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Information Content of Revised Earnings Forecasts, Market Learning, and Analyst Behavior

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INFORMATION CONTENT OF REVISED EARNINGS FORECASTS, MARKET LEARNING, AND ANALYST BEHAVIOR

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Dedication

To my beloved wife, Di Huang.

To my mother, father, and grandfather.

Thank you for your love, support and encouragement.

INFORMATION CONTENT OF REVISED EARNINGS FORECASTS, MARKET LEARNING, AND ANALYST BEHAVIOR

by

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DISSERTATION

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Abstract

In my first essay, I examine how the quality of private information and the quality of public information contained in analyst revised one-year-ahead earnings forecasts issued right after a quarterly earnings announcement affect the post-earnings announcement drift (PEAD). I find that high precision of private information contained in revised forecasts reduces the level of PEAD and that the precision of public information contained in the revised one-year-ahead earnings forecasts partially offset the reduction in PEAD. Moreover, I find the effect of precision of private information on PEAD decreases after Reg FD, which required in the year 2000 that analysts could not contact the firm insiders to obtain private information. The results suggest that high-quality private information contained in revised earnings forecasts reduces information uncertainty, which helps investors estimate the true distribution of firm value. The results also suggest that investors acknowledge the impact of legal events on the quality of information from information sources.

In my second essay, I empirically test the implication of Kuhnen (2015) by examining whether the impacts of firm characteristics on financial analysts' following decisions change depending on the on-going economy conditions. I also examine how analysts incorporate pessimism into their expectation of distribution of firm value after observing negative events. I find that analysts become less sensitive to firm size, shares outstanding, and stock volatility when making following decisions after observing bad outcomes. However, analysts are more sensitive to prior stock performance after observing these. In addition, I find that analysts fail to fully recognize the impact of the recession on the firm's performance on time, but they do incur asymmetric learning as analysts deliver forecasts with pessimistic bias after observing bad outcomes last year.

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Chapter 1: Introduction

My dissertation contains two essays. In my first essay, I shed light on the debate regarding the role of financial analysts by examining the effects of precision of private/ public information contained in revised one-year-ahead earnings forecasts on post-earnings announcement drift (PEAD). I find that high precision of private information contained in revised one-year-ahead forecasts reduces the level of PEAD and that the precision of public information partially offset the reduction in PEAD. The results suggest that high-quality private information reduces information uncertainty, which helps investors estimate the true distribution of firm value. I argue the results contribute to the literature of PEAD and the literature of information uncertainty, in addition to the debate of the role of financial analysts. Moreover, I concern whether the market understands the impact of legal events on the information embodied in revised analyst forecasts. I explore the question by conducting an event-study using Reg FD as the legal event. I find that the effect of precision of private information on PEAD decreases after Reg FD, which, in the year 2000, required that analysts cannot receive a firm's material information ahead of public investors and trade on it. The results indicate that investors acknowledge the impact of legal events on the quality of information contained in revised forecasts and add to the literature of market learning.

My second essay empirically tests the pessimistic bias in Kuhnen (2015) – whether professional market participants would have different expectations on a firm's future when valuing the firm after observing negative outcomes than when no negative outcomes exit - by examining whether the impacts of determinants of financial analysts' following change depending on the on-going economy conditions. I also consider how analysts incorporate pessimism bias into their expectation of distribution of firm value after observing adverse outcomes by examining the difference in signed forecast errors between good (post-good) and bad (post-bad) domains. I find

analysts become less sensitive to firm size, shares outstanding, and stock volatility after observing the bad outcomes. Moreover, I find that analysts fail to fully incorporate the impact of the recession in their forecasts on time, and that analysts suffer from pessimistic bias after they observe bad events in recession, and the impact continues even after bad times.

I argue my essay 2 contributes to the academic world in several aspects: first, This research provides empirical tests for the implication developed in Kuhnen (2015) by showing that professional market participants such as financial analysts further deviate from Bayesian rule during bad times than during good times; secondly, the research adds to the determinants of analyst following literature by showing that firm characteristics have different impacts on financial analyst's decision on following a firm during bad vs. good state of economy; moreover, the study contributes to financial optimism literature as the study shows that financial analysts become less optimistic in general during bad state of economy. My study shows the need for a new pricing model that incorporates the pessimistic bias.

