Double Agent: Analyst-Induced Information Asymmetry and Announcement Return Reversal

Linda H. Chen, Wei Huang, and George J. Jiang[☆]

December 2021

[☆] Linda H. Chen is from the Department of Accounting, College of Business and Economics, University of Idaho, Moscow, Idaho 83844-3161. Email address: lindachen@uidaho.edu. Tel: (208) 885-7153. Wei Huang is from the Accounting and Finance Department, College of St. Benedict and St. John's University, Collegeville, MN, 56321; email whuang@csbsju.edu. George J. Jiang is the Gary P. Brinson Chair of Investment Management in the Department of Finance and Management Science, Carson College of Business, Washington State University, Pullman, WA 99164; email george.jiang@wsu.edu; tel. (509) 335-4474; fax (509) 335-3857.

Double Agent: Analyst-Induced Information Asymmetry and Announcement Return Reversal

Abstract

We argue that financial analysts serve as double-agents in the financial market. On the one hand, analysts help attenuate information asymmetry between firm insiders and investors. On the other hand, the information possessed by analysts is by nature private and creates another layer of information asymmetry for uninformed investors. We further argue that the former effect takes place during normal market conditions, whereas the latter emerges during periods with rich private information. Contrasting stock return reversal around earnings announcements where private information intensifies prior to announcements with that during normal market conditions, we confirm our predictions on the roles of analysts. Specifically, while analyst activities weaken return reversal during normal market conditions, they exacerbate return reversal around earnings announcements. Decomposing the components of bid-ask spread, we show direct evidence that analyst revisions significantly increase adverse selection component prior to earnings announcements.

Keywords: Role of analysts; Information asymmetry; Adverse selection; Return reversal;

Earnings announcements

JEL Classification: G12; G14

I. Introduction

One well-established view in the finance literature is that financial analysts help attenuate information asymmetry. For instance, Brennan and Subrahmanyam (1995) show evidence that stocks followed by more analysts have lower information asymmetry, as measured by the adverse selection costs. Frankel and Li (2004) examine the profitability and intensity of insider trades and find that increased analyst following reduces information asymmetry. In fact, analyst coverage has been commonly used in the literature as a proxy for the level of information uncertainty and information asymmetry at the firm level (Chang, Dasgupta, and Hilary, 2006; Hilary, 2006; Derrien, Kecskes, and Mansi, 2016).

However, we argue that financial analysts serve as double-agents in the financial market. On the one hand, information produced by analysts helps reduce the information asymmetry between firm insiders and market participants. This effect takes place when analysts publish their research reports, make buy or sell recommendations, and issue earnings or sales forecasts and revisions (Cheynel and Levine, 2012). On the other hand, the information produced by analysts is by nature private before it is made public. The information possessed by analysts and their clients creates another layer of information asymmetry for uninformed investors (Irvine, Lipson, and Puckett, 2007). More importantly, we argue that the first scenario prevails during normal market conditions, whereas the second emerges when the information uncertainty is high and private information is rich. The sheer possibility that analysts or other sophisticated investors may possess superior information presents a risk to uninformed investors.

In this study, we examine the double-effect of financial analysts under two distinct informational settings: one is the period prior to earnings announcements with rich private information, the other is normal non-announcement days.[1] In particular, we contrast short-term stock return reversal around earnings announcements with that during normal market conditions. Existing studies document a significant reversal in short-term stock returns.[2] The literature generally attributes the short-term reversal to the effect of liquidity provision by risk-averse "market makers" (Campbell, Grossman, and Wang, 1993; Jegadeesh and Titman, 1995; Nagel, 2012).[3] Market makers demand high expected returns to compensate the inventory risk when providing liquidity. The literature also documents that short-term reversal around earnings announcements is significantly stronger than during non-announcement periods. So and Wang (2014) argue that the stronger short-term return reversal is due to an increase in inventory risk prior to earnings announcements.

The contrast of return reversal around earnings announcements with that during normal market conditions helps to highlight the roles of analysts under different information settings. If information production by analysts indeed attenuates information asymmetry and reduces adverse selection costs, we expect stocks with analyst coverage and analyst activities to have a weaker return reversal, controlling for other firm characteristics. On the other hand, as we argue in this study, if the information possessed by analysts creates another layer of information asymmetry for uninformed investors, particularly during periods with rich private information, we expect stocks

---

[1] Several studies argue or show evidence that there is strong information asymmetry prior to earnings announcements. For instance, Kim and Verrecchia (1994) argue that information asymmetry is likely more pronounced at earnings announcements because certain investors can make superior judgements on a firm's performance than others. Krinsky and Lee (1996) investigate the behavior of bid-ask spread and find a significant increase in adverse selection cost component around earnings announcements.

[2] Jegadeesh (1990) and Lehmann (1990) are among the first to show reversals in short-term stock returns at monthly and weekly horizons.

[3] The literature also provides other explanations of reversals in stock returns. Kaul and Nimalendran (1990) examine the short-term return reversal for NASDAQ firms and argue that the bid-ask error is the main source of return reversal. Cooper (1999) suggests overreaction as a plausible cause. Da, Liu and Schaumburg (2014) argue that both sentiment and liquidity can lead to short-term return reversal.

with analyst coverage and analyst activities to have a stronger return reversal around earnings announcements.

Our main findings are summarized as follows. Based on stocks with quarterly earnings announcement dates from IBES during the sample period from 1996 to 2017, we confirm that there is a significant return reversal around the earnings announcements. Consistent with So and Wang (2014), we construct pseudo announcement dates during normal market conditions and show that return reversal around the earnings announcement date is significantly stronger than that during non-announcement periods. We then perform several analyses to examine the effect of analysts on return reversal. First, we divide stocks into subsamples based on analyst coverage. Our results show that the presence of analyst coverage significantly weakens return reversal during non-announcement periods but exacerbates the return reversal around earnings announcements. Second, we use the number of earnings forecasts, the number of earnings revisions, and the magnitude of earnings revision as proxies for analyst activities. The results confirm that analyst activities help to weaken return reversal during normal market conditions but strengthen return reversal around earnings announcements. We further show that the results are robust even after controlling for various firm characteristics. The pattern is consistent with our argument that analysts help attenuate information asymmetry between firm insiders and market participants during normal market conditions but exacerbate information asymmetry between themselves/their clients and uninformed traders when private information is rich.

We then examine the role of analysts on return reversal separately for firms with high and low information uncertainty. Our argument is that for firms with higher information uncertainty, analysts play a stronger role of attenuating information asymmetry during normal market conditions and also exacerbating information asymmetry around earnings announcements. We use the standard deviation of unexpected earnings as a proxy of earnings uncertainty and divide stocks into subsamples with high and low earnings uncertainty. Affleck-Graves, Callahan, and Chipalkatti (2002) examine the bid-ask spread around earnings release and find that there is an increase in adverse selection component for firms with less predictable earnings but not for firms with more predictable earnings. Our results show that both the attenuating effect of analysts on normal return reversal and the exacerbating effect of analysts on announcement return reversal are stronger for firms with high earnings uncertainty.

One important question is whether analyst activities are informative of future earnings surprises. First, we argue that if analysts are informed, they should focus on firms with more private information. We use two proxies for earnings information content prior to announcement, namely the magnitude of analyst forecast error and the magnitude of abnormal announcement return during the earnings announcement window. We find that after controlling for information uncertainty, analysts issue more revisions for firms with more unexpected earnings. Further analysis shows that analyst revisions during the pre-announcement window have significant predictive power of earnings surprises. This is evidence that analysts tend to target firms with more private information and analyst revisions are informative of upcoming earnings announcements.

To examine whether investors react to analyst activities during the pre-announcement window, we examine the effect of analyst activities on trading activities. We use turnover to proxy for the level of trading activities and order imbalance to proxy for informed trading. Our results show that for stocks with analyst earnings forecasts or revisions, there is a significant increase in turnover during the pre-announcement period relative to the prior month. More importantly, for stocks with analyst earnings forecasts or revisions, we also find a significant increase in order imbalance during the pre-announcement period relative to the prior month. That is, investors do trade in response to information produced by analysts. Moreover, consistent with Campbell, Grossman, and Wang (1993 and Llorente, Michaely, Saar, and Wang (2002), we show that higher turnover attenuates return reversal during normal market conditions. In sharp contrast, our results show that higher turnover exacerbates return reversal around earnings announcements.

To further understand how investors react to analyst activities during the pre-announcement window, we separately examine private market reactions and public market reactions to analyst revisions. We use the time stamp of analyst revision in IBES to identify whether a revision is issued after market close and determine the revision date. If a revision is issued after market close, we classify the revision date as the next day. We then regress stock returns over the two days prior to revision and stock returns over the two days following the revision against analyst revisions. We interpret the former regression as private market reaction to analyst revisions and the latter as public market reaction to analyst revisions. Our results show that there are both significant private market reaction and public market reaction to analyst revisions. However, compared to market reactions to revisions during normal market conditions, there is a stronger private reaction to analyst revisions but a weaker public reaction to analyst revisions during the pre-announcement window. This is consistent with earlier finding that there is a significantly higher order imbalance or informed trading associated with analyst revisions. The results help to alleviate the concern that the patterns documented in our study may be driven by investor overreaction to analyst revision before the earnings announcement. More importantly, the results suggest that analysts are more likely to disclosure their earnings revisions to certain investors before public announcements (Irvine, Lipson, and Puckett, 2007). As such, uninformed investors or market makers become more cautious and demand higher returns for liquidity provision since are more likely trading against informed traders.

Finally, we examine whether analyst activities impact the bid-ask spread and its adverse-selection component during the pre-announcement window. Lee, Mucklow, and Ready (1993) find that bid-ask spreads widen and depths fall prior to earnings announcements, suggesting that liquidity providers use both spreads and depths to manage the risk associated with changes in information asymmetry. Our results show that the increase in the effective spread during the pre-announcement window is mainly driven by stocks with analyst earnings forecasts or revisions during the pre-announcement window. For realized spread, only stocks with analyst activities show a significant increase in realized spread during the pre-announcement window. To further examine what drives the increase in bid-ask spreads, we identify the adverse-selection component following the method proposed in Huang and Stoll (1997). Krinsky and Lee (1996) investigate the behavior of bid-ask spread and find a significant increase in adverse selection cost component around earnings announcements. Our results show that there is a significant increase in the adverse-selection component for stocks with analyst earnings forecasts or revisions. This is direct evidence that analyst earnings forecasts or revisions during the pre-announcement window induce information asymmetry.

The rest of the paper is structured as follows. Section II describes the data and variable constructions used in our study. Section III presents the results of the main empirical analysis. Section IV provides the results of further analysis. Section V is the conclusions.

II. Data

The sample in our empirical analysis consists of stocks with quarterly earnings announcement dates from IBES during the period from January 1996 to December 2017. The beginning of our sample period is consistent with So and Wang (2014). The total number of firm-quarter observations from IBES is 287,523 with 12,453 unique number of stocks. We restrict to common stocks (SHRCD = 10 or 11) traded on NYSE, AMEX, or NASDAQ (EXCHED = 1, 2, or 3) in the CRSP stock database. We also exclude stocks with a price less than $5 at the beginning of the quarter. This results in 221,701 firm-quarter observations with 10,025 unique number of stock. We further exclude stocks with missing observations of market capitalization and stocks with missing observations of returns on the announcement date. Our final sample includes 210,719 observations with 9,399 unique number of stocks with an average of 2,395 stocks per quarter.

One of the main variables used in our analysis is analyst coverage (COV), which is defined as the number of analysts covering a firm based on data from IBES. The other main variable is analyst forecast error (FE). Following Livnat and Mendenhall (2006), we compute analyst forecast error (FE) as follows:

$$FE_{i,t} = \frac{(X_{i,t} - \widetilde{X}_{i,t})}{P_{i,t}} \tag{1}$$

where $X_{i,t}$ is primary earnings per share before extraordinary items for firm i in quarter t, $\widetilde{X}_{i,t}$ is the median forecast of earnings per share reported to IBES in the 90 days prior to the earnings announcement, and $P_{i,t}$ is the price per share for firm i at the end of quarter t from Compustat. Both $X_{i,t}$ and $P_{i,t}$ are unadjusted for stock splits.

Stock returns and other firm characteristics are obtained from CRSP daily and monthly database, Compustat database, and IBES database. Following Fama and French (1993), market capitalization (SIZE) is calculated and updated at the end of each June as the stock price times the number of shares outstanding. The book-to-market ratio (BEME) is also calculated and updated at the end of each June using book value for the fiscal year ending in the calendar year t-1 divided by market capitalization at the end of December of year t-1. Book value is equal to the book value of stockholders' equity plus balance sheet deferred taxes and investment tax credits minus the book value of preferred stocks, as defined in Fama and French (1993). The Amihud (2002) illiquidity (ILLIQ) is calculated as the ratio of absolute daily return to dollar trading volume and averaged over the quarter, pre-multiplied by 10^6. Since the trading volume on NASDAQ is double counted before 2004, we follow Boehmer (2005) and adjust the trading volume of NASDAQ stocks by a factor of 0.7. After 2004, there are no longer significant differences in terms of the reporting of NYSE and NASDAQ trading volume as many stocks listed on NYSE or NASDAQ are traded on crossing networks and other venues (Gao and Ritter, 2010). Therefore, we do not adjust the trading volume of NASDAQ stocks after 2004. Following Ang, Hodrick, Xing, and Zhang (2006), idiosyncratic volatility (IVOL) is estimated under the Fama-French three-factor model:

$$r_{i,t} = \alpha_i + \beta_{i,MKT} MKT_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \varepsilon_{i,t} \tag{2}$$

The model is estimated using daily returns in a quarter, and idiosyncratic volatility ($IVOL_t$) is obtained as $\sqrt{\text{var}(\varepsilon_{i,t})}$. Momentum (MOM) is calculated as skip-one-month lagged cumulative 12-month returns. Earnings uncertainty (EU) is the standard deviation of analyst forecast error for a firm over the past 20 quarters with minimum 8 observations. Leverage (LEV) is calculated as book debt to total assets where book debt is total assets minus book equity.

Table 1 reports summary statistics of analyst coverage (COV), analyst forecast error (FE) and other firm characteristics. Each quarter, we calculate the cross-sectional summary statistics (5%, 25%, mean, median, 75%, 95%, and standard deviation) of each variable. The table reports the time-series average of those summary statistics. The results show that the average number of analysts covering a firm is about 8. The mean and median of analyst forecast errors are close to 0. This indicates that, on average, analysts' consensus forecasts are close to actual earnings per share. The average market cap (SIZE) is $5.572 billion during our sample period.

III. Main Empirical Analysis

A. Earnings Announcement Return Reversal and the Effect of Analyst Coverage

In this section, we first examine the earnings announcement return reversal over the sample period from 1996 to 2017, extending the sample period in existing studies. We follow So and Wang (2014) and calculate the pre-announcement return (PAR) for each earnings announcement as the cumulative abnormal return from t-4 to t-2, where t is the earnings announcement date. Each quarter, we assign stocks to PAR quintiles. We then calculate the mean of PAR and cumulative abnormal returns over different windows around earnings announcement (CAR[-1,+1], CAR[-1,+5], and CAR[+2,+5]) for each PAR quintiles each quarter. The abnormal return is the difference between the daily stock returns and the benchmark. The benchmark is the average size decile portfolio return, where size deciles are constructed each year based on the size in the end of year t-1.

Panel A of Table 2 reports the time-series average of various cumulative abnormal returns around the actual announcement date for different pre-announcement returns (PAR) quintiles. Consistent with the findings in So and Wang (2014), the results show clear return reversals around earnings announcements. The average announcement returns (CAR[-1, +1]) decrease monotonically across PAR quintiles, and firms with high PAR on average have significantly lower returns than firms with low PAR during the earnings announcement period. The results in Table 2 show that the return reversal is also significant over a longer announcement window CAR[-1, +5] and even during the post-announcement window CAR[+2, +5]. As noted earlier, So and Wang (2014) argue that the increase in inventory risk prior to earnings announcements leads to stronger short-term return reversal. In addition, we observe that differences in announcement returns

(CAR[-1, +1]) between high and low PAR quintiles are mostly driven by the higher returns of stocks in the low PAR quintile. This pattern is consistent with Levi and Zhang (2015), who argue that investors are reluctant to trade before earnings announcements due to high information asymmetry, and the effect is particularly strong for purchases. Liquidity selling by investors before earnings announcement leads to higher post-announcement prices.

As noted in the introduction, the literature documents a general reversal pattern in stock returns over short horizons. For instance, Jegadeesh (1990) and Lehmann (1990) show clear reversals in short-term stock returns at monthly and weekly horizons. They show that contrarian strategies based on stock returns in the previous week or month earn significantly positive abnormal returns. For the purpose of comparison, we also construct a pseudo earnings announcement sample and examine differences in magnitude between earnings-announcement return reversal and non-earnings-announcement return reversal. Following So and Wang (2014), we select a random number from a uniform distribution spanning 10 to 40 days. Then, we subtract the randomly selected number of trading days from the actual announcement dates to generate pseudo-announcement dates. Panel B of Table 2 reports the time-series average of cumulative abnormal returns around the pseudo announcement date for different pre-announcement returns (PAR) quintiles. Consistent with the literature, we also observe a significant return reversal for the pseudo announcement sample.

