Are short-sellers lured by analysts' consensus?*

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Abstract

We investigate whether short sellers process a specific type of public information: the quality of individual analysts' forecasts. Using U.S. data from 2006 to 2017, we find that short-selling activity increases after earnings announcements when firms miss key analysts' forecasts, above and beyond the consensus surprises. Also, higher shorting activity following missed key analyst forecasts predicts lower future returns, demonstrating that short sellers profit from trading on analyst-specific information. This behavior indicates that short sellers possess superior skills in interpreting public signals and distinguishing between high- and low-quality analysts. A quasi-experimental design based on exogenous reductions in key analyst coverage further supports our findings, showing that short-selling activity declines when key analysts stop covering firms. Additionally, short sellers react more strongly to downgrade recommendations issued by key analysts compared to non-key analysts. Our results provide new insights into how short sellers process public information, showing that they actively assess the quality of individual analysts when making trading decisions. This sheds light on the mechanisms behind their informational advantage and enhances our understanding of the specific sources of information they rely on.

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1 Introduction

How public information is processed by investors and reflected in asset prices is one of the main fundamental questions in the finance and accounting literature. One view in most of the early theoretical models is that once firms' specific information becomes public, this information is immediately known by all investors at a negligible cost and rapidly incorporated into prices (Diamond, 1985). However, more recent research acknowledges that acquiring and processing firms' disclosures can be costly and that there could be value in it for more sophisticated investors to take advantage of it. So, the question of whether sophisticated investors can extract valuable insights from public signals remains subject to debate. One type of investor that is considered as a good information processor in the literature are the short sellers. Short sellers are very active traders around the release of firms' public information, especially before and after earnings announcements,[1] however, we still know very little why short-sellers appear to be informed or what kind of information they are obtaining and processing (Boehmer et al., 2020; Reed, 2013).

In this paper, we investigate whether short sellers process a specific source of public information, that is, the characteristics (quality) of analysts when they provide useful information to investors, especially when making forecasts. If short sellers are able to extract valuable information from public signals, we expect that they will use their resources and ability to identify analysts' quality to trade. If this is the case, firms missing key analysts' benchmarks should be highly shorted after the earnings announcements, above and beyond the analyst's consensus. This would mean that short sellers do not trade speculatively or mechanically on the negative news relative to the consensus but rather on superior information they have on analysts and the surprise they could generate when firms miss their forecasts. We investigate this conjecture by examining whether differences in individual forecasts incrementally influence the decision of short sellers to trade and their profitability.

It is essential to consider the impact of individual forecasts on investors' decisions.

[1] See for example, Engelberg et al. (2012) and Boehmer et al. (2020) who show that the majority of short selling activity occurs around the publication of earnings either in anticipation of or after the news.

While the literature has traditionally focused on aggregate benchmarks, such as consensus analyst forecasts, recent research has begun to investigate whether investors' transactions extend beyond consensus-based information and instead rely on signals produced by high-quality analysts (Contreras and Marcet, 2021).[2] Although it seems intuitive that investors would take analyst heterogeneity into account when making trading decisions, identifying high-quality analysts entails both financial and cognitive costs, whereas obtaining consensus forecasts is relatively easy and inexpensive. As a result, investors appear to place significant weight on consensus figures despite the potential added value of individual forecasts (Michaely et al., 2023a; Kirk et al., 2014). We argue that the interaction between public news and the heterogeneity of analysts' forecasts provides an ideal framework for a more in-depth examination of not only the specific sources of information that short sellers process when trading, but also the timing and extent of the information-processing advantage they possess.

