
		(0.177)	(0.173)		(0.207)	(0.201)
Relss× mbe key		-0.217	-0.183		-0.225	-0.166
		(0.138)	(0.128)		(0.181)	(0.154)
Size	-0.009***	-0.009***	-0.010***	-0.016***	-0.016***	-0.019***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Return_{t-1}	-0.045***	-0.045***	-0.046***	-0.043**	-0.043**	-0.043***
	(0.016)	(0.016)	(0.001)	(0.021)	(0.021)	(0.001)
Return_{t-2}	-0.038**	-0.038**	-0.039***	-0.034*	-0.034*	-0.035***
	(0.015)	(0.015)	(0.001)	(0.020)	(0.020)	(0.001)
Perc miss (excl. key)			-0.440***			-0.841***
			(0.013)			(0.024)
Analyst coverage			0.003***			0.005***
			(0.000)			(0.000)
Analysts dispersion			-0.004***			-0.008***
			(0.001)			(0.001)
Constant	1.180***	1.180***	1.210***	1.335***	1.335***	1.390***
	(0.007)	(0.007)	(0.005)	(0.012)	(0.012)	(0.010)
Observations	7,588,858	7,588,858	6,459,060	7,581,316	7,581,316	6,453,025
R-squared	0.023	0.023	0.025	0.040	0.040	0.044
Cluster SE	Firm	Firm	Firm	Firm	Firm	Firm
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Qrtr-year FE	yes	yes	yes	yes	yes	yes

Table 6: Short selling around analysts' downgrades.

This table displays the results of short-trading activity around analyst downgrades. The dependent variable, $AbnRelss(t)_i$, is the abnormal relative number of stocks on loan for firm i on day t. Key_{ia} is a dummy variable that takes the value of one when the downgrade recommendation for firm i is made by an analyst a classified as key analyst, and zero otherwise. All variables are defined in Appendix A and are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level.

	Depedent variable: Abnormal relss					
Variables	(1)	(2)	(3)	(4)		
Key		-0.001	-0.002	-0.008**		
		(0.003)	(0.002)	(0.004)		
$t-5$	-0.003*					
	(0.002)					
$t-4$	-0.003	-0.000	-0.000	-0.000	$t-4\times$ Key	0.000
	(0.002)	(0.002)	(0.002)	(0.002)		(0.004)
$t-3$	0.009***	0.012***	0.012***	0.010***	$t-3\times$ Key	0.005
	(0.002)	(0.002)	(0.002)	(0.002)		(0.004)
$t-2$	0.012***	0.015***	0.015***	0.014***	$t-2\times$ Key	0.003
	(0.002)	(0.002)	(0.002)	(0.002)		(0.004)
$t-1$	0.026***	0.028***	0.029***	0.027***	$t-1\times$ Key	0.004
	(0.002)	(0.002)	(0.002)	(0.003)		(0.004)
$t=0$	0.050***	0.053***	0.052***	0.048***	$t=0\times$ Key	0.012***
	(0.002)	(0.002)	(0.002)	(0.003)		(0.005)
$t+1$	0.035***	0.037***	0.036***	0.034***	$t+1\times$ Key	0.006
	(0.002)	(0.002)	(0.002)	(0.003)		(0.005)
$t+2$	0.019***	0.021***	0.020***	0.017***	$t+2\times$ Key	0.009**
	(0.002)	(0.002)	(0.002)	(0.003)		(0.004)
$t+3$	0.013***	0.015***	0.014***	0.012***	$t+3\times$ Key	0.007*
	(0.002)	(0.002)	(0.002)	(0.003)		(0.004)
$t+4$	0.009***	0.012***	0.010***	0.009***	$t+4\times$ Key	0.003
	(0.002)	(0.002)	(0.002)	(0.003)		(0.004)
$t+5$	0.006***	0.008***	0.006***	0.004	$t+5\times$ Key	0.009**
	(0.002)	(0.002)	(0.002)	(0.003)		(0.004)
Observations	318,414	318,413	299,552	299,552		
R-squared	0.006	0.060	0.109	0.109		
Other controls	Yes	Yes	Yes	Yes		
Firm FE	No	Yes	Yes	Yes		
Year and Month FE	No	No	Yes	Yes		

Table 7: Short selling and a partial-exogenous reduction in key analysts' coverage.

This table displays the results of the exogenous reduction in key analysts' coverage and short trades. Panel A shows the matching statistics and Panel B show the trading activity after the shock. The dependent variable, $Relss(0,+5)_{i,q}$, is the relative number of stocks on loan for firm i in quarter q from day 0 (earnings annoucement date) to day +5. $Lost\ Key$: is a dummy variable that takes the value of one for the quarters three years after that the firm lost a key analyst, and zero otherwise. *Miss key* takes the value of one when firm i in a given quarter misses key analysts' EPS forecasts, and zero otherwise. All variables are defined in Appendix A and are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level.