More importantly, Panel C of Table 2 shows that compared to the return reversal during normal market conditions, the reversal around actual earnings announcements is stronger in terms of both significance and magnitude. The difference between the two samples is 0.711 for CAR[-1,+1] and 0.735 for CAR[-1,+5], both of which are significant at 1% level. So and Wang (2014) find a six-fold increase in earnings announcement return reversal relative to non-announcement return reversal during the period of 1996 to 2011. We confirm that the findings in So and Wang (2014) hold in our sample period. That is, return reversals during the earnings announcements period are significantly stronger than those during non-announcement periods.

As a robustness check of the findings in Table 2, we perform Fama-MacBeth (Fama and MacBeth, 1973) multivariate regressions where we control for the effect of various firm characteristics. Each quarter, we perform Fama-MacBeth regressions of cumulative abnormal return during the earnings announcement window (CAR[-1,1]) on PAR, various firm characteristics (X), and the interactions between PAR and X. To identify the effect of various firm characteristics on earnings announcement return reversal, we perform the regression jointly for the earnings announcement sample and pseudo sample. The regressions are specified as follows:

$$\begin{aligned} CAR[-1,1]_{i,t} = \alpha_t + \beta_{1t}PAR_{i,t} \quad &+\beta_{2t}X_{i,t} \quad +\beta_{3t}PAR * X_{i,t} \\ &+\beta_{4t}PAR * d^{EA}{}_{i,t} + \beta_{5t}X * d^{EA}{}_{i,t} + \beta_{6t}PAR * X * d^{EA}{}_{i,t} \\ &+\beta_{7t}FE * d^{EA}{}_{i,t} + \beta_{8t}d^{EA}{}_{i,t} + \varepsilon_{i,t} \qquad (3) \end{aligned}$$

where $CAR[-1,1]_{i,t}$ is the cumulative abnormal return of stock i from t-1 to t+1, and t is the earnings announcement date. $PAR_{i,t}$ is the cumulative abnormal return of stock i from t-4 to t-2. $X_{i,t}$ are control variables. The control variables include market capitalization (SIZE), book to market ratio (BEME), momentum (MOM), the Amihud illiquidity ratio (ILLIQ), idiosyncratic volatility (IVOL), and leverage (LEV). We also include interactions of $PAR_{i,t}$ with these control variables. d^{EA} is a dummy variable of the announcement, which equals to 1 if the observation is an actual earnings announcement and 0 otherwise. The terms not interacted with d^{EA} (i.e., $PAR * X_{i,t}$ in the first line of the above equation) identify the effect of certain firm characteristics on the return reversal during normal market conditions, whereas the terms interacted with d^{EA} (i.e., $PAR * X * d^{EA}{}_{i,t}$ in the second line of the above equation) identify the additional effect of certain firm characteristics on the return reversal around earnings announcements. For the actual earnings announcements, we also include earnings surprise, proxied by analyst forecast error (FE) (in the third line of the above equation) as a control variable.

Table 3 reports the time-series average of coefficient estimates of the quarterly regressions in Eq. (3) and their Newey-West t-statistics. For each regression specification, we report the coefficient estimates of terms not interacted with d^{EA} (i.e., $PAR * X_{i,t}$) in the first column, and the coefficient estimates of terms interacted with d^{EA} (i.e., (i.e., $PAR * X * d^{EA}{}_{i,t}$) in the second column. We observe a significantly negative sign for the coefficient of PAR and the coefficient of the interaction term PAR*d^{EA}. There is a significant return reversal during normal market conditions. The return reversal around earnings announcement is significantly stronger than during the normal market condition, even after controlling for various firm characteristics. The results confirm the findings in Table 2. In addition, we observe a significantly negative coefficient for SIZE*PAR*d^{EA}. That is, for large firms, the return reversal around earnings announcement is actually stronger than during normal market conditions. The significantly negative sign of MOM*d^{EA} indicate that for firms with strong prior returns, the abnormal returns during the announcement period are significantly lower. This result is consistent with the finding of Aboody, Lehavy, and Trueman (2010), who find that stocks with strongest prior 12-month returns have a significantly negative return after the earnings announcement. Moreover, consistent with prior literature, for liquid stocks, the reversal is weaker during normal market conditions. Avramov, Chordia, and Goyal (2006) find that stocks with high liquidity have less reversal than stocks with low liquidity. More interestingly, we observe that the coefficient of ILLIQ*PAR*d^{EA} is significantly positive. That is, for liquid stocks, the reversal around earnings announcement is actually stronger than during normal market conditions. Finally, as expected, earnings announcement returns are directly related to earnings surprises. The coefficient of earnings surprises (FE) is significantly positive for the actual earnings announcements.

Next, we examine the effect of analyst coverage on return reversal. Our main argument is that if information production by analysts attenuates information asymmetry and lower adverse selection costs during normal market conditions, we should expect that stocks with more analyst coverage have a weaker return reversal. On the other hand, if the information possessed by analysts during the pre-announcement period creates another layer of information asymmetry between analysts or their clients and uninformed investors, we should expect that stocks with more analyst coverage and analyst activities have a stronger return reversal around earnings announcements.

Each quarter, we extend the Fama-MacBeth regressions in Eq. (3) by including analyst coverage (COV) and its interaction with pre-announcement return (PAR*COV) as explanatory variables:

$$\begin{aligned} CAR[-1,1]_{i,\mathrm{t}} = \alpha_t + \beta_{1t} PAR_{i,t} \quad & + \beta_{2t} COV_{i,t} \quad + \beta_{3t} PAR * COV_{i,t} \\ & + \beta_{6t} PAR * d^{EA}{}_{i,t} + \beta_{2t} COV * d^{EA}{}_{i,t} + \beta_{4t} PAR * COV * d^{EA}{}_{i,t} \\ & + OtherTerms + \varepsilon_{i,t} \end{aligned} \tag{4}$$

where analyst coverage (COV) is the number of analysts covering the firm at the end of the previous quarter. Other terms are the same as in Eq. (3).

Table 4 reports the time-series average of coefficient estimates of quarterly regressions in Eq. (4) and their Newy-West t-statistics. First of all, the main results documented in Table 3, i.e., the significantly negative coefficients of PAR and PAR*d^{EA}, still hold in all three regressions in Table 4. Second, we note that the coefficient of PAR*COV is positive and significant. That is, consistent with the prevailing notion in the literature, there is a weaker return reversal for stocks with more analyst coverage. Third and more importantly, the results in Table 4 show that the coefficient of PAR*COV*d^{EA} is significantly negative. This suggests that for stocks with more analyst coverage, the return reversal around announcements is significantly stronger than that during normal market conditions. Note that COV is a lagged variable constructed at the end of the previous quarter. This alleviates the potential concern that analyst coverage may be influenced by trading activities prior to announcements. Regressions in columns (2) and (3) in Table 4 further confirm that the results are robust after controlling for various firm characteristics. Overall, the results in Table 4 support our conjecture that the presence of analyst coverage significantly weakens return reversal during normal market conditions but exacerbates the return reversal around earnings announcements.

B. Further Evidence on the Effect of Analyst Activities

The results presented in the previous sections show that analyst coverage has a significant effect on return reversal during both normal market conditions and around earnings announcements. In this section, we perform further analyses to examine the role of analyst activities. We use the number of earnings forecasts (#EF), the number of revisions (#REV), and average revision (REV) issued by analysts as proxies for analyst activities. The number of earnings forecasts (#EF) is the total number of earnings forecasts submitted by analysts for the current fiscal quarter during a given period. The number of revisions (#REV) is the total number of revisions issued by analysts for the current fiscal quarter during a given period. If the same analyst submitted an earnings forecast following an earlier forecast for the same fiscal quarter, the second forecast is counted as a revision. Average revision (REV) is calculated as the average of revisions submitted by analysts during a given period. The magnitude of an analyst revision is calculated as the difference in earnings-per-share (EPS) between the current forecast and the previous forecast for the same fiscal quarter.

First, we use the number of earnings forecast (#EF) as a proxy of analyst activities to examine the effect of earnings forecasts on return reversal in multivariate regressions. Each quarter, we perform Fama-MacBeth regressions similar to those in Eq. (3), i.e.,

$$
\begin{aligned}
CAR[-1,1]_{i,t} = \alpha_t + \beta_{1t} PAR_{i,t} \quad & + \beta_{2t} d^{\#EF}{}_{i,t} \quad + \beta_{3t} PAR * d^{\#EF}{}_{i,t} \\
& + \beta_{6t} PAR * d^{EA}{}_{i,t} + \beta_{2t} d^{\#EF} * d^{EA}{}_{i,t} + \beta_{4t} PAR * d^{\#EF} * d^{EA}{}_{i,t} \\
& + OtherTerms + \varepsilon_{i,t} \qquad (5)
\end{aligned}
$$

where the dummy variable $d^{\#EF}$ is equal to 1 if the number of EPS forecast (#EF) is higher than 0 and 0 otherwise. The number of EPS forecast (#EF) is the total number of forecasts submitted by analysts for the current fiscal quarter during pre-announcement from t-2 to t-4. Other terms are the same as in Eq. (3).

Table 5 Panel A reports the time-series average of coefficient estimates of quarterly regressions in Eq. (5) and their Newey-West t-statistics. The results show a significantly positive coefficient of PAR*$d^{\#EF}$ and a significantly negative coefficient of PAR*$d^{\#EF}$*d^{EA} in all three regression specifications. That is, similar to the effect of analyst coverage as documented earlier, earnings forecasts issued by analysts tend to weaken return reversal during normal market conditions but strengthen return reversal around earnings announcements.

In addition, we use the number of revisions (#REV) as a proxy of analyst activities to examine the effect of earnings revisions on return reversal in multivariate regressions. Each quarter, we perform Fama-MacBeth regressions similar to those in Eq. (3), i.e.,

$$CAR[-1,1]_{i,\mathrm{t}} = \alpha_t + \beta_{1t} PAR_{i,t} \quad + \beta_{2t} d^{\#REV}{}_{i,t} \quad + \beta_{3t} PAR * d^{\#REV}{}_{i,t}$$

$$+ \beta_{6t} PAR * d^{EA}{}_{i,t} + \beta_{2t} d^{\#REV} * d^{EA}{}_{i,t} + \beta_{4t} PAR * d^{\#REV} * d^{EA}{}_{i,t}$$

$$+ OtherTerms + \varepsilon_{i,t} \tag{6}$$

where the dummy variable $d^{\#REV}$ is equal to 1 if the number of revisions (#REV) is higher than 0 and 0 otherwise. The number of revisions (#REV) is the total number of revisions issued by analysts during the pre-announcement period from t-2 to t-4. Other terms are the same as in Eq. (3).

Table 5 Panel B reports the time-series average of coefficient estimates of quarterly regressions in Eq. (6) and their Newey-West t-statistics. The results show a significantly positive coefficient of PAR* $d^{\#REV}$ and a significantly negative coefficient of PAR* $d^{\#REV}$*d^{EA} in all three regression specifications. That is, earnings revisions issued by analysts have a similar effect as earnings forecasts documented earlier. That is, earnings revisions issued by analysts also tend to weaken return reversal during normal market conditions but strengthen return reversal around earnings announcements.

Finally, we use the magnitude of analyst revision (|REV|) as a proxy of analyst activities to further examine the effect of earnings revisions on return reversal in multivariate regressions. Da, Liu, and Schaumburg (2014) use analyst forecast revisions as a proxy for cash-flow news. Each quarter, we perform Fama-MacBeth regressions similar to those in Eq. (3), i.e.,

$$CAR[-1,1]_{i,\mathrm{t}} = \alpha_t + \beta_{1t} PAR_{i,t} \quad + \beta_{2t} d^{|REV|}{}_{i,t} \quad + \beta_{3t} PAR * d^{|REV|}{}_{i,t}$$

$$+ \beta_{6t} PAR * d^{EA}{}_{i,t} + \beta_{2t} d^{|REV|} * d^{EA}{}_{i,t} + \beta_{4t} PAR * d^{|REV|} * d^{EA}{}_{i,t}$$

$$+ OtherTerms + \varepsilon_{i,t} \tag{7}$$

where the dummy variable $d^{|REV|}$ is equal to 1 if the absolute value of analyst revision (|REV|) during the pre-announcement period t-2 to t-4 is higher than 0 and 0 otherwise. Other terms are the same as in Eq. (3). Compared to the dummy variable $d^{\#REV}$ based on the number of revisions, $d^{|REV|}$ is a stronger measure of analyst activities as it requires the average revision to be none-zero.

Table 5 Panel C reports the time-series average of coefficient estimates of quarterly regressions in Eq. (7) and their Newey-West t-statistics. Consistent with Panel B, the results in Panel C show that analyst revisions tend to weaken return reversal during normal market conditions but strengthen return reversal around earnings announcements. The coefficient estimates of PAR*$d^{|REV|}$ are significantly positive, and the coefficient estimates of PAR*$d^{|REV|}$*d^{EA} are significantly negative in all regressions.

The results in Table 5 confirm that analyst activities, as proxied by the number of earnings forecast, the number of revisions, and the magnitude of revisions, help to weaken return reversal during normal market conditions but strengthen return reversal around earnings announcements. The evidence is consistent with our argument that analysts help attenuate information asymmetry between firm insiders and market participants during normal market conditions but exacerbate information asymmetry between themselves or their clients and uninformed traders when private information is rich.

To provide further evidence that analyst activities before earnings announcements contribute to announcement return reversal, we decompose the pre-announcement returns (PAR) into two components: the component associated with analyst revisions and the residual. If analyst revisions do not contribute to return reversal around earnings announcements, the residual part should be the only term that has a negative relation with announcement returns. The results in Appendix Table A1 show that, as expected, the coefficients of both REV[-1,1] and FE are significantly positive. More importantly, the component that is associated with analyst earnings revision, only significantly negative when interacting with d^{EA}. The residual terms are significantly negative whether or not they interact with d^{EA}. This is evidence that analyst revisions directly contribute to the return reversal around earnings announcements.

C. Effect of Analyst Coverage: Firms with High Information Uncertainty

The results in the previous section show that analyst activities have a significant effect on return reversal during normal market conditions and around earnings announcements. As we argued earlier, this is because information production by analysts helps attenuate information asymmetry during normal market conditions but exacerbates information asymmetry prior to earnings announcements. In this section, we further argue that both the attenuating effect and the exacerbating effect on information asymmetry by analysts should be stronger for firms with high information uncertainty. In particular, for firms with high information uncertainty, there is likely more private information during the pre-announcement period, and information possessed by analysts increases adverse selection costs to uninformed investors.

To test the above conjecture, we identify stocks with high information uncertainty and examine the effect of analyst coverage on return reversal for these stocks. We use the standard deviation of earnings surprises as a proxy of earnings uncertainty. Affleck-Graves, Callahan, and Chipalkatti (2002) examine the bid-ask spread around earnings release and find that there is an increase in adverse selection component for firms with less predictable earnings but not for firms with more predictable earnings. The standard deviation of earnings surprises for a given firm is calculated based on analyst forecast error (FE) over the past 20 quarters with a minimum 8 observations. A firm is classified as having high information uncertainty in a quarter if the standard deviation of FE is above the median of all stocks.

Each quarter, we replicate the Fama-MacBeth regressions in Eq. (4) for stocks with high earnings uncertainty. Panel A of Table 6 reports the time-series average of coefficient estimates of quarterly regression and their Newey-West t-statistics. The results are consistent with those in Table 4, i.e., the coefficient of PAR*COV is significantly positive, and the coefficient of PAR*COV*d^{EA} is significantly negative. However, the coefficients of both PAR*COV and PAR*COV*d^{EA} are higher in magnitude and stronger in significance level than those in Table 4. Panel B of Table 5 reports the coefficients of PAR*COV and PAR*COV*d^{EA} for firms with high information uncertainty and the full sample of stocks. We also report differences between these two sets of coefficients and their statistics. The differences show that the coefficient of PAR*COV is significantly higher for firms with high information uncertainty than for the full sample of stocks. On the other hand, the coefficient of PAR*COV*d^{EA} is significantly lower for firms with high information uncertainty than for the full sample of stocks. The results are consistent across all regression specifications. That is, for firms with high information uncertainty, analyst coverage has a significantly stronger effect in reducing return reversal during normal market conditions. On the other hand, analyst coverage has a significantly stronger effect in strengthening return reversal around earnings announcements. This evidence is consistent with our conjecture that when there is more information uncertainty, analysts play a stronger role of both attenuating information asymmetry during normal market conditions and exacerbating information asymmetry prior to earnings announcements.