Focusing on US publicly traded firms in the period around earnings announcements from 2006 to 2017, we define key analysts based on Kirk et al. (2014) and consider 8 characteristics to create a score that allows us to have a key analysts forecast for each firm-quarter. The characteristics we employ are brokerage size, forecast frequency, all-star status, experience, number of companies covered, number of industries covered, forecast horizon and prior forecast accuracy. Using this classification, our first main finding is 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. Also, missing key analysts remains a significant factor explaining short selling even after controlling for past returns, firm size and abnormal liquidity around the publication of earnings. This suggests that, short selling do not rely only on negative news coming from

[2]Recent evidence also suggests that managers consider individual analyst EPS forecasts as performance targets and, importantly, manipulate earnings to meet or exceed these individual targets (Beardsley et al., 2021).

the consensus to trade, but also to certain type of negative news, the ones that comes from better quality analysts.

We then analyze whether short sellers make profits by processing this information, 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.

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 a key analyst 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. The source of exogenous variation stems from the classification of the same analyst across the portfolio of firms she was covering prior to leaving the industry. Following the approach of Kirk et al. (2014), an analyst may be classified as a key analyst for one firm while being considered a non-key analyst for another firm within her coverage.

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 loss 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, we 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. Also, 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.

One natural question that could underlie our results is if the use of analysts' quality to trade is relevant for short sellers, then we should observe that they apply this trading strategy in another context in which analysts are very active, for example, their recommendations. To perform this analysis, we use our classification of key vs. non-key analysts and 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 various ways. First, while prior research has examined the relationship between short sellers and analyst benchmarks, to the best of our knowledge, we are the first to document that short sellers process analyst-specific quality signals when making trading decisions. The existing literature primarily focuses on aggregate signals, such as consensus forecasts or recommendation downgrades, with mixed conclusions. For example, Christophe et al. (2010a) find abnormal shorting activity prior to analyst downgrades, suggesting that short sellers act on superior information. In contrast, Blau and Wade (2012a) observe abnormal shorting both prior to downgrades and upgrades, implying that short sellers may not be particularly informed about the direction of recommendation changes. Our study differs by showing that short sellers do not trade mechanically on consensus surprises alone, but instead selectively focus on individual analysts whose forecasts they perceive as more informative. This evidence suggests that short sellers possess a superior ability to evaluate the quality of public information sources, which enhances their trading profitability.

Second, our findings build on Engelberg et al. (2012), who show that short sellers capitalize on public information released during corporate news events, such as earnings announcements. While Engelberg et al. (2012) emphasize that short sellers' informational edge lies in their ability to interpret public information, our study takes this a step further by identifying what specific type of public information short sellers process, namely, the quality of individual analysts. We think this evidence fills an important gap in the literature by demonstrating that short sellers' decisions are influenced by analyst-level insights rather than aggregate benchmarks alone. But also, and perhaps, more importantly our findings help demystify the "black box" of information processing by sophisticated investors, offering direct evidence that short sellers carefully evaluate individual analysts to inform their trading strategies. This adds a new dimension to the understanding of short sellers' informational edge.

Third, we contribute to the growing literature on how analysts' heterogeneity affects investors' decisions and information dissemination in the stock markets (Kirk et al., 2014; Michaely et al., 2023b; Contreras and Marcet, 2021). Our results align with the view that processing this information is costly and that less informed investors appear to focus too much on aggregate measures. Earlier evidence has indicated that the consensus analyst forecast is a crucial benchmark for earnings (Brown and Caylor, 2005). Nevertheless, the consensus, usually measured as the mean or median of individual forecasts, fails to capture critical insights embedded in individual analyst predictions. In this respect, Michaely et al. (2023b) finds mixed results on investors' profitability when they rely on the information provided by high-quality analysts for trading decisions. Specifically, they show that trading using the EPS forecast of high-quality analysts does not yield additional profitability relative to just considering the EPS consensus, but the dispersion in EPS forecasts from high-quality analysts does. In contrast, our study focuses on specific short-seller trades and show that the EPS forecasts of high-quality analysts are indeed profitable. Contreras and Marcet (2021) find that insiders, that is, executives, officers and directors, utilize analysts' quality to hide their profitable sales. We contribute to this literature by showing 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.

Fourth, 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 suggest 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., 2010b; 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 short selling is concentrated after corporate news, mostly earnings announcements. While Blau and Wade (2012b) 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.