Chapter 2: Do Revised Forecasts Help the Market Understand Post-Earnings Announcement Drift?

2.1 Introduction

Conventional wisdom views financial analysts as important information agents. However, recent research suggests that the financial analysts may provide little information to the market through their services such as forecasts or recommendations. (Kim and Song, 2014; Loh and Stulz, 2010; Altinilic and Hansen, 2009; and Atinkilic, Balashov, and Hansen, 2013).

In this study, I shed some light on the question of the role of financial analysts in firm information environment by examining the role of financial analysts in reducing information uncertainty and hence the market underreaction. Specifically, I examine how post-earnings announcement drift, a capital market anomaly related to information uncertainty and market underreaction, is associated with information provided by financial analysts. I also examine whether the market acknowledges the informativeness of analyst earnings forecasts. The question is not only related to the role of financial analysts, but also to the capital market pricing dynamics and price discovery.

Post-earnings announcement drift (PEAD) has long been a mystery in financial research. PEAD happens when a firm's actual earnings from earnings announcement are different from what the stock market expected. The surprise component of the earnings predicts the direction toward which the future stock price would move. That is, when actual earnings are higher (lower) than expected earnings, the stock would have positive (negative) abnormal returns for a period after the actual earnings announcement. Prior work shows that the predictability of annual earnings surprises on abnormal stock returns is up to two months (Ball and Brown, 1968), and that quarterly earnings surprises have similar predictability (Jones and Litzenberger, 1970; Foster et al., 1984;

and Bernard and Thomas, 1989). Prior attempts to explain the PEAD focus on experimental design flaw (Ball, 1978; and Joy and Jones, 1979) and on premium of variables omitted from CAPM model (Ball, 1979; Foster, Olsen, and Shevlin, 1984; Ball, Kothari and Watts, 1993; and Bernard and Thomas, 1989). Those two explanations could not explain the PEAD as the PEAD continues to exist even after follow-up research addresses these aforementioned issues.

A third explanation argues that the market is just slow in adjusting or underreacts to earnings surprises (Ball, 1978). However, it is hard to explain why the market is slow in adjusting to earnings announcements. Earlier works indicate that high transaction cost or high information processing costs could explain the sign and but could not explain the magnitude of PEAD (Ball, 1978). More recent works focus on how the ability of market participants in processing price-related information may explain the slow adjustment and hence the PEAD. For example, literature states that market participants do not fully understand the implications of current earnings for future earnings, and thus need time to process information contained in earnings surprises and the resulting PEAD. (Freemand and Tse, 1989; Bernard and Thomas, 1989, 1990; Abarbanell and Bernard, 1992; Bartov, 1992; Ball and Bartov, 1996; Soffer and Lys, 1998). Other than the incapability of market participants in processing information timely, two more hypotheses, the behavioral hypothesis and the rational hypothesis, are proposed. Distinguishing the two hypotheses depends on whether investors fully follow Bayesian rules when processing new information. That is, whether investors are overconfident in the private information they possess.

The rational hypothesis argues that investors who fully follow Bayesian rules cannot observe complete information when the true distribution of firm value changes. The incomplete information structure creates uncertainty among investors, as they cannot decide whether the distribution has changed with certainty. As a result, they underreact to the news that arrives right

after the initial earnings surprise. And the underreaction affects the market returns (Timmermann, 1993; Morris, 1996; Lewellen and Shanken, 2002; Brav and Heaton, 2002; and Francis, et al., 2007).

The behavioral hypothesis argues that investors are quasi-rational. That is, those investors follow Bayesian rules to incorporate information into their beliefs on firm value, but are overconfident in the precision of private information possess. The overconfidence results in investors underreacting to new information regarding the true distribution of their investments. The level of overconfidence is even higher when the level of uncertainty is high, resulting in investors could not accurately estimate the distribution of their investments (Griffin and Tversky, 1992; Daniel, Hirshleifer, and Subrahmanyam, 1998; Hong and Stein, 1999; Liang, 2003; and Zhang, 2006a).