IV. Further Analysis

In the previous section, we find that analysts play an important but different role in influencing information asymmetry. In this section, we want to examine this relationship further. More specifically, we want to address the following research questions: First, do analysts focus on firms with more private information? Second, is analyst earnings revision informative of future earnings surprises? Third, how does the market react to analyst activities during the pre-announcement window? Fourth, how does such reaction affect return reversal around earnings announcements? In this section, we also show evidence to rule out the possibility that the findings of our study are driven by investor overreaction to analyst activities. Finally, we examine the effect of analyst activities on the bid-ask spread and the adverse selection component of the bid-ask spread during the pre-announcement window.

A. Information Production by Analysts during Pre-Announcement Window

According to the literature, analysts tend to cover large firms (Bhushan, 1989; Hong, Lim, Stein, 2000; Ackert and Athanassakos, 2003; Zhang, 2006) and firms with less information uncertainty (Alford and Berger, 1999; O'Brien and Bhushan, 1990; Lang and Lundholm, 1996; Chan and Hameed, 2006; Zhang, 2006; Yu, 2008). We examine the relation between analyst activities and information uncertainty, which is proxied by idiosyncratic volatility (IVOL) or earnings uncertainty (EU), as well as various firm characteristics. Each quarter, we perform Fama-MacBeth regressions of analysts' activities on various firm characteristic variables. Analysts' activities are measured by log(1+COV), log(1+#EF), and log(1+#REV). COV is analysts coverage, #EF is the number of earnings forecasts issued by analysts, and #REV is the number of revision. The other firm characteristics variables include market capitalization (SIZE), book to market ratio

(BEME), momentum (MOM), the Amihud illiquidity ratio (ILLIQ), and leverage (LEV). Table A2.1 of Appendix reports the time series average of coefficient estimates of quarterly regressions and their Newey-West t-statistics. As expected, firms with larger size, lower book to market ratio, lower illiquidity tend to have more analyst activities. These results show that analysts generally prefer firms with more information. Furthermore, the significant negative signs on the idiosyncratic volatility and earnings uncertainty indicate analysts' preference in firms with lower information uncertainty.

We then sort stocks into quintiles each quarter based on lagged idiosyncratic volatility (IVOL) or lagged earnings uncertainty (EU) to further investigate the relation between analysts' activities and information uncertainty. For each quintile, we calculate the average number of earnings forecasts issued by analysts (#EF) and the number of revision (#REV). Both variables are measured during the period t-2 to t-4 and the difference between t-4 to t-2 and t-26 to t-5 (excess measure). Panel A and B of Appendix Table A2.2 report the time series average of #EF and #REV as well as the differences in each variable between the top and bottom quintiles. We find that there is a monotonic decrease in analysts' activities with increasing information uncertainty. The differences between the top and bottom quintiles are all significant. The results in this table also indicate that analysts prefer firms with lower information uncertainty. Overall, the results reported in Appendix Table A2.1 and A2.2 confirm the findings in the prior literature that analysts tend to cover large firms and firms with less information uncertainty.

Next, we further examine analyst activities by controlling for information uncertainty. We first sort stocks into quintiles based on lagged earnings uncertainty (EU), and then within each EU quintile, the stocks are assigned to quintiles based on the magnitude of analyst forecast error (|FE|) or magnitude of abnormal announcement return (|CAR[-1, 1]|). We use EU to proxy for information uncertainty and use |FE| and |CAR[-1, 1]| to proxy for the information content in the earnings announcement. We calculate the time series average of the number of earnings forecasts issued by analysts (#EF) and the number of revision (#REV) for each quintile. Both variables are excess measures. Excess #EF is calculated as the difference in #EF between the period of t-4 to t-2 and that of t-26 to t-5. Excess #REV is calculated as the difference in #REV between the period of t-4 to t-2 and that of t-26 to t-5.

Table 7 Panel A reports the time series average of excess #EF and excess #REV for each EU and |FE| quintile, as well as the differences in each variable between the top and bottom quintiles. The results show that, after controlling for earnings uncertainty, the excess #EF and excess #REV are higher in the high |FE| quintile on average. Table 7 Panel B reports the time series average of excess #EF and excess #REV for each EU and |CAR[-1, 1]| quintile, as well as the differences in each variable between the top and bottom quintiles. We find a similar pattern in analysts' activities as in Panel A. After controlling for earnings uncertainty, on average, firms with higher |CAR[-1, 1]| have higher excess #EF and excess #REV. The results in Panel A and B of Table 7 indicate that, even though analysts prefer firms with lower information uncertainty, there are more analyst activities in firms with more information content in the earnings announcement after controlling for information uncertainty.

Next, each quarter, we assign stocks to pre-announcement return (PAR) quintiles using the breakpoints of the previous quarter. Table 7 Panel C reports the time series average of excess #EF and excess #REV for each quintile as well as differences between the average of the top and bottom PAR quintile (Q1|Q5) and the middle PAR quintile (Q3). The results show that excess #EF and excess #REV are significantly higher in the top and bottom quintile (more extreme pre-announcement returns) compared to the middle quintile. This further confirms our findings in

Panel A and B of Table 7, which is that there are more analysts activities in firms with more information content in the earnings announcement. Overall, the results in Table 7 indicate that analysts are more active in producing information for firms where is more information content in the earnings announcement.

B. Informativeness of Analyst Revisions during the Pre-Announcement Window

The results in the previous section show that, after controlling for information uncertainty, there are more analyst activities for firms with more private information. The key question is whether analysts possess private information. Prior literature documents that analysts activities are informative (Bradley, Liu and Pantzalis, 2013; Clement, Hales, and Xue, 2011; Francis and Soffer, 1997; Frankel, Kothari, and Weber, 2006; Ivkovic and Jegadeesh, 2004; Liu, 2011; Lys and Sohn, 1990; Ryan and Taffler, 2004; Stickel, 1991; Womack, 1996). In this section, we perform analysis to address the question of whether analyst earnings revision is informative for future earnings surprises.

We first sort stocks into quintiles based on lagged earnings uncertainty (EU), and then within each EU quintile, the stocks are sorted into quintiles based on the analyst forecast error (FE). Here we use EU to proxy for information uncertainty and use FE to proxy for earnings surprises. We calculate the time series average of the excess revision for each quintile. The revision is defined the same as the previous. The excess revision is the difference in average revision between the period of t-4 to t-2 and that of t-26 to t-5.

Table 8 Panel A reports the time series average of excess REV for each EU and FE quintile, as well as the differences in each variable between the top and bottom quintiles. The results indicate that, after controlling for earnings uncertainty, on average, stocks with higher analyst forecast error have significantly higher revisions.

As a robustness check on the findings in Table 8 Panel A, we perform Fama-MacBeth multivariate regressions to control for the effect of various firm characteristics. Each quarter, we perform Fama-MacBeth regressions of analyst forecast error (FE) on analyst revision (REV) during the pre-announcement window t-4 to t-2 and various firm characteristic variables. The regressions are specified as follows:

$$FE_{i,t} = \alpha_t + \beta_{1t} REV_{i,t} + \beta_{2t} X_{i,t} + \varepsilon_{i,t} \tag{8}$$

Where X is various firm characteristics, which include market capitalization (SIZE), book to market ratio (BEME), momentum (MOM), the Amihud illiquidity ratio (ILLIQ), idiosyncratic volatility (IVOL), earnings uncertainty (EU), and leverage (LEV).

Table 8 Panel B reports the time-series average of the coefficient estimates of the quarterly regressions in Eq. (8) and their Newey-West t-statistics. The results show that, after controlling for various firm characteristics, there is still a significant positive relation between revision and analyst forecast error. This confirmed our findings in the Panel A of Table 8.

C. Trading Activities during Pre-Announcement Window

Prior literature document that analysts' activities have significant impacts on investors trading activities (Ajinkya, Atiase, and Gift, 1991; Balakrishnana and Taori, 2017; Bamber, Barron, and Stober, 1999; Barron, 1995; Chae, 2005; Holden and Stuerke, 2008; Juergens and Lindsey, 2009; Ryan and Taffler, 2004; Womack, 1996; Ziebart, 1990). In this section, we present evidence to substantiate our argument that analysts' activities directly impact investors' trading activities. Specifically, we examine differences in trading volume between stocks with analyst earnings forecasts or revisions and those without. We use turnover and order imbalance as a proxy for trading activity. Turnover is defined as the trading volume divided by the number of shares outstanding. The trading volume on NASDAQ is adjusted the same way as we compute the Amihud illiquidity ratio (ILLIQ). Order imbalance is the absolute value of the difference between the daily buy dollar volume and daily sell dollar volume. The buy and sell dollar volume from the WRDS intraday indicator database. For each stock, we compute the excess turnover, which is the difference in turnover during the pre-announcement period t-4 to t-2 and that of t-26 to t-5. Excess order imbalance is defined the same as excess turnover.

Each quarter, we calculate the mean and standard deviation of the excess turnover and excess order imbalance for the whole sample of stocks and separately for stocks with analyst earnings forecasts or revisions and those without for both actual announcement sample and pseudo announcement sample. Table 9 reports the time-series average of these statistics as well as their Newey-West t-statistics for the means.

For the actual announcement sample, the full sample results in Table 9 Panel A show that overall, there is a decrease in turnover during the pre-announcement window. The average excess turnover is significantly negative. This is consistent with evidence documented in the existing literature (Chae, 2005; Kim, Kim, and Kim, 2020). Kim and Verrecchia (1994) argue that despite the reduction in liquidity before earnings announcements, informed opinions driven by public disclosure may lead to an increase in trading volume. Therefore, we further separate stocks with analyst earnings forecast or revision and those without. The results in Table 9 Panel A show that the lower turnover during the pre-announcement period is mostly driven by stocks without analyst earnings forecast or revision. On average, for stocks without analyst activities, there is a significant decrease in turnover during the pre-announcement period relative to the month before. On the other hand, for stocks with analyst earnings forecast or revision, the average turnover during the pre-announcement period is significantly higher than that during the month before. The results also show that there are much higher cross-sectional variations of turnover for stocks with analyst earnings forecast or revision. We also use the excess sum of daily buy and sell dollar volume to proxy for the trading activities and perform the same analysis. The results are the same as the Panel A of Table 9. Only for stocks with analyst forecast or revision, the sum of dollar volume is significantly higher than that during the month before. The table is available upon request.

Panel B of Table 9 reports the results for excess order imbalance. We find a similar pattern as the excess turnover results in Table 9 Panel A. Only the stocks with analyst earnings forecast or revision the excess order imbalance is significantly positive. These results indicate that the average order imbalance is significantly higher than that during the month before for stocks with analyst activities. These findings suggest that analyst earnings forecast or revision clearly affects trading activities during the pre-announcement period.

To further examine the effect of turnover on the return reversal, we perform Fama-MacBeth regressions of cumulative abnormal return during the earnings announcement window (CAR[-1,1]) on PAR and its interaction with excess turnover during the pre-announcement window, with various firm characteristics included as control variables:

$$\begin{aligned} CAR[-1,1]_{i,\mathrm{t}} = \alpha_t + \beta_{1t} PAR_{i,t} \quad & + \beta_{2t} ETO_{i,t} \quad + \beta_{3t} PAR * ETO_{i,t} \\ & + \beta_{6t} PAR * d^{EA}{}_{i,t} + \beta_{2t} ETO * d^{EA}{}_{i,t} + \beta_{4t} PAR * ETO * d^{EA}{}_{i,t} \\ & + OtherTerms + \varepsilon_{i,t} \end{aligned} \tag{9}$$

where the excess turnover (ETO) is defined as the difference of turnover between t-4 to t-2 and t-26 to t-5. Other terms are the same as in Eq. (3).

Table 10 reports the time-series average of coefficient estimates of quarterly regressions in Eq. (9) and their Newey-West t-statistics. The results show that in all regression specifications, the coefficients of PAR*ETO are significantly positive. This is consistent with findings in Campbell, Grossman, and Wang (1993) and Llorente, Michaely, Saar, and Wang (2002) that higher turnover attenuates return reversal during normal market conditions. In contrast, the coefficients of PAR*ETO*d^{EA} are significantly negative in all regressions. That is, high excess turnover during the pre-announcement period leads to a stronger return reversal around earnings announcements. Given that liquidity traders are reluctant to trade prior to earnings announcements, high trading activities are likely associated with private information possessed by investors or public information released by analysts. Such trading induces adverse selection, which in turn leads to a stronger return reversal.

D. Private and Public Market Reactions to Analyst Revisions

In the previous section, we find that analysts' activities clearly affect trading activities during the pre-announcement period. In this section, we perform further analysis to understand how investors react to analyst revisions during the pre-announcement period. Previous literature document that analysts revisions are likely to generate strong market reaction (Clement, Hales, and Xue, 2011; Clement and Tse, 2003; Copeland, Dolgoff, and Moel, 2004; Francis and Soffer, 1997; Gleason and Lee, 2003; Hugon and Muslu, 2010; Park and Stice, 2000; Stickel, 1991). In this study, we are interested in whether investors react to the private information content of analyst revisions. For each analyst revision, we use the time stamp in IBES to identify whether the revision is issued after market close. If a revision is announced after market close, we classify the revision date as the next trading day. This is because public market reaction to the revision would be reflected in the next trading-day return. We then regress stock returns over the two days prior to revision and stock returns over the two days following the revision against analyst revisions. We interpret the former regression as private market reaction to analyst revisions and the latter as public market reaction to analyst revisions.

Each quarter, we perform Fama-MacBeth multivariate regressions of cumulative abnormal return during the pre-revision window (CAR[t-2, t-1]) or the revision window (CAR[t, t+1]) on analyst revisions (REV), co-current revisions (CREV), and various firm characteristics (X). To identify the effect of revision and various firm characteristics on pre-announcement return, we perform the regression jointly for the earnings announcement sample and pseudo sample. The regressions are specified as follows:

$$\begin{aligned} CAR[t-2,t-1]_{i,t} = {} & \alpha_t + \beta_{1t}REV_{i,t} + \beta_{2t}REV_{i,t} * d^{EA}{}_{i,t} + \beta_{3t}CREV[t-2,t-1]_{i,t} \\ & + \beta_{4t}CREV[t-2,t-1]_{i,t} * d^{EA}{}_{i,t} + \beta_{5t}X_{i,t} + \beta_{6t}X * d^{EA}{}_{i,t} \\ & + \beta_{7t}d^{EA}{}_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{10}$$

$$\begin{aligned} CAR[t,t+1]_{i,t} = {} & \alpha_t + \beta_{1t}REV_{i,t} + \beta_{2t}REV_{i,t} * d^{EA}{}_{i,t} + \beta_{3t}CREV[t-2,t-1]_{i,t} \\ & + \beta_{4t}CREV[\,t+1]_{i,t} * d^{EA}{}_{i,t} + \beta_{5t}X_{i,t} + \beta_{6t}X * d^{EA}{}_{i,t} \\ & + \beta_{7t}d^{EA}{}_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{11}$$

where revision (REV) is measured during the pre-announcement window [-4, -2]. The cumulative announcement return (CAR) is measured the during the pre-revision window [t-2, t-1] in Eq. (10) or during the revision window [t, t+1] in Eq. (11). The co-current revision (CREV) is measured during is measured the during the pre-revision window [t-2, t-1] in Eq. (10) or during the revision window [t+1] in Eq. (11). X is various firm characteristics, which include market capitalization (SIZE), book to market ratio (BEME), momentum (MOM), the Amihud illiquidity ratio (ILLIQ), idiosyncratic volatility (IVOL), and leverage (LEV). d^{EA} is a dummy variable of the announcement, which equals to 1 if the observation is an actual earnings announcement and 0 otherwise.

Table 11 Panel A reports the time-series average of coefficient estimates of quarterly regressions in Eq. (10) and their Newey-West t-statistics. The results show that the coefficient on REV and REV* d^{EA} is significantly positive in all regressions. These results indicate that some investors act on the revision information before the actual announcement of the revision and this effect even more pronounced during the earnings announcement period. Table 11 Panel B reports the time-series average of coefficient estimates of quarterly regressions in Eq. (10) and their Newey-West t-statistics. The results show that the coefficient on REV is significantly positive in all regressions. However, the coefficient on REV* d^{EA} are significantly negative in all regressions. These results indicate that when the analyst announce the revision, there is a positive relation between analyst revision and market reaction during the normal market condition. However, this relation is significantly weaker during the earnings announcement period.

E. Bid-Ask Spread and Adverse-Selection Component during Pre-Announcement Window

In this section, we further examine whether analyst activities impact the bid-ask spread and its adverse-selection component during the pre-announcement window. Lee, Mucklow, and Ready (1993) show that bid-ask spreads widen and depths fall in anticipation of earnings announcements. Libby, Mathieu, and Robb (2002) use changes in quoted bid-ask spreads and depths (relative to the average value in the non-announcement period) as proxies for changes in information asymmetry in the market. They also find that that spreads are wider and depths are smaller before the release of earnings announcements. Krinsky and Lee (1996) investigate the behavior of bid-ask spread and find a significant increase in adverse selection cost component around earnings announcements.