Our results on short selling trading with key analysts forecasts after rather than before the publication of earnings are in line with the idea that short-sellers are better at interpreting public information, but we add to this literature by identifying a particular source of public information that short sellers use to make trading decisions: the quality of individual analysts making earnings forecasts. Our results show that short sellers increase their positions after earnings announcements when firms miss forecasts made by key analysts, rather than simply reacting to consensus surprises. This behavior suggests that short sellers are not acting on foreknowledge of future fundamental information, but instead possess superior skills in interpreting public signals, specifically differentiating between high- and low-quality analysts.

Finally, we also talk to the large debate on whether sophisticated investors extract value from public information (Gârleanu and Pedersen, 2018; Kim and Verrecchia, 1997; Grossman and Stiglitz, 1980). The evidence in this regard is mixed, but recent papers show that asset managers who actively acquire public information tend to outperform those who don't. For example, Crane et al. (2023) shows that hedge funds that actively acquire large sets of public information tend to outperform funds that do not. Similarly, Chen et al. (2020) show that mutual funds that actively track insider trades obtain profits. In line with this evidence, we show that more sophisticated investors extract value from public information, but we add to these papers by showing through a specific channel, identifying analysts' quality and how they process this information to make it valuable.

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 question whether sophisticated investors can extract value from public signals remains open. The theoretical predictions on this regard are mixed. According to Grossman and Hart (1980) there is value in acquiring and processing public information if the benefits of it outweight the costs. Gârleanu and Pedersen (2018) complement this view showing that asset managers could outperform in an active market when fees reflect investors' cost for searching an asset manager and managers cost of gathering and processing information. In contrast, the model Berk and Green (2004), in line with Fama (1970) Efficient Market Hypothesis (EMH), predicts that all managers will deliver zero outperformance after fees in competitive markets. A more nuanced view is offered by Kim and Verrecchia (1997), who suggest that public information can be valuable when used in conjunction with private information.

The empirical evidence on this regard is also mixed. For example, some articles show that large investors, such as mutual funds, pension funds, and institutions, generally process disclosure information more effectively than small investors, but they often fail to fully exploit value-relevant information. Also, studies show that even sell-side analysts often fail to fully incorporate disclosure information into their forecasts and recommendations (Abarbanell and Bernard, 1992; Bradshaw et al., 2001; Engelberg et al., 2020).

Short sellers are among that group of large, sophisticated investors. And even when there is evidence that they use firms disclosures to trade, there is little pondering about the nature of the information they are processing around these corporate events. We use forecasts issued by different quality of analysts to identify one source of information short sellers process. It's well established in the literature that the 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 investors' decision to trade (Kirk et al., 2014; Michaely et al., 2023b).

In line with Michaely et al. (2023b), we argue that identifying better quality analysts requires the 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) argues, 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 process all available public information to trade, then they spot key analysts' forecasts to trade around the earnings announcements. Here it is important to make a distinction regarding the timing of their trades, 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 known before, relative to key analysts predictions. If not, one could imply that their trading decision could be based on private information. So our first hypothesis is as follows:

$H1_0$: Short selling is higher in the days following the publication of earnings in firms that miss key analysts' forecasts on top of the analyst's consensus for a given quarter.

Then, the timing of their trades is relevant, as the literature is divided on whether short sellers use only public signals or trade on foreknowledge of future, let's say, insider information.[3] For example, some studies suggest that short sellers use private information and are able to predict future negative news. For instance, there is evidence 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., 2010b), 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 to bad news events. Similarly, Engelberg et al. (2012) find 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.

[3] It is important to note that it's beyond the scope of the study to make the distinction regarding the source of private information. Generally, the literature has posed that institutional investors might gain early information by receiving stock recommendations from analysts, practice that is commonly referred to as "tipping" (Irvine et al., 2007), or by conducting independent research and arrive at similar conclusions about stocks than analysts, prompting them to trade as if they had received inside information (Kadan et al., 2018).

Then, if short sellers use analysts' quality to trade with 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.