Under both the rational and behavioral hypotheses, investors underreact to information released right after earnings announcements due to uncertainty in estimating the true distribution of their investments. Zhang (2006a) argues that the volatile underlying asset value and poor information result in uncertainty, suggesting that better information decreases uncertainty. The investor underreaction may be reduced if information signals arrive right after earnings announcement could help reduce the uncertainty.

One type of information that may help calm investors' uncertainty after earnings announcements are analyst revised earnings forecast issued by a financial analyst. Prior literature shows that earnings forecasts issued by financial analysts are informative. In particular, characteristics of forecasts such as forecast error, forecast dispersion, the number of analyst following and length of following, and forecast revisions are informative to investors (Conroy et al., 1998; Park and Stice, 2000; Bonner et al., 2003; Clement and Tse, 2003). Revised earnings

forecasts are usually known for bringing forecast revisions to market. Gleason and Lee (2003) document that forecast revisions trigger price adjustments. Revised earnings forecasts themselves are informative as well. For example, Amiram, Owens, and Rozenbaum (2016) document a reduced level of information asymmetry between sophisticated investors (e.g. institutional investors with buyer side analysts) and unsophisticated investors (e.g. regular investors) following analyst revised earnings forecasts issued in the post-earnings announcement period. Collectively, revised earnings forecasts issued right after earnings announcements are informative in general. As a result, revised forecasts could impact information uncertainty and hence the security market underreaction to earnings surprise.

Revised earnings forecasts convey different kinds of information. They contain publicly available information such as firm disclosed information, business press coverage, and macroeconomic information, as well as private information such as analysts' efforts and industry expertise (Stickle, 1993; Bartov and Bodnar, 1994; Rogers and Grand, 1997). For instance, Barron et al. (1998) indicate that analyst forecasts contain both public information and private information. They document that informativeness of analyst forecasts is related to the precision of information common to all analysts (public information) and the precision of information specific to each financial analyst (private information). Barron et al. (1998) propose a measure of the precision of common information and a measure of the precision of private information. They argue that the precision of information could be interpreted as to what extent analysts rely on public/private information in preparing their earnings forecasts. The two measures have been widely used in the literature to proxy for the quality of private portion and the quality of the public portion of the information contained in analyst forecasts. For instance, Mohanram and Sunder (2006) use these

measures to examine the effect of accounting event on financial analysts' reliance on private information and public information.

It is interesting to explore how the precision of those two kinds of information contained in revised earnings forecasts affect market underreaction to information contained in earnings announcements. If revised earnings forecasts could reduce rational investors' underreaction, it could do so via reducing information uncertainty. The reduction of information uncertainty could be made through the precision of public information as analysts confirm the informativeness of selected publicly available information to investors. It is also possible that analysts reveal high-quality private information to investors that complements the existing information and reduces the uncertainty.

However, analysts may be inefficient at processing information or underreact to price-relevant information contained in earnings announcements (Abarbanell and Bernard, 1992; Abarbanell, 1991; and Abarbanell and Bushee, 1997). Under this condition, the precision of information (both private and public) contained in revised analyst earnings forecasts is low in general, which means no new information and no effects on market underreaction (Kim and Song, 2014; Loh and Stulz, 2010; Altinilic and Hansen, 2009; and Atinkilic, Balashov, and Hansen, 2013). The effect of precision of information on PEAD is an empirical question.