We used three measures of spread from the WRDS intraday indicator database. Quoted spread is the simple average of second-by-second percent quoted spread as defined in Eq. (12)

$$QuotedSpread_k = (A_k - B_k)/M_k \tag{12}$$

Where A_k is the asking quote of trade k, B_k is the bidding quote of trade k, M_k is the Bid-ask mid-price $M_k = (B_k + A_k)/2$.

However, quoted spread might not accurately reflect the execution costs since the actual transaction can be executed inside the quotes at better prices (Ahn, Cao, and Choe, 1996; Huang, and Stoll, 1996; Petersen and Fialkowski, 1994). Therefore, we also include the effective spread which can better measure the execution costs (Huang and Stoll, 1996).

Effective spread is the simple averaged percentage effective spread based on the Lee-Ready method as defined in Eq. (13)

$$EffectiveSpread_k = 2D_k(P_k - M_k)/M_k \tag{13}$$

Where D_k equal to 1 if trade k is a buy, and equal to -1 if trade k is a sell. P_k is the price of trade k. M_k is defined the same as in Eq. (12).

According to Huang and Stoll (1996), a dealer might not realize the effective spread when he/she trades with an informed trader. Therefore, we also include the realized spread, which measures the revenues earned by the market maker (Huang and Stoll, 1996; Stoll, 1989). Realized spread is the simple averaged percentage realized spread based on the Lee-Ready method as defined in Eq. (14)

$$RealizedSpread_k = 2D_k(P_k - M_{k+5})/M_k \tag{14}$$

Where D_k and P_k are defined the same as Eq. (14). M_{k+5} is the bid-ask mid-point five minutes after the kth trade.

The excess spreads are calculated as the differences in the average spread between the per-announcement period from t-4 to t-2 and the month before from t-26 to t-5. For each variable, we calculate the mean and standard deviation of each variable for each quarter. Table 12 Panel A, B, and C reports the time series average of these statistics as well as their Newey-West t-statistics for the means for both the actual announcement sample and the pseudo announcement sample. The results are reported for the full sample of stocks as well as the subsamples of stocks with (without) analyst earnings forecast and stocks with (without) analyst earnings revision.

For the actual announcement sample, the excess effective spread (Panel B of Table 12), results show that, on average, the spreads are wider, evidence of the higher cost of immediacy during the pre-announcement period than during the month before. That is, the spreads increase during the pre-announcement window, consistent with findings in Kim and Verrecchia (1994). The results also show that the increase in the effective spread is more significant for stocks with analyst earnings forecast or revision.

The excess realized spread, Panel C of Table 12, shows that, on average, only stocks with analyst earnings forecast or revision have spread significantly increase during the pre-announcement period. For the pseudo announcement sample, the full sample and subsample results are not significant for all three spread measurements.

The adverse selection component of the spread (ALPHA) is estimated using Huang and Stoll (1997) method. Huang and Stoll (1997) decompose the bid-ask spread into three components: adverse selection, inventory holding, and order processing cost. Following Huang and Stoll (1997) and Henker and Wang (2006), we estimate the following equation each day for each stock

$$\Delta M_t = (\alpha + \beta)\frac{S_{t-1}}{2}Q_{t-1} - \alpha(1 - 2\pi)\frac{S_{t-2}}{2}Q_{t-2} + e_t \tag{15}$$

where

- M_t: quote midpoint
- α: adverse selection component of the spread
- β: inventory holding component of the spread
- S_t: effective spread
- Q_t: trade indicator, Q_t = 1 for buyer initiated trades and Q_t = -1 for seller initiated trades
- π: the probability of a trade reversal

We obtained intraday transactions data from NYSE Trade and Quote (TAQ). We combine all trades at the same time and price, and advance trades by five seconds to adjust for late reporting. The effective spread is calculated as the difference between the absolute value of the price and the quote midpoint multiply by two. The quote midpoint is calculated as the average of bid and ask. We compare the price to the current quote midpoint to identify the trade indicator. If the trade price is higher than the quote midpoint, Q_t = 1. If the trade price is higher than the quote midpoint, Q_t = -1. If the price is the same as the quote as suggested by Lee and Ready (1991), we use the "tick test" to identify the trade. The probability of a trade reversal, π, is estimated based on $Q_t = (1 - 2\pi)Q_{t-1} + u_t$.

The excess adverse selection of the bid-ask spread is calculated as the differences in average adverse selection component of the bid-ask spread between the per-announcement period from t-4 to t-2 and the month before from t-26 to t-5. We calculate the mean and standard deviation of the excess adverse selection component of the bid-ask spread for each quarter for both the actual announcement sample and the pseudo announcement sample. The results are reported for the full sample of stocks as well as the subsamples of stocks with (without) analyst earnings forecast and stocks with (without) analyst earnings revision.

Panel D of Table 12 reports the time series average for the excess adverse selection component of the bid-ask spread. The results for the actual announcement sample show that, on average, there is a higher proportion of the spread attributable to adverse selection during the pre-announcement period than during the month before. This result is consistent with Krinsky and Lee (1996), which find a significant increase in adverse selection cost component around earnings announcements. If we look at the subsample results, we can find that this result is mainly driven by the subsamples with analyst forecast or reversion. The results show that, on average, there is a significant increase in adverse-selection component for stocks with analyst forecast or reversion during the pre-announcement period. For the subsamples without analyst activities, the excess adverse selection component of the spread is much weaker. These results provide direct evidence that analyst activities exacerbate information asymmetry during the pre-announcement period. For the pseudo sample, the results are not significant.

V. Conclusion

This paper examines the role of analysts under different information settings. We find that analyst coverage and activities attenuate the return reversal during non-announcement periods but exacerbate the return reversal around earnings announcements. This effect is mainly concentrated on firms with high earnings uncertainty. In further analysis, we show that after controlling for information uncertainty, analysts tend to cover firms with more asymmetric information. We also show that analyst revision informative of future earnings surprises. In addition, investors trade in response to information released by analysts during the pre-announcement window, and such reaction exacerbates return reversal around earnings announcements. However, we rule out the possibility that our findings are driven by investor overreaction to analyst activities. Finally, we show that there is a significant increase in bid-ask spreads for stocks with analyst earnings forecasts or revisions. The increase in bid-ask spreads for stocks with analyst earnings forecasts or revisions is mainly driven by the adverse-selection component. Overall, our findings indicate that financial analysts help attenuate information asymmetry during normal market conditions but aggravate information asymmetry prior to earnings announcements when there is rich private information. These findings confirm our argument that financial analysts serve as double-agents in the financial market.

References

Aboody, D., R. Lehavy and B. Trueman, 2010, Limited attention and the earnings announcement returns of past stock market winners, *Review of Accounting Studies*, 15(2), 317–344.

Acharya, V.V., DeMarzo, P., Kremer, I., 2011. Endogenous information flows and the clustering of announcements. *American Economic Review* 101, 2955–2979.

Ackert, L. F. and G. Athanassakos, 2003, A Simultaneous Equations Analysis of Analysts' Forecast Bias, Analyst Following, and Institutional Ownership, *Journal of business finance & accounting*, 30 (7-8): 1017-1042.

Alford, A. W. and P. G. Berger, 1999, A Simultaneous Equations Analysis of Forecast Accuracy, Analyst Following, and Trading Volume, *Journal of Accounting, Auditing & Finance*, Vol. 14, Issue 3.

Altınkılıç̧ , O., Hansen, R. S., & Ye, L., 2006, Can analysts pick stocks for the long-run? *Journal of Financial Economics*, 119(2), 371–398.

Affleck-Graves, J., Callahan, C., Chipalkatti, N., 2002. Earnings predictability, information asymmetry, and market liquidity. *Journal of Accounting Research* 40, 561-583.

Ahn, H., C. Q. Cao, H. Choe, 1996, Tick Size, Spread, and Volume, *Journal of Financial Intermediation*, Vol. 5, Issue 1, Pages 2-22

Ajinkya, B. B., R. K. Atiase, and M. J. Gift, 1991, Volume of Trading and the Dispersion in Financial Analysts' Earnings Forecasts, *The Accounting Review*, Vol. 66, No. 2, pp. 389-401

Ali, A., L.S. Hwang and M.A. Trombley, 2000, Accruals and future stock returns: Tests of the naïve investor hypothesis, *Journal of Accounting*, *Auditing and Finance*, 15(2), pp.161-181.

Alford, A. W. and P. G. Berger, 1999, A Simultaneous Equations Analysis of Forecast Accuracy, Analyst Following, and Trading Volume, *Journal of Accounting, Auditing & Finance*, Vol. 14, Issue 3

Amihud, Y., 2002, Illiquidity and stock returns, *Journal of Financial Markets*, 5: 31–56.

Amihud, Y. and H. Mendelson, 1980. Dealership market: market making with inventory. *Journal of Financial Economics* 8, 31–53.

Amiram, D., Owens, E., and Rozenbaum, O., 2016. Do information releases increase or decrease information asymmetry? New evidence from analyst forecast announcements, *Journal of Accounting and Economics* 62, 121-138.

Ang, A., R. Hodrick, Y. Xing and X. Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance*, 51, 259-299.

Atkins, A. B., and E. A. Dyl, 1997, Transactions costs and holding periods for common stocks, *Journal of Finance*, 52, 309-325.

Avery, C., and P. B. Zemsky, 1998, Multidimensional uncertainty and herd behavior in financial markets, *American Economic Review*, 88, 724–748.

Avramov, D., T. Chordia, and A. Goyal, 2006, Liquidity and autocorrelations in individual stock returns, *Journal of Finance* 61, 2365-2394

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.

Balakrishnana, K. and P. Taori, 2017, Information Asymmetry and Trading in Dark Pools: Evidence From Earnings Announcement and Analyst Recommendation Revisions, working paper

Ball, R., and P. Brown, 1968, An empirical evaluation of accounting income numbers, *Journal of Accounting Research*, 6: 159-178.

Ball, R., Kothari, S., 1991. Security returns around earnings announcements. *Accounting Review* 66, 718-738.

Bamber, L. S., O. E. Barron, and T. L. Stober, 1999, Differential Interpretations and Trading Volume, *Journal of Financial and Quantitative Analysis*, Vol. 34, Issue 3

Banerjee, A., 1992, A simple model of herd behavior, *Quarterly Journal of Economics*, 107: 797–817.

Barber, M., De George, E., Lehavy, R., Trueman, B., 2013. The earnings announcement premium around the globe. *Journal of Financial Economics* 108,118–138.

Barron, O. E., 1995, Trading Volume and Belief Revisions That Differ among Individual Analysts, *The Accounting Review*, Vol. 70, No. 4, pp. 581-597

Barron, O.E., D. Byard, and O. Kim, 2002. Changes in analysts' information around earnings announcements. *Accounting Review* 77(4): 821-846.

Bartov, E., S. Radhakrishnan, and I. Krinsky, 2000, Investor sophistication and patterns in stock returns after earnings announcements, *Accounting Review*, 75(1), pp.43-63.

Bernard, V. L., and J. K. Thomas, 1990, Evidence that stock prices do not fully reflect the implications of current earnings for future earnings, *Journal of Accounting and Economics*, 13, 305-340.

Bhattacharya, N., 2001. Investors' trade size and trading responses around earnings announcements: An empirical investigation. *The Accounting Review*, *76*(2), pp.221-244.

Bhattacharya, N., H. Desai, and K. Venkataraman. 2013., Does Earnings Quality Affect Information Asymmetry? Evidence from Trading Costs. *Contemporary Accounting Research* 30 (2): 482–516.

Bhojraj, S., P. Hribar, M. Picconi, and J. McInnis, 2009. Making sense of cents: an examination of firms that marginally miss or beat analyst forecasts. *Journal of Finance*, 64: pp. 2361-88.

Bhushan, R., 1989, Firm characteristics and analyst following, *Journal of Accounting and Economics* 11, 255-274

Bhushan, R., 1994, An informational efficiency perspective on the post-earnings-announcement drift, *Journal of Accounting & Economics*, 18: 45–65.

Bikhchandani, S., D. Hirshleifer, and I. Welch, 1992, A theory of fads, fashion, custom, and cultural change as information cascade, *Journal of Political Economy*, 100 (5): 992-1026.

Bikhchandani, S., and S. Sharma, 2001, Herd behavior in financial markets, *IMF Staff Papers*, 49: 279–310.

Boehmer, E., 2005, Dimensions of execution quality: Recent evidence for US equity markets, *Journal of Financial Economics*, Vol 78, Issue 3, Pages 553-582

Bradley, D., X. Liu, C. Pantzalis, 2013, Bucking the Trend: The Informativeness of Analyst Contrarian Recommendations, *Financial Management*, Vol. 43, Issue 2, pp. 391-414

Bradshaw, M. T., L. D. Brown, and K. Huang, 2013, Do sell-side analysts exhibit differential target price forecasting ability? *Review of Accounting Studies,* Volume 18, pages 930–955

Brennana, M. J, and A. Subrahmanyam, 1995, Investment analysis and price formation in securities markets, *Journal of Financial Economics*, Vol 38, Issue 3, Pages 361-381

Brown, N., K. Wei, and R. Wermers, 2014, Analyst recommendations, mutual fund herding, and overreaction in stock prices, *Management Science*, 60(1), pp 1-20.

Call, A., Chen, S., and Tong, Y., 2009, Are analysts' earnings forecasts more accurate when accompanied by cash flow forecasts? *Review of Accounting Studies*, 14 (2-3): 358–391.

Campbell, J., S. Grossman, and J. Wang, 1993, Trading volume and serial correlation in stock returns. *Quarterly Journal of Economics* 108, 905-939.

Chae, J., 2005, Trading volume, information asymmetry, and timing information. *Journal of Finance*, 60(1), 413–442

Chan, K. and A. Hameed, 2006, Stock Price Synchronicity and Analyst Coverage in Emerging Markets, *Journal of Financial Economics*, Vol 80, 115-147.

Chang, X., S. Dasgupta, and G. Hilary, 2006, Analyst Coverage and Financing Decisions, *The Journal of Finance*, Vol 61, Issue 6, Pages 3009-3048

Cheynel, E. and C. B. Levine, 2012, Analysts' sale and distribution of non fundamental information, *Review of Accounting Studies*, Vol 17, Pages 352–388

Chopra, N., Lakonishok, J. and Ritter, J. R., 1992, Measuring abnormal performance. Do stocks overreact? *Journal of Financial Economics*, 31: 235–68.

Chordia, T., A. Subrahmanyam. and Q. Tong, 2014, Have capital market anomalies attenuated in the recent era of high liquidity and trading activity? *Journal of Accounting and Economics*, 58, pp. 41-58.

Clement, M. B., J. Hales, Y. Xue, 2011, Understanding analysts' use of stock returns and other analysts' revisions when forecasting earnings, *Journal of Accounting and Economics*, Volume 51, Issue 3, Pages 279-299

Clement, M. B., Tse, S. Y., 2003. Do investors respond to analysts' forecast revisions as if forecast accuracy is all that matters? *The Accounting Review*, Vol. 78, No. 1, pp. 227–249 .

Cohen, R. B., P. A. Gompers, and T. Vuolteenaho, 2002, Who underreacts to cash flow news? Evidence from trading between individuals and institutions, *Journal of Financial Economics*, 66, 409–462.

Cohen, D. A., Dey, A., Lys, T. Z., and S. V. Sunder, 2007, Earnings announcement premia and the limits to arbitrage, *Journal of Accounting and Economics*, 43(2), 153-180.

Coller, M.,Yohn,T.,1997. Management forecasts and information asymmetry: An examination of bid-ask spreads. *Journal of Accounting Research* 35, 181–191.

Cooper, M. 1999, Filter Rules Based on Price and Volume in Individual Security Overreaction, *The Review of Financial Studies*, Vol 12, Issue 4, Pages 901–935

Copeland, T., Dolgoff, A., and Moel, A., 2004, The role of expectations in explaining the cross-section of stock returns. *Review of Accounting Studies*, 9, 149-188.

Corwin, S.A. and J.F. Coughenour, 2008, Limited attention and the allocation of effort in securities trading, *Journal of Finance* 63, 3031-3067.

Coval, J.D. and Moskowitz, T.J., 2001. The geography of investment: Informed trading and asset prices. *Journal of political Economy*, *109*(4), pp.811-841.

Da, Z., Q. Liu, and E. Schaumburg, 2014, A closer look at the short-term return reversal, *Management Science* 60, 658-674.

De Bondt, W. F. M., and R. Thaler, 1985, Does the stock market overreact? *Journal of finance*, 40(3), 793-805.

De Bondt, W. F. M. and Thaler, R. H., 1987, Further evidence on investor overreaction and stock market seasonality, *Journal of Finance*, 62(3): 557–81.

Della Vigna, S. and J.M. Pollet, 2009, Investor inattention and Friday earnings announcements, *Journal of Finance* 64, 709-749

Derrien, F, A. Kecskés, and S. A. Mansi, 2016, Information asymmetry, the cost of debt, and credit events: Evidence from quasi-random analyst disappearances, *Journal of Corporate Finance*, Vol. 39, Pages 295-311

Devenow, A. and I. Welch, 1996. Rational herding in financial economics, *European Economic Review*, 40: 603–615.