$H1_a$: Short selling is higher in the days prior the publication of earnings in firms that miss key analysts' forecasts as opposed to missing the consensus for a given quarter.

We next move to the profitability of short sales around earnings announcements. The literature is mixed regarding whether releasing 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 signals for investors. If this is the case, short sellers trading after the publication of earnings in firms with key analysts making forecasts should have fewer opportunities to exploit profitable trades. On the other side, another stream of the literature suggests that investors could have different interpretations of the same public news, and therefore, this event 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:

$H2_0$: Short sales in firms that miss key analysts' forecasts are more profitable than in firms that miss the consensus

$H2_a$: Short sales in firms that miss key analysts' forecasts are not 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.[4] 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,[5] 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 is 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 EA_0 and EA_1, respectively. The numbering of earnings announcements then goes up from EA_1 to the future and down from EA0 to the past. During the period prior to EA_0, we capture analysts' forecasts, which are referred to EA_0, 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 EA_0. 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.

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

[5] 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.

3.1 Key analysts classification

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 forecasts for a given firm. *Accuracy* corresponds to the absolute value of analysts' forecast 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: $Miss\ key_{i,q}$ 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:

$$Y_{i,q} = \beta_0 + \beta_1 Miss\ key_{i,q} + \beta_2 Miss\ consensus_{i,q} + \delta' \cdot X_{i,q} + \alpha_i + \gamma_t + \epsilon_i \tag{1}$$

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 forecast 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 meets or beats 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 Appendix A.

4 Summary statistics

Table 1 presents the distribution of firm-quarters based on forecasts by key analysts and the consensus. Our sample consists of 73,561 firm-quarters with analysts' forecasts, of which 34,801 (47%) correspond to instances where firms missed the analysts' consensus forecast (Miss Consensus = 1). Within this group, 24,159 firm-quarters (33%) reflect cases where firms missed key analysts' forecasts.

The remaining 49,402 firm-quarters (67%) represent cases where firms met or exceeded the consensus forecast. Notably, in 32,623 firm-quarters (44%), firms met or exceeded both key analysts' forecasts and the consensus. Interestingly, in 18,022 (25%) of firm-quarters firms missed both the key analysts' forecasts and the consensus, while 8.4% of firm-quarters correspond to instances where firms missed key analysts' forecasts but met the consensus forecast.

Insert Table 1 about here.

In Table 2, presents summary statistics for the key variables used in our analysis. Panel A reports statistics for the full sample of firm-quarters, while Panels B and C provide separate statistics for firm-quarters in which firms either missed key analysts' forecasts (Panel B) or met or exceeded key analysts' forecasts (Panel C). As expected, short sellers trade a higher volume of shares in quarters when firms miss key analysts' forecasts. Additionally, firms in Panel B exhibit a more negative earnings surprise (Sue) compared to those in Panel C, which results in a more negative market reaction following earnings announcements.

Regarding firm characteristics, firms that miss key analysts' forecasts (Panel B) tend to be smaller in size, less profitable (as indicated by a higher book-to-market ratio), and have lower past returns. These firms also have fewer analysts covering them and exhibit higher dispersion in analysts' forecasts, indicating greater uncertainty about their future performance. However, the magnitude of these differences is not particularly large, suggesting that the groups are relatively comparable in their overall characteristics.

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. (2010b)), 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. (2008) 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 analyst 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.[6] 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 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

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

and long horizon information.[7]. 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 Ham et al. (2020). 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.

Insert Table 8 about here.