Panel A: Matching stats	Treated Mean	Control Mean	Mean Test p-value	Wilcoxon p-value
Size	6.86	6.75	0.416	0.188
Book-to-Market	0.83	0.81	0.805	0.909
N° Firms	480	750		

Panel B: Diff-in-Diff regression	Depedent variable: Relss		
Variables	(1)	(2)	(3)
Miss consensus	0.0000	0.0000	0.0001
	(0.0001)	(0.0001)	(0.0001)
Miss key	0.0003***	0.0002***	
	(0.0001)	(0.0001)	
Lost Key	0.0001	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0001)
Miss key × Lost Key	-0.0001**		
	(0.0001)		
Miss consensus × Lost Key		0.0001	0.0001
		(0.0001)	(0.0001)
Constant	0.0006	0.0006	0.0006
	(0.0009)	(0.0009)	(0.0009)
Observations	19,976	19,976	19,976
R-squared	0.4198	0.4198	0.4185
Other controls	Yes	Yes	Yes
Firm,Year and Qtr FE	Yes	Yes	Yes

Table 8: Regressions on future earnings realizations and analyst' forecasts.

This table displays firm and quarter fixed effects regressions on future earnings over short selling after earnings announcements and our main explanatory variables, the dummies for miss key analysts and miss analysts' consensus. As dependent variable, we measure future earnings realizations as: (1) earnings one quarter ahead $earn_{i,t+q1}$ and the current quarter earnings $earn_{i,t}$ (seasonalized) or (2) next quarter earnings $earn_{i,t+q1}$ and earnings 4 quarters back $earn_{i,t-q3}$ (seasonally adjusted). The main independent variables are: $Relss(0, +5)$ which measures short selling activity at window (0,+5) after earnings announcements. $Missconsensus$, which is a dummy variable that takes the value of one when firm i in a given quarter meets or beats the EPS consensus of all analysts, and zero otherwise. *Miss key* takes the value of one when firm i in a given quarter misses key analysts' EPS forecasts, and zero otherwise. All variables are defined in Appendix A and are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level.

	Dependent variable: Future earnings			
	Season		Adjusted	
Variables	(1)	(2)	(3)	(4)
Relss (0,+5)	-0.0031***	-0.0030***	-0.0013	-0.0010
	(0.0007)	(0.0007)	(0.0010)	(0.0010)
Miss consensus	0.0115***	0.0115***	-0.0021***	-0.0021***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Miss key	0.0002	0.0002	-0.0011***	-0.0011***
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Relss (0,+5) /times miss consensus	0.0044***	0.0044***	-0.0021	-0.0022*
	(0.0012)	(0.0012)	(0.0013)	(0.0013)
Relss (0,+5) /times miss key	-0.0013	-0.0014	-0.0017	-0.0019
	(0.0011)	(0.0011)	(0.0013)	(0.0013)
Sue	0.2673***	0.2683***	0.2784***	0.2789***
	(0.0072)	(0.0072)	(0.0078)	(0.0077)
Eaar	0.0271***	0.0265***	0.0243***	0.0240***
	(0.0019)	(0.0019)	(0.0023)	(0.0023)
Size	-0.0027***	-0.0027***	-0.0012	-0.0008
	(0.0004)	(0.0004)	(0.0008)	(0.0008)
B/M ratio	0.0032***	0.0031***	0.0030***	0.0030***
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Past returns (1 year)	0.0035***	0.0031***	0.0115***	0.0110***
	(0.0003)	(0.0003)	(0.0006)	(0.0007)
Abnormal amihud		-0.0006***		-0.0002
		(0.0002)		(0.0002)
Analysts' dispersion		-0.0009***		-0.0025***
		(0.0003)		(0.0004)
Analysts' coverage		0.0166***		0.0139***
		(0.0030)		(0.0037)
Constant	0.0142***	0.0155***	0.0112**	0.0122**
	(0.0028)	(0.0028)	(0.0057)	(0.0058)
Observations	69,105	69,105	57,390	57,390
R-squared	0.2366	0.2379	0.2878	0.2891
Firm FE	Firm	Firm	Firm	Firm
Quarter-Year FE	yes	yes	yes	yes

Figure 1: Timings of earnings announcements and related abnormal returns.

This figure shows relative timings of aggregate informed trading during the response window and relative timings of future post-trading abnormal returns. Everything is arranged relatively to the earnings announcement that is set as day t. We take into account only trading days. Accordingly, we establish (i) the earnings-announcement window, which starts on day $t-1$ and ends on day $t+1$; (ii) the response window when insiders and short sellers trade, which starts on day t and ends on day $t-5$, $t-10$, $t+5$ and $t+10$ or ; and (iii) the future-return window, which starts on day $t+6$ and runs for h days up to day $t+6+h$.