Devos, E., W. Hao, A. K. Prevost, U. Wongchoti, 2015, Stock return synchronicity and the market response to analyst recommendation revisions, *Journal of Banking & Finance*, Volume 58, Pages 376-389.

Dey, Malay K., and B. Radhakrishna, 2007, Who trades around earnings announcement? Evidence from TORQ data, *Journal of Business, Finance & Accounting* 34, 269-291.

Diamond, D. and R. Verrecchia, 1991, Disclosure, liquidity, and the cost of capital, *Journal of Finance* 46, 1325-1359

Drake, M. S., Rees, L., and Swanson, W. P., 2001, 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.

Drake, M., D. Roulstone, and J. Thornock, 2015, The determinants and consequences of information acquisition via EDGAR, *Contemporary Accounting Research*, 32: 1128-1161.

Eleswarapu, V. R., R. Thompson, and K. Venkataraman, 2009, The Impact of Regulation Fair Disclosure: Trading Costs and Information Asymmetry, *Journal of Financial and Quantitative Analysis*, Vol 39, Issue 2

Engelberg, J., McLean, R.D. and Pontiff, J., 2018. Anomalies and news, *Journal of Finance,* Vol 73, Issue 5, pp. 1971-2001.

Fama, E. F. and J. D. MacBeth,1973, Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy* 81 (3): 607–636.)

Fama, E. F. and K. R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics*, 33, 3-56.

Fields, T., Lys, T., Vincent, L., 2001. Empirical research on accounting choice. *Journal of Accounting and Economics* 31, 255–307.

Forbes, W. P. and L. C. L. Skerratt, 1992, Analysts' Forecast Revisions and Stock Price Movements, *Journal of Business Finance & Accounting*, Vol. 19, No. 4, pp. 555-69.

Foster, G., 1977, Quarterly accounting data: Time-series properties and predictive-ability results, *Accounting Review*, January, pp. 1-21.

Foster, G., C. Olsen, and T. Shevlin, 1984, Earnings releases, anomalies, and the behavior of security returns, *Accounting Review*, 574-603.

Francis, J., R. Lafond, P. Olsson, and K. Schipper, 2007, Information uncertainty and post-earnings-announcement-drift, *Journal of Business Finance & Accounting*, 34(3–4), 403–433.

Francis, J. and L. Soffer, 1997, The Relative Informativeness of Analysts' Stock Recommendations and Earnings Forecast Revisions, *Journal of Accounting Research*, Vol. 35, No. 2, pp. 193-211

Frankel, R., S. P. Kothari, J. Weber, 2006, Determinants of the informativeness of analyst research, *Journal of Accounting and Economics*, Vol 41, Issues 1–2, Pages 29-54

Frankel, R. and X. Li, 2004, Characteristics of a firm's information environment and the information asymmetry between insiders and outsiders, *Journal of Accounting and Economics*, Vol. 37, Issue 2, Pages 229-259

Freeman, R. N., 1987, The association between accounting earnings and security returns for large and small firms, *Journal of Accounting Research*, 9: 195–228

Froot, K., D. Scharfstein and J. Stein, 1992, Herd on the street: Informational inefficiencies in a market with short-term speculation, *Journal of Finance*, 47: 1461–1484.

Gao, X., and J. R. Ritter, 2010, The marketing of seasoned equity offerings, *Journal of Financial Economics*, Vol 97, Issue 1, Pages 33-52

Gleason C. A. and C. M. C. Lee, 2003, Analyst Forecast Revisions and Market Price Discovery, *The Accounting Review*, Vol. 78, No. 1, pp. 193-225

Glosten, L. and P. Milgrom, 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics* 14, 71-100

Graham, J. R., 1999, Herding among investment newsletters: Theory and evidence, *Journal of Finance*, 54,169-182.

Grossman, S. and M. Miller, 1988, Liquidity and market structure, *Journal of Finance* 43, 617-633

Gutierrez, R. C., and E. K. Kelley. 2008. The long-lasting momentum in weekly returns. *Journal of Finance* 63:415–47.

Healy, P.M. and K.G. Palepu, 2001, Information asymmetry, corporate disclosure, and the capital market: a review of the empirical disclosure literature, *Journal of Accounting and Economics* 31, 405-440.

Heflin, F., and K. W. Shaw, 2009, Blockholder Ownership and Market Liquidity, *Journal of Financial and Quantitative Analysis*, Vol. 35 Issue 4

Hendershott, T., C. Jones, and A. Menkveld, 2011. Does Algorithmic Trading Improve Liquidity? *Journal of Finance*, 66: 1-33.

Hendershott, T. and A. Menkveld, 2014, Price pressure. *Journal of Financial Economics* 114 405-423

Henker, T. and J. X. Wang, 2006, On the importance of timing specifications in market microstructure research, *Journal of Financial Markets*, vol 9, pp. 162-179

Hilary, G., 2006, Organized labor and information asymmetry in the financial markets, *Review of Accounting Studies*, Vol 11, Pages 525–548

Hirshleifer, D., A. Subrahmanyam, and S. Titman, 1994, Security analysis and trading patterns when some investors receive information before others, *Journal of Finance*, 49, 1665-1698.

Hirshleifer, D. S. Lim and S. Teoh, 2009, Driven to distraction: extraneous events and underreaction to earnings news, *Journal of Finance* 64, 2289-2325

Ho, L. J., Liu, C. and Ziebart, D. A., 1998, Price reversal and drift following earnings announcements, *Financial Review*, 33: 145–60.

Holden, C. W., P. S. Stuerke, 2008, The Frequency of Financial Analysts' Forecast Revisions: Theory and Evidence about Determinants of Demand for Predisclosure Information, *Journal of Business Finance & Accounting*, Vol. 58, Issue 7-8, Pages 860-888

Holden, C. W. and A. Subrahmanyam, 2002, News events, information acquisition, and serial correlation. *Journal of Business* 75(1), 1–32

Hong, H., T. Lim and J. C. Stein, 2000, Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies, *The Journal of Finance*, Vol. 55, No. 1, pp. 265-295

Huang, R. D. and H. R. Stoll, 1996, Dealer versus auction markets: A paired comparison of execution costs on NASDAQ and the NYSE, *Journal of Financial Economics*, Volume 41, Issue 3, Pages 313-357

Huang, R. D. and H. R. Stoll, 1997, The Components of the Bid-Ask Spread: A General Approach, *The Review of Financial Studies*, 10, 4.

Hugon, A., and V. Muslu, 2010, Market demand for conservative analysts, *Journal of Accounting and Economics*, Volume 50, Issue 1, Pages 42-57

Hussain, S. 1996, Over-Reaction by Security Market Analysts: The Impact of Broker Status and Firm Size. *Journal of business finance & accounting*. 23 (9-10): 1223-1244

Irvine, P., M. Lipson, A. Puckett, 2007, Tipping, *The Review of Financial Studies*, Vol 20, Issue 3, Pages 741–768

Ivkovic, Z., N. Jegadeesh, 2004. The timing and value of forecast and recommendation revisions. *Journal of Financial Economics* 73, 433-463.

Jegadeesh N., 1990, Evidence of predictable behavior of security returns. *Journal of Finance* 45:881–898.

Jegadeesh, N. and S. Titman, 1995, Short-horizon return reversals and the bid-ask spread. *Journal of Financial Intermediation* 4, 116-132.

Johnson, T., So, E., 2018, Asymmetric Trading Costs Prior to Earnings Announcements: Implications for Price Discovery and Returns, *Journal of Accounting Research* 56(1) 217_263.

Juergens, J.L., Lindsey, L., 2009, Getting Out Early: An Analysis of Market Making Activity at the Recommending Analyst's Firm. *The Journal of finance*. 64(5):2327-2359.

Jung, M., Keeley, J., & Ronen, J., 2019, The predictability of analyst forecast revisions. *Journal of Accounting, Auditing & Finance*, 34(3), 434–457

Kadan, O., R. Michaely, and P. C. Moulton, 2018, Trading in the Presence of Short-Lived Private Information: Evidence from Analyst Recommendation Changes, *Journal of Financial and Quantitative Analysis*, Vol 53, Issue 4

Kandel, E., and N. Pearson. 1995. Differential interpretation of public signals and trade in speculative markets. *Journal of Political Economy* 103 (4): 831-872.

Kaul, G. and M. Nimalendran, 1990, Price reversals: bid-ask errors or market overreaction? *Journal of Financial Economic* 28, 67-93

Kim, J., Kim, R, Kim, S., 2020,Does financial statement comparability mitigate delayed trading volume before earnings announcements? *Journal of Business Research*, 107, 62-85

Kothari, S.P., Shu, S., Wysocki, P.D., 2009. Do managers withhold bad news? *Journal of Accounting Research* 47, 241–276.

Kim, O. and R.E. Verrecchia. 1994. Market liquidity and volume around earnings announcements. *Journal of accounting and economics* 17(1-2): 41-67.

Krinsky, I., and J. Lee. 1996. Earnings announcements and the components of the bid-ask spread. *Journal of Finance* 51 (4): 1523-1535.

Lang, M. H. and R. J. Lundholm, 1996, Corporate Disclosure Policy and Analyst Behavior, *The Accounting Review*, Vol. 71, No. 4, pp. 467-492

La Porta, R., J. Lakonishok, A. Shleifer and R. Vishny, 1997, Good news for value stocks: further evidence on market efficiency. *Journal of Finance* 52, 859-874

Lee, C.M.C., 1992, Earnings news and small traders: An intraday analysis, *Journal of Accounting and Economics* 15, 265-302.

Lee, C., B. Mucklow; and M. J. Ready, 1993, Spreads, Depths, and the Impact of Earnings Information: An Intraday Analysis. *Review of Financial Studies* 6: 345–74.

Lee, C., M.J. Ready, and P.J. Seguin, 1994, Volume, volatility, and New York stock exchange trading halts. *Journal of Finance* 49, 183-214

Lehmann B., 1990, Fads, martingales and market efficiency. *Quarterly Journal of Economics*. 105:1–28.

Levi, S. and X. Zhang, 2015, Asymmetric decrease in liquidity trading before earnings announcements and the announcement return premium, *Journal of Financial Economics* Vol. 118, Issue 2, 383-398

Libby, T., R. Mathieu, and S. W. G. Robb, 2010, Earnings Announcements and Information Asymmetry: An Intra-Day Analysis, *Contemporary Accounting Research*, Vol. 19, Issue 3 pp. 449-472

Liu, M. H., 2011, Analysts' Incentives to Produce Industry-Level versus Firm-Specific Information, *The Journal of Financial and Quantitative Analysis*, Vol. 46, No. 3, pp. 757-784

Livnat, J., and R. R. Mendenhall, 2006, Comparing the post-earnings announcement drift for surprises calculated from analyst and time series forecasts, *Journal of Accounting Research*, 44(1), 177–205.

Llorente, G., R. Michaely, G. Saar, and J. Wang, 2002, Dynamic volume-return relation of individual stocks, *Review of Financial Studies* 15, 1005-1047

Loh, R.K., G.M Mian, 2006. Do accurate earnings forecasts facilitate superior investment recommendations? *Journal of Financial Economics* 80, 455-483.

Lou, D., 2012. A flow-based explanation for return predictability. *Review of Financial Studies*, 25, pp.3457-3489

Lyon, J., B. Barber, and C. Tsai, 1999, Improved methods for tests of long-run abnormal stock returns, *Journal of Finance*, 54, 165-201.

Lys, T., and S. Sohn., 1990, The Association between Revisions of Financial Analysts' Earnings Forecasts and Security-Price Changes, *Journal of Accounting and Economics* 13, 341–363.

Madhavan, A. and S. Smidt, 1993, An analysis of changes in specialist inventories and quotations. *Journal of Finance* 48, 1595-1628.

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

Michaely, R., Rubin, A., and Vedrashko, A., 2013, Firm heterogeneity and investor inattention to Friday earnings announcements. Working paper, Cornell University.

Nagel, S., 2005, Short sales, institutional investors and the cross-section of stock returns, *Journal of Financial Economics*, 78, 277–309.

Nagel, S., 2012, Evaporating liquidity. *Review of Financial Studies* 25, 2005-2039.

Newey, W., and K. West, 1987, A simple, positive semi-definite, heteroscedastic and autocorrelation consistent covariance matrix, *Econometrica*, 55, 703-708.

Ng, J., T. O. Rusticus, and R. S. Verdi, 2008, Implications of transaction costs for the post–earnings announcement drift, *Journal of Accounting Research*, 46(3), 661-696.

O'Brien, P. C. and R. Bhushan, 1990, Analyst Following and Institutional Ownership, *Journal of Accounting Research* Vol. 28, pp. 55-76

Ou, J. A. and Penman, S. H., 1989, Financial statement analysis and the prediction of stock returns, *Journal of Accounting and Economics*, 11(4): 295–330.

Park, C.W., Stice, E.K., 2000. Analyst forecasting ability and the stock price reaction to forecast revisions. *Review of Accounting Studies*, Volume 5, pages259–272.

Pastor, L. and R. Stambaugh, 2003. Liquidity risk and expected stock returns. *Journal of Political Economy* 111, 642-685.

Patell, J. and M. Wolfson, 1981. The ex ante and ex post price effects of quarterly earnings announcements reflected in option and stock prices. *Journal of Accounting Research* 19, 434-458

Petersen, M. A. and D. Fialkowski, 1994, Posted versus effective spreads: Good prices or bad quotes? *Journal of Financial Economics*, Volume 35, Issue 3, Pages 269-292

Rippington, F. A. and Taffier, R. J., 1995, The information content of firm financial disclosures, *Journal of Business Finance and Accounting*, 22(3): 345–61

Ryan, P. and R. J. Taffler, 2004, Are Economically Significant Stock Returns and Trading Volumes Driven by Firm-specific News Releases?, *Journal of Business Finance & Accounting*, Vol. 31, Nos. 1&2, pp. 49–82

Sadka, R., 2006, Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk, *Journal of Financial Economics*, 80, 309-349.

Scharfstein, D.S., and J.C. Stein, 1990, Herd behavior and investment, *American Economic Review*, 80: 465–479.

Shanthikumar, D., 2012, Consecutive Earnings Surprises: Small and Large Trader Reactions, *The Accounting Review* 87: 1709-1736.

Shumway, T.,1997, The delisting bias in CRSP Data, *Journal of Finance*, 52, 327–340.

Stickel, S. E., 1991, Common Stock Returns Surrounding Earnings Forecast Revisions: More Puzzling Evidence, *The Accounting Review*, 66, 402–416.

So, E.C. and S. Wang, 2014. News-driven return reversals: Liquidity provision ahead of earnings announcements. *Journal of Financial Economics* 114, 20–35.

Stoll, H. R., 1989, Inferring the Components of the Bid-Ask Spread: Theory and Empirical Tests, *The Journal of Finance*, Vol. 44, Issue 1, Pages 115-134

Subrahmanyam, A., 2005. Distinguishing between rationales for short-horizon predictability of stock returns. *Financial Review* 40, 11-35.

Tetlock, P.C., 2010. Does public financial news resolve asymmetric information? *Review of Financial Studies* 23, 3520-3557.

Wermers, R., 1999, Mutual fund herding and the impact on stock prices, *Journal of Finance*, 54, 581-622.

Womack, K. L., 1996, Do brokerage analysts' recommendations have investment value? *The Journal of Finance*, 51(1), 137–167

Yu, F., 2008, Analyst coverage and earnings management, *Journal of Financial Economics* Volume 88, Issue 2, Pages 245-271

Zarowin, P.,1989, Does the stock market overreact to corporate earnings information? *Journal of Finance*, 44(5): 1385–400.

Zhang, X. F. 2006, Information Uncertainty and Analyst Forecast Behavior. *Contemporary accounting research*, 23(2): 565-590.

Zhang, X. F. 2006, Information Uncertainty and Stock Returns, *The Journal of finance*, 61 (1): 105-137.

Zhang, Y., 2008. Analyst responsiveness and the post-earnings-announcement drift. *Journal of Accounting and Economics*, *46*(1), pp.201-215.