In this paper, I examine the effects of the precision of private information and precision of common information contained in revised earnings forecasts in addition to earnings surprise on PEAD. I use quarterly earnings announcements and one-year-ahead analyst forecasts in this analysis. The PEAD is measured as the 60-days cumulative return on a zero-investment portfolio after a firm's quarterly earnings announcement. The portfolio is constructed by buying firms with the highest rank (most positive) of quarterly earnings surprise and selling firms with the lowest

rank (most negative)of quarterly earnings surprise. Quarterly earnings surprise is calculated as the difference between actual quarterly earnings and mean analyst forecast for the corresponding quarter. Mean forecast is calculated from those forecasts issued within 45 days before the actual announcement day. To make the result more interpretable, I group all firm quarters into deciles based on the earnings surprise. By construction, each decile has roughly the same number of observations. Decile 0 contains firms with the most negative earnings surprise while decile 9 contains firms with the most positive earnings surprise. I then scale the decile numbers by 9 to get the scaled decile numbers and use these scaled numbers in the regression analysis.

I follow Barron et al. (1998) to construct the private information precision measure and public information precision measure. I first identify analysts who issue at least one one-year-head forecast within 45 days before next quarterly earnings announcement and at least one one-year-ahead forecast revision within 30 days after the same quarterly earnings announcement. For the fourth quarter, I use two-year-ahead forecast instead. I keep firm quarters with at least two analysts that fit the requirements. Precision measures are then calculated using those revised forecasts issued by analysts after quarterly earnings announcements, along with other variables in Barron et al. (1998) formulas. I divide all firm quarters into deciles based on the precision of public information and the precision of private information and use the scaled decile numbers in the analysis as well.

To examine the effects of precision of private information and precision of public information in revised earnings forecasts on PEAD, interaction terms between each of these two precision measures and earnings surprise are created and evaluated in the regression analysis.

The results show that the precision of information contained in revised one-year-ahead earnings forecasts issued right after an actual quarterly earnings announcement has an explanatory

power in addition to the earnings surprise on the post-earnings announcement drift. Precision of private information contained in revised forecasts reduces the market underreaction to information and helps reduce PEAD, while the effect is partially offset by precision of public information in revised earnings forecasts.

I provide a few robustness checks on the main results. First, I calculate market-adjusted abnormal returns based on five different indexes and use these market-adjusted abnormal returns as the dependent variable in regression analysis. Second, I use additional controlling variables that are shown to influence the post-earnings announcement drift in prior literature to address the potential omitted variables problem. The results are robust to those additional tests.

In addition, I use a Pseudo-event study to examine whether the explanatory power of revised earnings forecasts comes from information precisions I propose. The Reg FD that takes effect in 2000 forbids financial analysts from privately contacting the firm to get insider information ("selective disclosure"). Moreover, the regulation requires firms to make public announcements if firms want to disclose any material information. Mohanram and Sunder (2006) examine how Reg FD affect financial analysts' operation using the measures developed in Barron et al. (1998). Mohanram and Sunder (2006) find that public information environment doesn't change significantly before and after the regulation. Moreover, Mohanram and Sunder (2006) further find that analysts spend more efforts on generating private information as those analysts lose connections with firms. One would expect that precision of public information in analyst forecasts would not change significantly during pre- and post-Reg FD and that the private information content of revised analyst forecast would change from reflecting insider information in the pre-Reg FD period to private information generated through analysts' research efforts in the post-Reg FD times. One would also expect that investors learn about the change in information.

Then, I would expect that investors' reaction to private information in post-Reg FD period is different from their reaction to private information in post-Reg FD period as the investors acknowledge the precision of such information changes after Reg FD. The investors' reaction to the precision of public information contained in revised earnings forecast would be similar across two periods. The results suggest that private information precision contributes more to PEAD before the Reg FD, while the effect of public information precision on PEAD stays the same before and after Reg FD.

The results that precision of private information contained in the revised annual earnings forecasts helps reduce post-earnings announcement drift add to the debate over the role of financial analysts. These results show that analysts benefit investors by producing useful price-related private information in their revised earnings forecasts. This work also adds to the literature of post-earnings forecast drift as I find that relying on relatively high-quality private information in preparing analyst earnings forecasts helps reduce PEAD. This study contributes to the information uncertainty literature as the results suggest that private information precision contained in revised earnings forecast issued right after quarterly earnings announcement helps reduce overall information uncertainty. Moreover, the results suggest that the market acknowledges the informativeness of information source, and these results add to the growing literature of learning in the capital market.