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

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

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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

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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	16,779	18,022	34,801
Total	49,402	24,159	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)
Variables	*(t+1, t+5)*		*(t+1, t+10)*	
Relss	-0.084***	-0.073***	-0.195***	-0.189***
	(0.016)	(0.016)	(0.028)	(0.028)
Miss top	-0.007***	-0.005***	-0.006***	-0.005***
	(0.000)	(0.001)	(0.001)	(0.001)
Miss consensus	-0.008***	-0.008***	-0.009***	-0.009***
	(0.000)	(0.000)	(0.000)	(0.001)
Mbe top	0.010***	0.010***	0.010***	0.010***
	(0.000)	(0.000)	(0.000)	(0.000)
Relss × miss key		-0.805***		-0.876***
		(0.187)		(0.221)
Relss × miss consensus		-0.282*		0.229
		(0.159)		(0.186)
Relss × mbe key		-0.185		-0.264*
		(0.118)		(0.141)
Size	-0.008***	-0.008***	-0.015***	-0.015***
	(0.000)	(0.000)	(0.000)	(0.000)
Return_{t-1}	-0.014***	-0.014***	-0.017***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.001)
Return_{t-2}	-0.018***	-0.018***	-0.017***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.001)
Perc miss (excl. key)	-0.417***	-0.416***	-0.809***	-0.808***
	(0.012)	(0.012)	(0.023)	(0.023)
Analyst coverage	0.002***	0.002***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Analysts dispersion	-0.004***	-0.004***	-0.008***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	1.157***	1.157***	1.303***	1.303***
	(0.004)	(0.004)	(0.008)	(0.008)
Observations	6,459,060	6,459,060	6,453,025	6,453,025
R-squared	0.012	0.012	0.023	0.023
cluster SE	firm	firm	firm	firm
Firm FE	Yes	Yes	Yes	Yes
Qrtr-year FE	Yes	Yes	Yes	Yes

Table 5 continued from previous page

Panel B:	Dependent variable: Buy and hold raw returns			
	(1)	(2)	(3)	(4)
Variables	*(t+1, t+5)*		*(t+1, t+10)*	
Relss	-0.151***	-0.140***	-0.327***	-0.322***
	(0.018)	(0.018)	(0.031)	(0.031)
Miss top	-0.008***	-0.006***	-0.009***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Miss consensus	-0.009***	-0.009***	-0.010***	-0.011***
	(0.000)	(0.001)	(0.001)	(0.001)
Mbe top	0.009***	0.010***	0.007***	0.007***
	(0.000)	(0.000)	(0.000)	(0.001)
Relss × miss key		-0.875***		-0.921***
		(0.206)		(0.240)
Relss × miss consensus		-0.267		0.312
		(0.173)		(0.201)
Relss × mbe key		-0.183		-0.166
		(0.128)		(0.154)
Size	-0.010***	-0.010***	-0.019***	-0.019***
	(0.000)	(0.000)	(0.000)	(0.000)
Return_{t-1}	-0.046***	-0.046***	-0.043***	-0.043***
	(0.001)	(0.001)	(0.001)	(0.001)
Return_{t-2}	-0.039***	-0.039***	-0.035***	-0.035***
	(0.001)	(0.001)	(0.001)	(0.001)
Perc miss (excl. top)	-0.440***	-0.440***	-0.841***	-0.841***
	(0.013)	(0.013)	(0.024)	(0.024)
Analyst coverage	0.003***	0.003***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
Analysts dispersion	-0.004***	-0.004***	-0.008***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	1.210***	1.210***	1.390***	1.390***
	(0.005)	(0.005)	(0.010)	(0.010)
Observations	6,459,060	6,459,060	6,453,025	6,453,025
R-squared	0.025	0.025	0.044	0.044
cluster SE	firm	firm	firm	firm
Firm FE	Yes	Yes	Yes	Yes
Qrtr-year FE	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.

	Dependent 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 $t+6+h$.