Ziebart, D. A., 1990, The Association between Consensus of Beliefs and Trading Activity Surrounding Earnings Announcements, *The Accounting Review*, Vol. 65, No. 2, pp. 477-488

Table 1. Summary Statistics of Analyst Coverage and Firm Characteristics

This table reports summary statistics of analyst coverage (COV), analyst forecast error (FE) and other firm characteristics. Firm characteristics include market capitalization (SIZE), book to market ratio (BEME), momentum (MOM), the Amihud illiquidity ratio (ILLIQ), idiosyncratic volatility (IVOL), earnings uncertainty (EU), and leverage (LEV). COV is the number of analysts covering a firm. FE is the difference between primary earnings per share before extraordinary items in a quarter and its median of forecast reported to IBES in the 90 days prior to earnings announcement, scaled by price per share at end of the quarter. SIZE is calculated at the end of each June as stock price times the total number of shares outstanding. BEME is calculated at the end of each June using book value for the fiscal year ending in calendar year t-1 divided by market capitalization at the end of December of year t-1. MOM is calculated as skip-one-month lagged cumulative 12-month returns. ILLIQ is calculated as the ratio of absolute daily return to dollar trading volume and averaged over a quarter, pre-multiplied by 10^6. IVOL is the standard error of residuals of the Fama-French 3-factor model estimated from daily returns over a quarter. EU is the standard deviation of analyst forecast error for a firm over the past 20 quarters with minimum 8 observations. LEV is calculated as book debt to total assets where book debt is total assets minus book equity. Each quarter, we compute the mean, median, standard deviation (StDev), 5th, 25th, 75th and 95th percentiles and the number of observations (N) for each variable. The table reports the time series average of these statistics. The sample period is from January 1996 to December 2017.

Variable	N	5%	25%	Mean	Median	75%	95%	StDev
COV	2,395	0.852	3.159	8.003	6.148	11.318	21.398	6.580
FE	2,395	-0.009	0.000	0.000	0.000	0.002	0.008	0.019
SIZE ($bil)	2,395	0.096	0.345	5.572	0.973	3.097	21.776	20.175
BEME	1,815	0.094	0.246	0.526	0.418	0.673	1.266	0.479
MOM	2,360	-0.404	-0.101	0.203	0.102	0.353	1.106	0.603
ILLIQ	2,395	0.000	0.001	0.207	0.006	0.032	0.422	2.083
IVOL	2,395	0.010	0.015	0.023	0.021	0.029	0.046	0.013
EU	2,016	0.000	0.001	0.009	0.003	0.006	0.028	0.045
LEV	1,815	0.117	0.286	0.457	0.455	0.610	0.829	0.216

Table 2. Return Reversal: Actual vs. Pseudo Earnings Announcements

For each earnings announcement, we compute the pre-earnings-announcement return (PAR) as the cumulative abnormal return from t-4 to t-2, where t is the earnings announcement date. Stocks are then assigned to quintiles based on PAR using the breakpoints of the previous quarter. Panel A reports the time series averages of the PAR and cumulative abnormal returns (CAR[-1,+1], CAR[-1,+5] and CAR[+2,+5]) around the announcement date. Panel B reports the time series averages returns of pseudo earnings announcements. The pseudo earnings announcement dates are generated by subtracting a randomly selected number of trading days from the actual announcement date. The randomly selected numbers are drawn from a uniform distribution spanning 10-40 days. Panel A and Panel B also reports the differences in returns between the top and bottom PAR quintiles, as well as their Newy-West t-statistics. Panel C reports the differences in returns between Panel A and Panel B and their Newy-West t-statistics. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1996 to December 2017.

Panel A: Averages CARs across actual pre-announcement return (PAR) quintiles

	PAR	CAR[-1,+1]	CAR[-1,+5]	CAR[+2,+5]
Q1 (Low PAR)	-5.488	0.624	0.700	0.076
Q2	-1.654	0.352	0.356	0.005
Q3	-0.048	0.223	0.208	-0.015
Q4	1.598	0.100	0.074	-0.026
Q5 (High PAR)	5.793	-0.264	-0.381	-0.117
Low-High	-11.281***	0.887***	1.081***	0.193***
	(-12.72)	(4.58)	(4.61)	(2.60)

Panel B: Averages CARs across pseudo pre-announcement return (PAR) quintiles

	PAR	CAR[-1,+1]	CAR[-1,+5]	CAR[+2,+5]
Q1 (Low PAR)	-5.630	0.101	0.200	0.099
Q2	-1.663	-0.029	-0.028	0.001
Q3	-0.066	-0.005	0.002	0.007
Q4	1.547	-0.028	-0.047	-0.019
Q5 (High PAR)	5.697	-0.076	-0.146	-0.070
Low-High	-11.327***	0.177***	0.346***	0.169
	(-13.46)	(3.97)	(3.06)	(1.31)

Panel C: Differences in CARs spreads between actual and pseudo announcements

	PAR	CAR[-1,+1]	CAR[-1,+5]	CAR[+2,+5]
Diff of Low-High	0.046	0.711***	0.735***	0.024
	(0.37)	(4.70)	(3.65)	(0.21)

Table 3. Return Reversal: Multivariate Regressions Controlling for Firm Characteristics

Each quarter, we perform Fama-MacBeth regressions of cumulative abnormal returns during the earnings announcement window (CAR[-1,1]) on pre-earnings-announcement return (PAR) and its interaction with various control variables (Xs). CAR[-1,1] are computed for both actual and pseudo earnings announcements. d^{EA} is equal to 1 if the observation is an actual announcement and 0 otherwise. The control variables include market capitalization (SIZE), book to market ratio (BEME), momentum (MOM), the Amihud illiquidity ratio (ILLIQ), idiosyncratic volatility (IVOL), and leverage (LEV). Earnings surprise, as measured by analyst forecast error (FE), is included as a control variable for actual earnings announcements. All variables are defined in Table 1. The table reports time series average of coefficient estimates of quarterly regressions and their Newey-West t-statistics. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1996 to December 2017.

	(1)		(2)		(3)	
	Xs	Xs*d^{EA}	Xs	Xs*d^{EA}	Xs	Xs*d^{EA}
PAR	-1.993***	-2.691***	-1.882***	-2.939***	-1.979***	-2.567***
	(-4.35)	(-3.07)	(-5.13)	(-3.33)	(-4.10)	(-2.82)
SIZE			0.219	-0.827***	0.190	-0.920***
			(1.56)	(-4.24)	(1.04)	(-4.62)
SIZE*PAR			0.333	-1.111**	0.176	-1.083*
			(0.76)	(-1.96)	(0.37)	(-1.84)
BEME			0.830**	-0.268	0.879**	-0.526
			(2.10)	(-0.58)	(2.12)	(-1.12)
BEME*PAR			-0.371	0.072	-0.211	-0.010
			(-0.86)	(0.16)	(-0.52)	(-0.02)
MOM			1.431***	-2.013***	1.554***	-1.802***
			(3.31)	(-3.19)	(3.78)	(-3.10)
MOM*PAR			-0.466	0.428	-0.454	0.320
			(-1.31)	(1.01)	(-1.29)	(0.78)
ILLIQ					-0.088	1.030**
					(-0.24)	(1.97)
ILLIQ*PAR					-2.450***	1.905***
					(-5.15)	(3.01)
IVOL					-0.203	-0.230
					(-0.32)	(-0.30)
IVOL*PAR					-0.077	-0.683
					(-0.23)	(-1.28)
LEV					0.520*	0.610
					(1.74)	(1.17)
LEV*PAR					0.113	-0.123
					(0.29)	(-0.29)
FE		1.365***		1.482***		1.500***
		(6.71)		(6.85)		(6.87)
d^{EA}		-0.000		-0.139**		-0.137**
		(-1.04)		(-2.29)		(-2.23)
Intercept	-0.000		0.054		0.070*	
	(-0.36)		(1.12)		(1.79)	
N	4,775		4,700		4,700	
Adj. R^2 (%)	1.377		1.742		2.297	

Table 4. Return Reversal: Effect of Analyst Coverage

Each quarter, we perform Fama-MacBeth regressions of cumulative abnormal return during the earnings announcement window (CAR[-1,1]) on the pre-announcement return (PAR), its interaction with analyst coverage (COV), and interactions with various control variables. The control variables include market capitalization (SIZE), book to market ratio (BEME), momentum (MOM), the Amihud illiquidity ratio (ILLIQ), idiosyncratic volatility (IVOL), and leverage (LEV). All variables are defined in Table 1. The table reports time series average of coefficient estimates of quarterly regressions and their Newey-West t-statistics. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1996 to December 2017.

	(1)		(2)		(3)	
	Xs	Xs*d^{EA}	Xs	Xs*d^{EA}	Xs	Xs*d^{EA}
PAR	-1.738***	-3.000***	-1.820***	-3.060***	-2.006***	-2.616***
	(-3.81)	(-3.49)	(-3.78)	(-3.46)	(-4.65)	(-2.87)
PAR*COV	1.371***	-1.689***	1.413***	-1.577***	0.986***	-1.234***
	(3.64)	(-4.40)	(3.80)	(-4.45)	(4.72)	(-3.99)
COV	-0.462	-0.137	-0.481	0.118	-0.543*	0.262
	(-1.62)	(-0.37)	(-1.42)	(0.26)	(-1.66)	(0.59)
SIZE			0.384*	-0.872***	0.364	-1.005***
			(1.85)	(-3.66)	(1.61)	(-3.96)
SIZE*PAR			-0.562*	-0.139	-0.384	-0.416
			(-1.70)	(-0.25)	(-1.05)	(-0.75)
BEME			0.734*	-0.256	0.780*	-0.495
			(1.80)	(-0.53)	(1.85)	(-1.02)
BEME*PAR			-0.242	-0.079	-0.135	-0.131
			(-0.54)	(-0.17)	(-0.32)	(-0.30)
MOM			1.387***	-1.998***	1.507***	-1.751***
			(3.26)	(-3.14)	(3.70)	(-3.01)
MOM*PAR			-0.359	0.287	-0.375	0.211
			(-1.03)	(0.69)	(-1.10)	(0.52)
ILLIQ					-0.184	1.091**
					(-0.53)	(2.07)
ILLIQ*PAR					-2.334***	1.740***
					(-4.85)	(2.67)
IVOL					-0.267	-0.201
					(-0.42)	(-0.27)
IVOL*PAR					0.028	-0.800
					(0.08)	(-1.50)
LEV					0.547*	0.582
					(1.85)	(1.12)
LEV*PAR					0.107	-0.104
					(0.27)	(-0.24)
FE		1.365***		1.482***		1.499***
		(6.71)		(6.85)		(6.87)
d^{EA}		-0.006		-0.142**		-0.137**
		(-0.42)		(-2.38)		(-2.22)
Intercept	-0.004		0.049		0.063	
	(-0.41)		(1.07)		(1.63)	
N	4,775		4,700		4,700	
Adj. R^2 (%)	1.449		1.808		2.356	

Table 5. Return Reversal: Further Evidence on the Effect of Analyst Activities

Each quarter, we perform Fama-MacBeth regressions of cumulative abnormal return during the earnings announcement window (CAR[-1,1]) on the pre-announcement return (PAR), its interaction with a dummy variable based on the number of EPS forecast ($d^{\#EF}$) (Panel A), number of revision ($d^{\#REV}$) (Panel B), the magnitude of revision ($d^{|REV|}$) (Panel C), and interactions with various control variables. The control variables (FCs) include market capitalization (SIZE), book to market ratio (BEME), momentum (MOM). Other FCs include the Amihud illiquidity ratio (ILLIQ), idiosyncratic volatility (IVOL), and leverage (LEV). The number of EPS forecast (#EF) is calculated as total number of analysts submitted EPS forecast for the current fiscal quarter before the earnings announcement from t-2 to t-4. The dummy variable $d^{\#EF}$ is equal to 1 if #EF is higher than 0 and 0 otherwise. The number of revision (#REV) is calculated as total number of revision for this announcement before the earnings announcement from t-2 to t-4. The dummy variable $d^{\#REV}$ is equal to 1 if #REV is higher than 0 and 0 otherwise. Analyst revision (REV) is the average of the revisions issued by analysts before earnings announcement from t-2 to t-4. The dummy variable $d^{|REV|}$ is equal to 1 if the absolute value of revision |REV| is higher than 0 and 0 otherwise. All variables are defined in Table 1. The table reports time series average of coefficient estimates of quarterly regressions and their Newey-West t-statistics. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1996 to December 2017.

Panel A: Results based on the Number of Earnings Forecasts

	(1)		(2)		(3)	
	Xs	Xs*d^{EA}	Xs	Xs*d^{EA}	Xs	Xs*d^{EA}
PAR	-2.752***	-2.151**	-2.750***	-2.417**	-2.840***	-2.233**
	(-6.11)	(-2.25)	(-5.87)	(-2.44)	(-6.93)	(-2.18)
PAR*$d^{\#EF}$	2.905***	-1.678***	2.981***	-1.415**	2.806***	-1.222**
	(4.41)	(-5.22)	(4.55)	(-2.42)	(4.45)	(-2.15)
$d^{\#EF}$	-0.108	0.133	-0.179	0.465	-0.346	0.602
	(-0.16)	(0.22)	(-0.26)	(0.69)	(-0.48)	(0.88)
FCs			Yes	Yes	Yes	Yes
Other FCs					Yes	Yes
FE		1.364***		1.485***		1.504***
		(6.71)		(6.86)		(6.88)
d^{EA}		-0.010		-0.251		-0.280
		(-0.06)		(-1.17)		(-1.36)
Intercept	0.020		0.094		0.156	
	(0.12)		(0.49)		(0.78)	
N	4,783		4,709		4,709	
Adj. R^2 (%)	1.421		1.784		2.289	

Panel B: Results based on the Number of Revisions

	(1)		(2)		(3)	
	Xs	Xs*d^{EA}	Xs	Xs*d^{EA}	Xs	Xs*d^{EA}
PAR	-2.767***	-2.129**	-2.779***	-2.378**	-2.882***	-2.180**
	(-6.18)	(-2.17)	(-6.05)	(-2.35)	(-7.18)	(-2.09)
PAR*$d^{\#REV}$	3.077***	-1.655***	3.189***	-1.432**	3.024***	-1.252**
	(7.43)	(-5.06)	(5.63)	(-2.12)	(4.88)	(-2.08)
$d^{\#REV}$	0.039	0.043	-0.011	0.345	-0.189	0.467
	(0.06)	(0.07)	(-0.02)	(0.52)	(-0.27)	(0.70)
FCs			Yes	Yes	Yes	Yes
Other FCs					Yes	Yes
FE		1.365**		1.485***		1.504***
		(6.71)		(6.86)		(6.88)
d^{EA}		0.018		-0.215		-0.240
		(0.11)		(-1.07)		(-1.27)
Intercept	0.001		0.072		0.134	
	(0.01)		(0.40)		(0.72)	
N	4,783		4,709		4,709	
Adj. R^2 (%)	1.425		1.787		2.290	

Panel C: Results based on the Magnitude of Revisions

	(1)		(2)		(3)	
	Xs	Xs*d^{EA}	Xs	Xs*d^{EA}	Xs	Xs*d^{EA}
PAR	-2.631***	-2.087**	-2.573***	-2.330**	-2.661***	-2.017**
	(-5.70)	(-2.29)	(-5.31)	(-2.53)	(-6.26)	(-2.11)
PAR*$d^{\lvert REV\rvert}$	2.953***	-2.429***	2.923***	-2.365***	2.719***	-2.048***
	(4.72)	(-4.48)	(4.32)	(-5.59)	(4.83)	(-3.04)
$d^{\lvert REV\rvert}$	0.018	-0.457	-0.130	-0.182	-0.261	-0.091
	(0.03)	(-0.55)	(-0.24)	(-0.20)	(-0.46)	(-0.10)
FCs			Yes	Yes	Yes	Yes
Other FCs					Yes	Yes
FE		1.363***		1.481***		1.498***
		(6.70)		(6.84)		(6.86)
d^{EA}		0.109		-0.092		-0.102
		(0.80)		(-0.53)		(-0.63)
Intercept	0.037		0.127		0.163	
	(0.45)		(1.23)		(1.56)	
N	4,773		4,700		4,700	
Adj. R^2 (%)	1.450		1.815		2.364	

Table 6. Return Reversal: Effect of Analyst Coverage and Information Uncertainty

Each quarter, we divide the full stock sample into two subsamples based on earnings uncertainty (EU). Firms with standard deviation above the median are classified as having high earnings uncertainty. We perform Fama-MacBeth regressions of cumulative abnormal return during the earnings announcement window (CAR[-1,1]) on the pre-announcement return (PAR), its interaction with analyst coverage (COV), and interactions with various control variables for firms with high earnings uncertainty. Panel A reports the regression results for firms with high earnings uncertainty. Panel B reports the comparison between firms with high earnings uncertainty and the full sample results in Table 4. The control variables (FCs) include market capitalization (SIZE), book to market ratio (BEME), momentum (MOM). Other FCs include the Amihud illiquidity ratio (ILLIQ), idiosyncratic volatility (IVOL), and leverage (LEV). All variables are defined in Table 1. The table reports time series average of coefficient estimates of quarterly regressions and their Newey-West t-statistics. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1996 to December 2017.