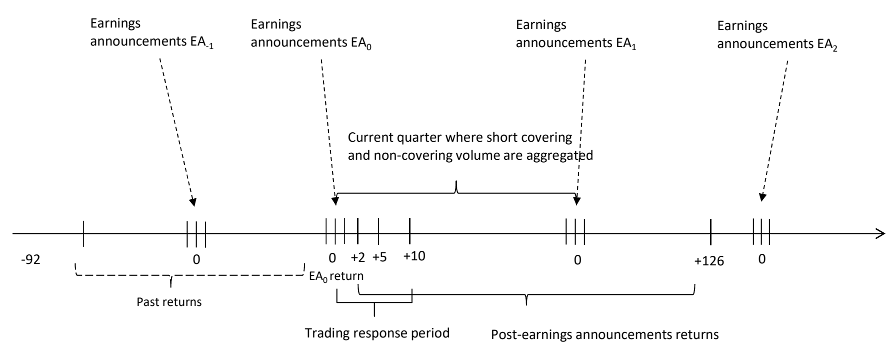

Figure 2: Key and non-key analyst downgrades. The figures show the average abnormal short-trading activity before and after analyst downgrades.

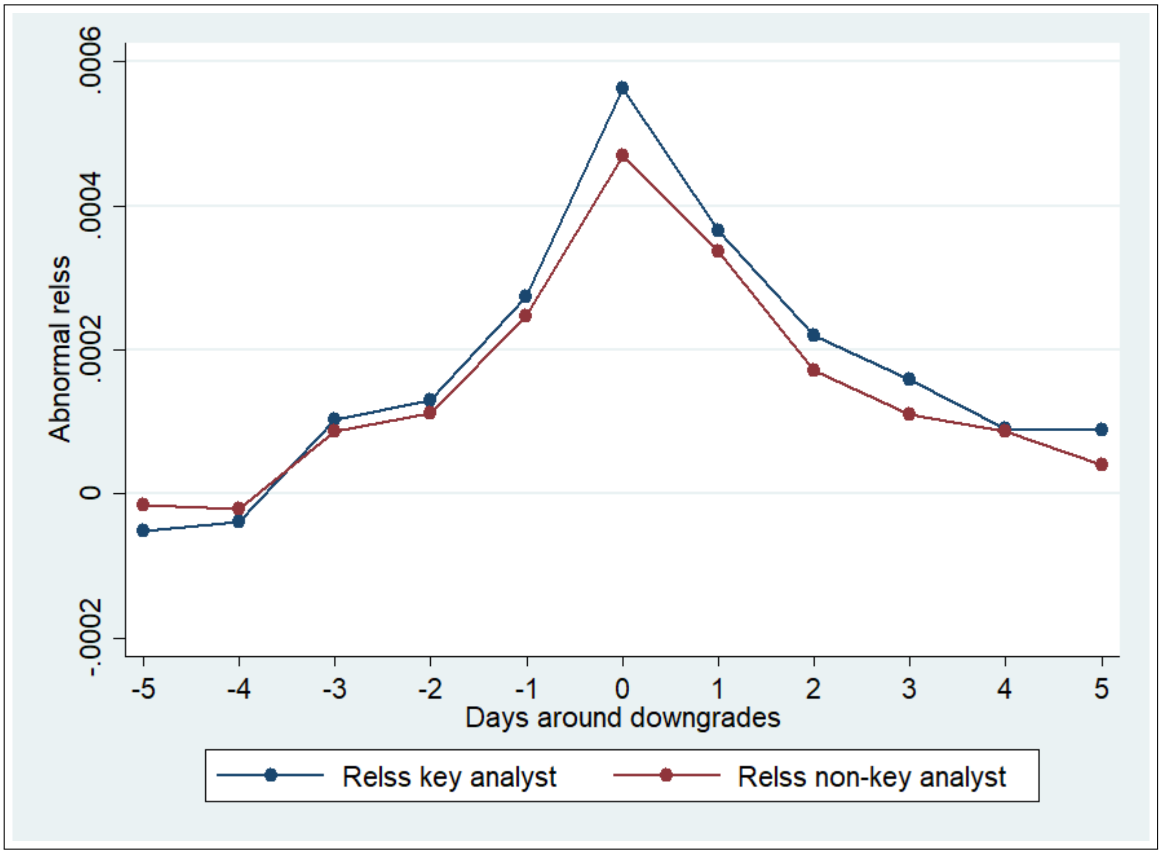

Figure 3: Key analyst and exogenous shock

$$
Analyst \rightarrow \begin{bmatrix} APPL \\ MSFT \\ DELL \\ GE \\ TWTR \\ META \end{bmatrix} \rightarrow \begin{bmatrix} Non-Key \\ Key \\ Non-Key \\ Non-Key \\ Non-Key \\ Key \end{bmatrix} \rightarrow \begin{bmatrix} Control\ Firm \\ Treated \\ Control\ Firm \\ Control\ Firm \\ Control\ Firm \\ Treated \end{bmatrix}
$$