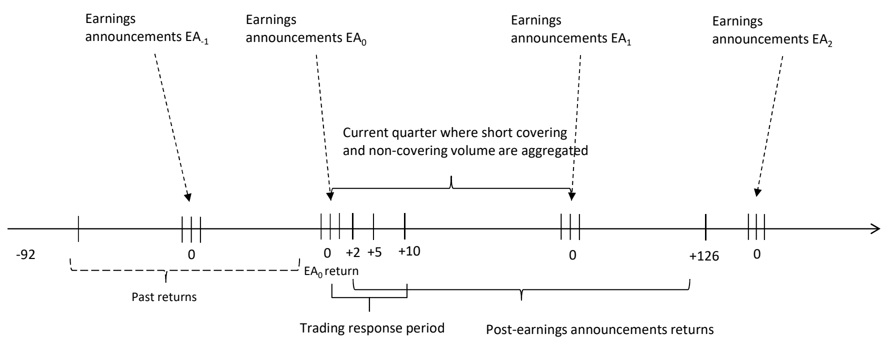

Figure 2: Key and non-key analyst downgrades. The figures show the average abnormal short-trading activity before and after analyst downgrades.

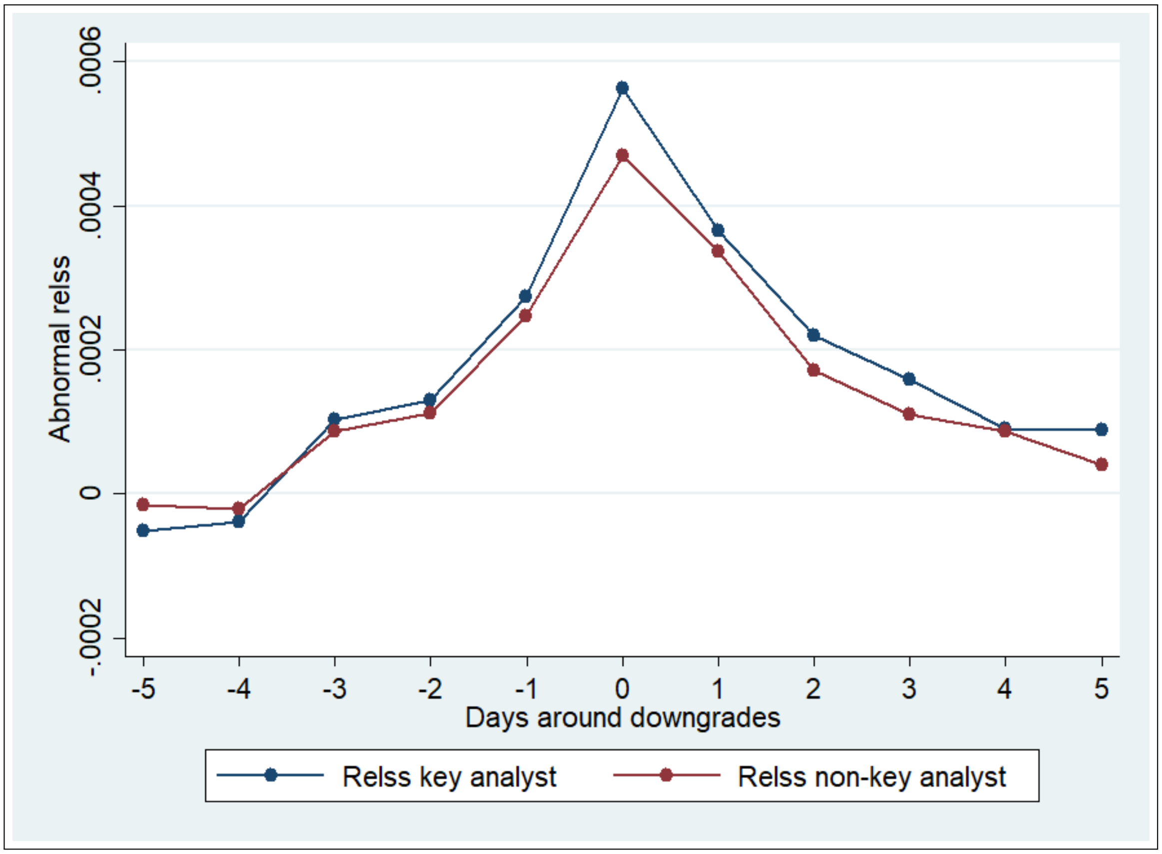

Figure 3: Key analyst and exogenous shock

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