Panel A: Firms with High Earnings Uncertainty

	(1)		(2)		(3)	
	Xs	Xs*d^{EA}	Xs	Xs*d^{EA}	Xs	Xs*d^{EA}
PAR	-0.972*	-4.210***	-0.590	-4.131***	-1.109	-2.999***
	(-1.72)	(-4.26)	(-0.87)	(-3.82)	(-1.59)	(-2.57)
PAR*COV	2.551***	-3.012***	2.452***	-3.078***	1.861***	-2.454***
	(4.21)	(-4.36)	(4.09)	(-5.79)	(4.11)	(-5.55)
COV	-0.638	-1.116	-0.579	-1.002	-0.676	-0.753
	(-1.20)	(-1.55)	(-0.95)	(-1.18)	(-1.18)	(-0.89)
FCs			Yes	Yes	Yes	Yes
Other FCs					Yes	Yes
FE		1.556***		1.564***		1.586***
		(5.36)		(5.35)		(5.36)
d^{EA}		-1.126***		-1.100***		-1.186***
		(-2.62)		(-2.85)		(-2.74)
Intercept	0.393		0.200		0.269	
	(1.16)		(0.63)		(0.77)	
N	2,012		2,010		2,010	
Adj. R^2 (%)	2.075		2.496		3.121	

Panel B: Difference between Firms with High Earnings Uncertainty and Full Sample

	(1)		(2)		(3)	
	Xs	Xs*d^{EA}	Xs	Xs*d^{EA}	Xs	Xs*d^{EA}
			Firms with High Earnings Uncertainty			
PAR*COV	2.551***	-3.012***	2.452***	-3.078***	1.861***	-2.454***
	(4.21)	(-4.36)	(4.09)	(-5.79)	(4.11)	(-5.55)
			Full Sample			
PAR*COV	1.371***	-1.689***	1.413***	-1.577***	0.986***	-1.234***
	(3.64)	(-4.40)	(3.80)	(-4.45)	(4.72)	(-3.99)
			Differences			
PAR*COV	1.180***	-1.323***	1.039***	-1.501***	0.875**	-1.220**
	(2.82)	(-3.50)	(2.74)	(-3.34)	(2.22)	(-2.52)

Table 7. Information Production by Analysts during Pre-Announcement Window

In Panel A, each quarter, stocks are sorted into quintiles first based on the lagged earnings uncertainty (EU), and then within each EU quintile, stocks are further sorted into quintiles based on the absolute value of analyst forecast error (|FE|). In Panel B, each quarter, stocks are sorted into quintiles first based on the lagged earnings uncertainty (EU), and then within each EU quintile, stocks are further sorted into quintiles based on the absolute value of abnormal announcement returns (|CAR[-1,1]|). In Panel C, each quarter, stocks are sorted into quintiles based on pre-announcement return (PAR). FE and EU are defined the same as Table 1. CAR[-1, 1] is defined the same as Table 2. PAR is the pre-earnings-announcement return calculated as the cumulative abnormal return from t-2 to t-4. Excess #EF (Ex#EF[-4,-2]) or excess #REV (Ex#REV[-4,-2]) is the difference between t-4 to t-2 and t-26 to t-5. The number of EPS forecast (#EF) is calculated as the total number of analysts submitted EPS forecast for the current fiscal quarter during period t-2 to t-4. The number of revisions (#REV) is calculated as the total number of revisions for this announcement during period t-2 to t-4. The table reports the time series averages of each variable in each quintile, the differences in each variable between the top and bottom quintiles, as well as their Newy-West t-statistics. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1996 to December 2017.

Panel A Results Based on Earnings Surprises

|FE| Quintile	EU Quintile					
	1 (L)	2	3	4	5 (H)	Average
			Ex#EF[-4,-2]			
1 (L)	0.208	-0.002	-0.085	-0.058	-0.080	-0.003
2	0.378	0.003	-0.004	-0.053	-0.058	0.053
3	0.326	0.048	-0.020	-0.062	-0.039	0.051
4	0.326	0.056	-0.053	-0.084	-0.049	0.039
5 (H)	0.308	0.094	-0.059	-0.060	-0.052	0.046
Q5-Q1	0.100**	0.095**	0.026	-0.002	0.028	0.049**
NW-t	(2.18)	(2.04)	(0.66)	(-0.08)	(0.91)	(2.52)
			Ex#REV[-4,-2]			
1 (L)	0.164	-0.014	-0.081	-0.056	-0.069	-0.011
2	0.314	-0.010	-0.005	-0.052	-0.051	0.039
3	0.277	0.026	-0.025	-0.050	-0.030	0.040
4	0.285	0.039	-0.051	-0.069	-0.048	0.031
5 (H)	0.267	0.077	-0.057	-0.058	-0.052	0.035
Q5-Q1	0.103***	0.090**	0.023	-0.002	0.017	0.046***
NW-t	(2.69)	(2.13)	(0.64)	(-0.10)	(0.59)	(2.58)

Panel B Results Based on Announcement Returns

|CAR| Quintile	EU Quintile					
	1 (L)	2	3	4	5 (H)	Average
			Ex#EF[-4,-2]			
1 (L)	0.290	-0.033	-0.048	-0.087	-0.072	0.010
2	0.284	0.009	-0.064	-0.112	-0.063	0.011
3	0.325	0.004	-0.090	-0.062	-0.058	0.024
4	0.292	0.085	-0.018	-0.080	-0.053	0.045
5 (H)	0.357	0.134	0.000	0.025	-0.032	0.097
Q5-Q1	0.067	0.168***	0.048	0.112***	0.040**	0.087***
NW-t	(1.18)	(2.70)	(1.21)	(3.93)	(2.07)	(3.50)
			Ex#REV[-4,-2]			
1 (L)	0.243	-0.032	-0.044	-0.075	-0.068	0.005
2	0.242	-0.002	-0.066	-0.104	-0.059	0.002
3	0.273	-0.008	-0.085	-0.056	-0.048	0.015
4	0.244	0.054	-0.022	-0.067	-0.043	0.033
5 (H)	0.308	0.106	-0.003	0.017	-0.031	0.079
Q5-Q1	0.065	0.138**	0.041	0.092***	0.037**	0.075***
NW-t	(1.30)	(2.53)	(1.19)	(3.82)	(1.97)	(3.42)

Panel C. Results based on Pre-announcement Returns

	PAR Quintile					
	1 (L)	2	3	4	5 (H)	Q1|Q5 - Q3
Ex#EF[-4, -2]	0.049	-0.002	0.006	0.044	0.060	0.048***
						(3.13)
Ex#REV[-4, -2]	0.044	-0.002	0.001	0.034	0.040	0.041***
						(2.94)

Table 8. Informativeness of Analyst Activities during Pre-Announcement Window

In Panel A, each quarter, stocks are sorted into quintiles first based on lagged earnings uncertainty (EU), and then within each EU quintile, stocks are further sorted into quintiles based on analyst forecast error (FE). Panel A reports the time series averages of analyst revisions during the pre-announcement window t-2 to t-4 (REV[-4,-2]) in each quintile, the differences in REV between the top and bottom quintiles, as well as their Newy-West t-statistics. In Panel B, each quarter, we perform Fama-MacBeth regressions of analyst forecast error (FE) on analyst revision (REV[-4,-2]) and various firm characteristic variables. The firm characteristic variables include market capitalization (SIZE), book to market ratio (BEME), momentum (MOM), the Amihud illiquidity ratio (ILLIQ), idiosyncratic volatility (IVOL), earnings uncertainty (EU), and leverage (LEV). Analyst revision (REV[-4,-2]) is the average of the revisions during period t-2 to t-4. The revision is calculated as the difference between the EPS forecast for the current fiscal quarter and the previous EPS forecast of the same analyst for the same quarter and the next quarter. All other variables are defined in Table 1. Panel B reports the time series average of coefficient estimates of quarterly regressions and their Newey-West t-statistics. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1996 to December 2017.

Panel A. Informativeness of Analyst Revisions

	EU Quintile					
FE Quintile	1 (L)	2	3	4	5 (H)	Average
1 (L)	-0.006	-0.005	-0.007	-0.008	-0.017	-0.009
2	-0.005	-0.005	-0.006	-0.007	-0.007	-0.006
3	-0.005	-0.005	-0.009	-0.005	-0.004	-0.006
4	-0.004	-0.003	-0.003	-0.002	-0.001	-0.002
5 (H)	-0.002	-0.003	-0.002	-0.001	-0.005	-0.003
Q5-Q1	0.004***	0.003**	0.005***	0.007***	0.012***	0.006***
NW-t	(3.22)	(2.23)	(4.73)	(5.55)	(3.09)	(6.21)

Panel B. Multivariate Regressions of FE

	(1)	(2)	(3)	(4)
REV [-4, -2]	0.010***	0.011***	0.010**	0.010**
	(3.60)	(2.78)	(2.53)	(2.43)
SIZE		0.004***	-0.002	0.002**
		(3.14)	(-1.64)	(2.09)
BEME		-0.022**	-0.020*	-0.017*
		(-2.07)	(-1.92)	(-1.71)
MOM		0.027***	0.030***	0.028***
		(4.36)	(4.71)	(4.61)
ILLIQ			-0.002	-0.007
			(-0.23)	(-0.64)
IVOL			-0.041***	
			(-3.83)	
EU				-1.239***
				(-2.86)
LEV			-0.003	0.003
			(-0.74)	(0.91)
Intercept	0.005***	0.008***	0.001	0.014***
	(3.24)	(4.01)	(0.26)	(4.16)
N	2,015	1,740	1,740	1,740
Adj. R^2 (%)	0.995	1.529	2.287	2.791

Table 9. Trading Activities during Pre-Announcement Window

This table reports summary statistics of excess turnover (Panel A) and excess order imbalance (Panel B) during the pre-announcement window for the full sample of stocks, subsample of stocks with and without analyst earnings forecast, and subsample of stocks with and without analyst earnings revision for both actual announcement sample and the and Pseudo sample. Turnover is the trading volume divided by number of shares outstanding. Order imbalance is the absolute value of the difference between the daily buy dollar volume and daily sell dollar volume. The buy and sell dollar volume from the WRDS intraday indicator database. Excess turnover is defined as the difference in average daily turnover between the period of t-4 to t-2 and that of t-26 to t-5. Excess order imbalance is defined similarly. We calculate the mean and standard deviation of each variable each quarter for each sample. The table reports the time series average of the means as well as their Newy-West t-statistics. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1996 to December 2017.

Panel A: Excess Turnover

	Pseudo		Actual	
	Mean	Std.Dev.	Mean	Std.Dev.
Full Sample	-0.009 (-1.52)	0.882	-0.008* (-1.71)	0.737
With Earnings Forecast	0.098*** (8.71)	1.013	0.080*** (11.26)	0.889
Without Earnings Forecast	-0.049*** (-9.19)	0.784	-0.043*** (-9.43)	0.641
With Earnings Revision	0.104*** (8.90)	1.029	0.084*** (12.12)	0.899
Without Earnings Revision	-0.049*** (-8.96)	0.785	-0.042*** (-9.04)	0.642

Panel B. Excess Order Imbalance

	Pseudo		Actual	
	Mean	Std.Dev.	Mean	Std.Dev.
Full Sample	-0.002 (-0.07)	8.094	0.012 (0.31)	7.255
With Earnings Forecast	0.336*** (3.62)	12.100	0.139*** (3.23)	11.851
Without Earnings Forecast	-0.120*** (-4.96)	5.588	-0.043 (-1.50)	4.029
With Earnings Revision	0.375*** (3.66)	12.358	0.154*** (3.14)	11.975
Without Earnings Revision	-0.120*** (-4.98)	5.640	-0.044 (-1.47)	4.250

Table 10. Return Reversal: Effect of Turnover during Pre-Announcement Window

Each quarter, we perform Fama-MacBeth regressions of cumulative abnormal return during the earnings announcement window (CAR[-1,1]) on the pre-announcement return (PAR), its interaction with the excess turnover (ETO) during the pre-announcement window t-2 to t-4, and interactions with various control variables. Excess turnover is defined as the difference in average daily turnover between the period of t-4 to t-2 and that of t-26 to t-5. Turnover is defined in Table 9. The control variables include market capitalization (SIZE), book to market ratio (BEME), momentum (MOM), the Amihud illiquidity ratio (ILLIQ), idiosyncratic volatility (IVOL), and leverage (LEV). All variables are defined in Table 1. The table reports time series average of coefficient estimates of quarterly regressions and their Newey-West t-statistics. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1996 to December 2017.

	(1)		(2)		(3)	
	Xs	Xs*d^{EA}	Xs	Xs*d^{EA}	Xs	Xs*d^{EA}
PAR	-2.516***	-2.179**	-2.439***	-2.322***	-2.4828***	-2.123**
	(-5.01)	(-2.47)	(-4.60)	(-2.61)	(-5.33)	(-2.27)
PAR*ETO	0.674***	-0.717***	0.688***	-0.820***	0.624***	-0.728**
	(2.83)	(-4.10)	(2.80)	(-2.81)	(2.99)	(-2.20)
ETO	1.267	0.288	0.968	0.157	0.729	0.225
	(0.19)	(1.37)	(1.44)	(0.24)	(1.17)	(0.37)
FCs			Yes	Yes	Yes	Yes
Other FCs					Yes	Yes
FE		1.368***		1.485***		1.498***
		(6.71)		(6.85)		(6.86)
d^{EA}		-0.070***		-0.197***		-0.176**
		(-2.85)		(-3.00)		(-2.74)
Intercept	0.021		0.077		0.088**	
	(1.33)		(1.51)		(2.08)	
N	4,773		4,700		4,700	
Adj. R^2 (%)	1.674		2.029		2.532	

Table 11. Private and Public Market Reactions to Analyst Revisions

Each quarter, we perform Fama-MacBeth regressions of cumulative abnormal return CAR on the analysts revision (REV), co-current revision (CREV) and interactions with various control variables (Xs). Revision is defined in Table 5, and it is measured during the pre-announcement window [-4, -2]. CARs are measured during the pre-revision window CAR [t-2, t-1] (Panel A) and revision window [t, t+1]. CREV is measured during is measured the during the pre-revision window [t-2, t-1] (Panel A) or during the revision window [t+1] (Panel B). Time t is the revision announcement day. If the revision is announced after market, the announcement date is the next work day. CARs are computed for both actual and pseudo earnings announcements. d^{EA} is equal to 1 if the observation is an actual announcement and 0 otherwise. The control variables include market capitalization (SIZE), book to market ratio (BEME), momentum (MOM), the Amihud illiquidity ratio (ILLIQ), idiosyncratic volatility (IVOL), and leverage (LEV). All variables are defined in Table 1. The table reports time series average of coefficient estimates of quarterly regressions and their Newey-West t-statistics. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1996 to December 2017.

Panel A: Private Market Reaction to Revisions (Days [t-2, t-1])

	(1)		(2)		(3)	
	Xs	Xs*d^{EA}	Xs	Xs*d^{EA}	Xs	Xs*d^{EA}
REV	0.298***	0.123***	0.327**	0.139**	0.323**	0.126**
	(2.65)	(3.54)	(2.09)	(2.33)	(2.03)	(2.29)
CREV	0.591***	-0.539	0.703***	-0.672	0.739***	-0.747
	(2.89)	(-1.59)	(2.66)	(-1.51)	(2.78)	(-1.65)
SIZE			0.089***	-0.083**	0.058**	-0.046
			(2.63)	(-2.13)	(2.05)	(-1.34)
BEME			0.120	-0.176*	0.102	-0.113
			(1.52)	(-1.75)	(1.30)	(-1.12)
MOM			-0.025	0.098	-0.010	0.062
			(-0.36)	(1.05)	(-0.16)	(0.75)
ILLIQ					-0.683	-12.127
					(-0.09)	(-1.08)
IVOL					-0.152**	0.216
					(-2.13)	(1.67)
LEV					0.149***	-0.180**
					(3.45)	(-2.71)
d^{EA}		0.163**		0.189***		-0.615
		(2.36)		(2.63)		(-0.76)
Intercept	-0.273***		-0.329***		-0.591	
	(-3.69)		(-4.03)		(-0.96)	
N	860		717		717	
Adj. R^2 (%)	0.392		1.354		2.708	

Panel B: Public Market Reaction to Revisions (Days [t, t+1])

	(1)		(2)		(3)	
	Xs	Xs*d^{EA}	Xs	Xs*d^{EA}	Xs	Xs*d^{EA}
REV	0.833***	-0.513***	1.031***	-0.757***	1.036***	-0.762***
	(5.14)	(-2.99)	(4.37)	(-3.36)	(4.33)	(-3.41)
CREV	0.924**	0.226	0.773**	0.336	0.820**	0.311
	(1.97)	(0.34)	(1.97)	(0.48)	(1.98)	(0.45)
SIZE			0.055***	-0.016	0.034**	-0.001
			(2.84)	(-0.73)	(1.97)	(-0.04)
BEME			0.025	-0.008	-0.003	0.037
			(0.38)	(-0.10)	(-0.05)	(0.49)
MOM			0.089	0.113	0.111	0.107
			(1.41)	(1.57)	(1.65)	(1.57)
ILLIQ					-1.504	1.904
					(-0.13)	(0.14)
IVOL					-0.245***	0.272**
					(-2.91)	(2.10)
LEV					0.001	0.053
					(0.02)	(0.66)
d^{EA}		0.259***		0.247***		0.086
		(4.28)		(4.27)		(0.13)
Intercept	-0.178***		-0.208***		-0.145	
	(-3.60)		(-4.59)		(-0.23)	
N	866		722		722	
Adj. R^2 (%)	0.433		1.369		2.794	

Table 12. Bid-Ask Spread and Adverse Selection Component during Pre-Announcement Window

This table reports summary statistics of excess quoted bid-ask spread (Panel A), excess effective bid-ask spread (Panel B), excess realized bid-ask spread (Panel C), and the excess adverse selection component of the spread (Panel D) during the pre-announcement window for the full sample of stocks, subsample of stocks with and without earnings forecast, and subsample of stocks with and without earnings revision for both actual announcement sample and Pseudo sample. Quoted spread is the simple average of second-by-second percent quoted spread. Effective spread is the simple averaged percentage effective spread based on Lee-Ready method. Realized spread is the simple averaged percentage realized spread based on Lee-Ready method. All three spread variables are obtained from WRDS intraday indicator database. The adverse selection component of the spread is estimated using the Huang and Stoll (1997) method as detailed in Section IV.E. The excess spread is defined as the difference in average daily spread between the period of t-4 to t-2 and that of t-26 to t-5. The excess adverse selection component of the spread is defined similarly. We calculate the mean and standard deviation of each variable each quarter for each sample. The table reports the time series average of means as well as their Newy-West t-statistics. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1996 to December 2017.

Panel A: Excess Quoted Spread (%)

	Pseudo		Actual	
	Mean	Std.Dev.	Mean	Std.Dev.
Full Sample	0.0027 (0.88)	0.3184	-0.0024 (-0.53)	0.2930
With Earnings Forecast	-0.0047 (-1.52)	0.1920	-0.0038 (-1.39)	0.1752
Without Earnings Forecast	0.0055 (1.05)	0.3532	-0.0024 (-0.51)	0.3248
With Earnings Revision	-0.0044 (-1.43)	0.1913	-0.0033 (-1.14)	0.1766
Without Earnings Revision	0.0052 (0.99)	0.3500	-0.0026 (-0.56)	0.3214

Panel B: Excess Effective Spread (%)

	Pseudo		Actual	
	Mean	Std.Dev.	Mean	Std.Dev.
Full Sample	0.0026 (1.26)	0.2335	0.0039* (1.94)	0.2338
With Earnings Forecast	0.0032 (1.14)	0.1543	0.0027** (1.97)	0.1379
Without Earnings Forecast	0.0024 (0.91)	0.2562	0.0044* (1.77)	0.2605
With Earnings Revision	0.0033 (1.19)	0.1534	0.0026* (1.82)	0.1383
Without Earnings Revision	0.0024 (0.88)	0.2539	0.0046* (1.80)	0.2578

Panel C: Excess Realized Spread (%)

	Pseudo		Actual	
	Mean	Std.Dev.	Mean	Std.Dev.
Full Sample	-0.0027 (-0.71)	1.0798	-0.0055 (-0.88)	1.2094
With Earnings Forecast	-0.0117 (-1.39)	0.5063	0.0033** (2.16)	0.1953
Without Earnings Forecast	0.0010 (0.14)	1.1066	-0.0090 (-1.10)	1.4229
With Earnings Revision	-0.0116 (-1.35)	0.5114	0.0034** (2.03)	0.1950
Without Earnings Revision	0.0008 (0.11)	1.0977	-0.0088 (-1.10)	1.4107

Panel D: Excess Adverse Selection Components of Spread

	Pseudo		Actual	
	Mean	Std.Dev.	Mean	Std.Dev.
Full Sample	0.035 (1.25)	0.453	0.045*** (2.86)	0.423
With Earnings Forecast	0.008 (1.55)	0.362	0.053*** (2.71)	0.381
Without Earnings Forecast	0.076 (1.48)	0.526	0.042 (1.68)	0.445
With Earnings Revision	0.004 (0.69)	0.356	0.060*** (2.72)	0.386
Without Earnings Revision	0.071 (1.50)	0.519	0.041* (1.71)	0.436

Appendix

A1 Return Reversal: Decomposing the Effect of Analyst Revision

This section provides further evidence that analyst activities before earnings announcements contribute to announcement return reversal, we decompose the pre-announcement returns (PAR) into two components: the component associated with analyst revisions and the residual. If analyst revisions do not contribute to return reversal around earnings announcements, the residual part should be the only term that has a negative relation with announcement returns.

Each quarter, we first perform the following Fama-MacBeth regression:

$$PAR_{i,t} = a_t + b_{1,t} * REVQ0_{it} + b_{2,t} * REVQ1_{it} + b_3 * REVY0_{it} + \varepsilon_{i,t} \quad (1)$$

where $REVQ0_{it}$ is the analyst earnings reversion for the current fiscal quarter, $REVQ1_{it}$ is the analyst earnings reversion for the next fiscal quarter, and $REVY0_{it}$ is the analyst earnings reversion for the current fiscal year. All analyst earnings revisions are measured during the pre-announcement period from t-4 and t-2, where t is the earnings announcement date. Based on the coefficient estimates in Eq. (1), we then decompose $PAR_{i,t}$ into two components: $\overline{PAR}_{i,t}$ and $\widehat{PAR}_{i,t}$ as follows:

$$\overline{PAR}_{i,t} = \hat{a} + \hat{b}_1 * REVQ0_{i,t} + \hat{b}_2 * REVQ1_{i,t} + \hat{b}_3 * REVY0_{i,t} \quad (2)$$

$$\widehat{PAR}_{i,t} = PAR_{i,t} - \overline{PAR}_{i,t} \quad (3)$$

where $\hat{a}$is the estimate of the intercept α_t, $\hat{b}_1$ is the estimate of the coefficient of $REVQ0_{i,t}$, $\hat{b}_2$is the estimate of the coefficient of $REVQ1_{i,t}$, and $\hat{b}_3$is the estimate of the coefficient of $REVY0_{i,t}$. $\overline{PAR}_{i,t}$ is the component that is associated with analyst earnings revision, whereas $\widehat{PAR}_{i,t}$ is the residual term.

Finally, we perform the Fama-MacBeth regression of cumulative abnormal return during the earnings announcement window (CAR[-1,1]) on both $\overline{PAR}$ and $\widehat{PAR}$, with other control variables:

$$CAR[-1,1]_{i,t} = \alpha_t + \beta_{1t}\overline{PAR}_{i,t} + \beta_{2t}\overline{PAR} * d^{EA}{}_{i,t} + \beta_{3t}\widehat{PAR}_{i,t} + \beta_{4t}\widehat{PAR} * d^{EA}{}_{i,t} + \beta_{5t}REV[-1,1]_{i,t} + \beta_{6t}REV[-1,1] * d^{EA}{}_{i,t} + \beta_{7t}d^{EA}{}_{i,t} + \beta_{8t}FE * d^{EA}{}_{i,t} + \varepsilon_{i,t} \quad (4)$$

where analyst earnings revisions during the announcement window (REV[-1,1]) is included to control for their effect on earnings announcement returns. Analyst revision is defined as the analyst revise his/her earnings forecast after that analyst release the earnings forecast for the firm. Analyst forecast error is defined the same as in the paper. d^{EA} is a dummy variable of the announcement, which equals to 1 if the observation is an actual earnings announcement and 0 otherwise. We include interactions of d^{EA}. For the actual earnings announcements, we also include analyst forecast error (FE) as a control variable.

Table A1. Return Reversal: Decomposing the Effect of Analyst Revision

Each quarter, we run the following cross-sectional regressions:

$$PAR_{i,t} = a_t + b_{1,t} * REVQ0_{it} + b_{2,t} * REVQ1_{it} + b_3 * REVY0_{it} + \varepsilon_{i,t}$$

where $REVQ0$ is the analyst revision for the current quarter, $REVQ1$ is the analyst revision for the next quarter, and $REVY0$ is analyst revision for the current year. $\overline{PAR}$ is the projected PAR based on the regression, and $\widehat{PAR}$ is the residual. We then perform Fama-MacBeth regression of earnings announcement window return (CAR[-1,1]) on $\overline{PAR}$ and $\widehat{PAR}$.

$$CAR[-1,1]_{i,t} = \alpha_t + \beta_{1t}\overline{PAR}_{i,t} + \beta_{2t}\overline{PAR} * d^{EA}{}_{i,t} + \beta_{3t}\widehat{PAR}_{i,t} + \beta_{4t}\widehat{PAR} * d^{EA}{}_{i,t} + \beta_{5t}REV[-1,1]_{i,t} + \beta_{6t}REV[-1,1] * d^{EA}{}_{i,t} + \beta_{7t}d^{EA}{}_{i,t} + \beta_{8t}FE * d^{EA}{}_{i,t} + \varepsilon_{i,t}$$

CAR[-1,1] are computed for both actual and pseudo earnings announcements. d^{EA} is equal to 1 if the observation is an actual announcement and 0 otherwise. The control variables include analyst revision during announcement window (REV [-1, 1]) and analyst forecast error (FE). The table reports time series average of coefficient estimates of quarterly regressions and their Newey-West t-statistics. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1996 to December 2017.

	(1)		(2)		(3)	
	Xs	Xs*d^{EA}	Xs	Xs*d^{EA}	Xs	Xs*d^{EA}
$\overline{PAR}$	0.008	-0.309***			0.005	-0.311***
	(0.15)	(-3.21)			(0.11)	(-3.23)
$\widehat{PAR}$			-0.022***	-0.027***	-0.022***	-0.028***
			(-5.45)	(-3.16)	(-5.45)	(-3.17)
REV [-1, 1]	0.030***	0.097***	0.031***	0.094***	0.031***	0.097***
	(8.25)	(8.46)	(8.37)	(8.33)	(8.19)	(8.52)
FE		0.129***		0.131***		0.131***
		(13.17)		(13.55)		(13.58)
d^{EA}		-0.000		-0.000		-0.000
		(-1.40)		(-1.16)		(-1.38)
Intercept	-0.000		-0.000		-0.000	
	(-0.73)		(-0.38)		(-0.73)	
N	4,790		4,790		4,790	
Adj. R^2 (%)	2.084		2.362		2.413	

A2. Information Uncertainty and Analyst Activities

In this section, we examine the relation between analyst activities and various firm characteristics as well as the information uncertainty, which is proxied by idiosyncratic volatility (IVOL) or earnings uncertainty (EU). The other firm characteristics variables (X) include market capitalization (SIZE), book to market ratio (BEME), momentum (MOM), the Amihud illiquidity ratio (ILLIQ), and leverage (LEV).

Each quarter, we perform Fama-MacBeth regressions of analysts' activities on various firm characteristic variables. Analysts' activities are measured by log(1+COV), log(1+#EF), and log(1+#REV). COV is analysts coverage, #EF is the number of earnings forecasts issued by analysts, and #REV is the number of revision. The regressions are specified as follows:

$$\log(1+Y)_{i,t} = \alpha_t + \beta_{1t}X_{i,t} + \beta_{2t}IVOL_{i,t} + +\varepsilon_{i,t}$$

$$\log(1+Y)_{i,t} = \alpha_t + \beta_{1t}X_{i,t} + \beta_{2t}EU_{i,t} + +\varepsilon_{i,t}$$

Where Y denotes COV, #EF, or #REV.

Table A2.1 reports the time-series average of coefficient estimates of quarterly regression in the above equations and their Newey-West t-statistics.

Each quarter, we sort stocks into quintiles based on IVOL or EU. We calculate the time series average of the following analyst activities: number of analyst EPS forecast during the pre-announcement window t-4 to t-2 (#EF[-4,-2]), number of analyst revision during the pre-announcement window t-4 to t-2 (#REV[-4,-2]), and the excess measure of both variables (Ex#EF[-4,-2] and Ex#REV[-4,-2]) . The excess measure is defined as the difference between t-4 to t-2 and t-26 to t-5.

Table A2.2 Panel A reports the time series average of #EF[-4,-2], Ex#EF[-4,-2], #REV[-4,-2], and Ex#REV[-4,-2] for each IVOL quintiles as well as well as the differences in each variable between the top and bottom quintiles.

Table A2.2 Panel B reports the time-series average of #EF[-4,-2], Ex#EF[-4,-2], #REV[-4,-2], and Ex#REV[-4,-2] for each EU quintiles as well as well as the differences in each variable between the top and bottom quintiles.

Table A2.1 Determinants of Analyst Coverage and Activities

Each quarter, we perform Fama-MacBeth regressions of analysts' activities on various firm characteristic variables. Analysts' activities are measured by log(1+COV), log(1+#EF), and log(1+#REV). COV is analysts coverage, #EF is the number of earnings forecasts issued by analysts, and #REV is the number of revision. The firm characteristic variables include market capitalization (SIZE), book to market ratio (BEME), momentum (MOM), the Amihud illiquidity ratio (ILLIQ), idiosyncratic volatility (IVOL), earnings uncertainty (EU), and leverage (LEV). Number of EPS forecast (#EF) is calculated as the total number of analysts submitted EPS forecast for the current fiscal quarter during period t-4 to t-2. Numbers of revision (#REV) is calculated as the total number of revision for this announcement during period t-4 to t-2. If the same analyst submitted an earnings forecast for before and resubmitted another forecast during the period, this is counted as one revision. All other variables are defined in Table 1. The table reports time series average of coefficient estimates of quarterly regressions and their Newey-West t-statistics. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1996 to December 2017.

	Log (1+COV)		Log (1+#EF)		Log (1+#REV)	
	(1)	(2)	(3)	(4)	(5)	(6)
SIZE	0.219***	0.228***	0.127***	0.129***	0.122***	0.123***
	(38.09)	(39.22)	(11.24)	(11.28)	(10.34)	(10.31)
BEME	-0.167***	-0.160***	-0.028***	-0.027***	-0.023***	-0.022***
	(-21.40)	(-19.46)	(-12.52)	(-11.78)	(-10.24)	(-9.74)
MOM	-0.069***	-0.074***	-0.002	-0.003	-0.004	-0.005
	(-5.10)	(-5.78)	(-0.54)	(-0.77)	(-1.02)	(-1.19)
ILLIQ	-3.089***	-3.116***	-0.054***	-0.055***	-0.050***	-0.051***
	(-2.57)	(-2.57)	(-9.24)	(-9.67)	(-8.89)	(-9.21)
IVOL	-0.103***		-0.013***		-0.010***	
	(-7.94)		(-4.72)		(-3.52)	
EU		-4.383***		-0.668***		-0.606***
		(-6.10)		(-5.92)		(-5.73)
LEV	0.048***	0.068***	0.018***	0.020***	0.020***	0.022***
	(6.39)	(7.40)	(5.96)	(7.07)	(6.85)	(7.60)
Intercept	-0.382***	-0.343***	-0.176***	-0.170***	-0.161***	-0.155***
	(-7.32)	(-6.60)	(-24.29)	(-25.73)	(-20.14)	(-21.42)
N	1,740	1,740	1,740	1,740	1,740	1,740
Adj. R^2 (%)	15.573	15.422	7.608	7.633	7.550	7.575

Table A2.2 Information Uncertainty and Analyst Activities during Pre-Announcement Window

Each quarter, stocks are assigned to quintiles based on lagged idiosyncratic volatility (IVOL) (Panel A) or lagged earnings uncertainty (EU) (Panel B). Number of EPS forecast (#EF) is calculated as the total number of analysts submitted EPS forecast for the current fiscal quarter during period t-4 to t-2. Numbers of revision (#REV) is calculated as the total number of revision for this announcement during period t-4 to t-2. Excess #EF or excess #REV is the difference between t-4 to t-2 and t-26 to t-5. All other variables are defined in Table 1. The table report the time series average of the number of earnings forecasts issued by analysts (#EF) and the number of revision (#REV) for each quintile, as well as differences in each variable between the top and bottom quintiles and their Newy-West t-statistics. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1996 to December 2017.

Panel A: Results based on IVOL

	IVOL Quintile					
	1 (L)	2	3	4	5 (H)	Q1-Q5
#EF[-4, -2]	0.962	0.845	0.777	0.665	0.527	0.435*** (5.78)
Ex#EF[-4, -2]	0.152	0.083	0.050	-0.026	-0.105	0.257*** (6.18)
#REV[-4, -2]	0.805	0.707	0.643	0.545	0.426	0.379*** (5.41)
Ex#REV[-4, -2]	0.132	0.073	0.036	-0.030	-0.095	0.227*** (5.76)

Panel B: Results based on EU

	EU Quintile					
	1 (L)	2	3	4	5 (H)	Q1-Q5
#EF[-4, -2]	1.345	0.931	0.729	0.589	0.497	0.849*** (6.40)
Ex#EF[-4, -2]	0.309	0.040	-0.044	-0.063	-0.056	0.365*** (3.81)
#REV[-4, -2]	1.123	0.773	0.607	0.487	0.406	0.717*** (5.84)
Ex#REV[-4, -2]	0.262	0.024	-0.044	-0.057	-0.050	0.312*** (3.60)