The rest of the paper is organized as follows. In section 2.2 I present related literature. I develop my hypotheses in section 2.3. Sample construction and variable development are in section 2.4. I discuss my empirical test methods in section 2.5. Empirical results are presented in section 2.6. I have the conclusion and discussion in section 2.7.

2.2 Literature Review

2.2.1 Predictability of earnings announcements and possible explanations

Prior work shows the predictability of actual earnings announcements on abnormal stock returns. Ball and Brown (1968) are the first to note that even after the earnings are announced, the estimated cumulative abnormal returns continue to move in the same direction with earnings surprise. Stocks experience positive cumulative abnormal returns after "good news" and negative cumulative abnormal returns after "bad news." Foster, Olsen, and Shevlin (1984), among others, replicate the phenomenon. They find that a zero-investment portfolio with a long position in highest quarterly earnings surprise decile and a short position in lowest quarterly earnings surprise decile yields an annualized abnormal return of 25% during the 60-trading day period after quarterly earnings announcements. Jones and Litzenberger (1970) find that the market does not incorporate information from quarterly earnings announcements into price immediately. Latane, Joy, and Jones (1970) document that investors could use quarterly earnings announcements and a simple Earnings/Price (E/P) ratio sort-rank analysis to find stocks that would outperform the market in the next six months.

In their reviews, Ball (1978) and Joy and Jones (1979) discuss studies on PEAD. Ball (1978) shows that extant studies document the consistent existence of excess returns after firm public earnings announcements. Joy and Jones (1979) shows that the PEAD exits for quarterly earnings announcements. Those results appear to be contrary to the argument that the market is efficient and stock prices adjust toward correct position immediately after new information arrives in the market. Several later studies use more refined methods, larger sample sizes, or even foreign country data to avoid the problems mentioned in those two review papers, such as database flaws, failure in properly adjusting security risk, and shifts in security risk, etc., but those studies show

that the predictability of earnings announcements still exists (Latane and Jones, 1979; Bidwell and Riddle, 1981; and Rendlemand, Jones, and Latane, 1982). For example, Rendlemand, Jones, and Latane (1982) use a new sample that includes a large number of stocks and corresponding daily returns and adjusts security risk using Scholes and Williams (1977) method. Rendlemand, Jones, and Latane (1982) find that quarterly earnings surprise still predicts future stock performance. Livnat and Mendenhall (2006) use two definitions of earnings surprise to examine PEAD. They define the first earnings surprise based on the difference between actual earnings and mean analyst forecasts. The second earnings surprise is defined as the difference between actual earnings and expected earnings calculated from a time series model using data from COMPUSTAT database. Both definitions of earnings surprise confirm the existence of PEAD, but the extent of the drift is different. Livant and Mendelhall (2006) argue the difference may be due to different information captured by two types of earnings surprise.

Prior literature proposes several possible explanations for PEAD. The first explanation is summarized by Ball (1978) and Joy and Jones (1979). They point out that early works on PEAD attribute the anomaly to experimental design flaws that include data source problems, stock price record timing problems, shifting of securities' relative risk, errors in estimating securities' relative risk, etc. Ball (1978) summarizes that experimental design flaws cannot explain the magnitude of the abnormal returns after earnings announcements and that the anomaly still exists after the flaws are addressed. For example, Litzenberger, Joy, and Jones (1971) expand on a previous study from Latane, Joy, and Jones (1970) by adding ex-ante risk analysis to take care of the missing risk factor problem, but still find similar result as in Latane, Joy, and Jones (1970). That is, investors can use quarterly earnings announcements and E/P ratio sort-rank analysis to predict future stock performance. Other studies address the test design problems, measures of the rate of return, and

risk factor problems, and find that the abnormal returns after earnings announcements remain (Basu, 1975; Basu, 1977; Joy, Litzenberger and McEnally, 1977; Brown, 1978 and Latane and Jones, 1979). That is, they still find PEAD, or predictability of earnings announcement, on future stock returns.

A second explanation focuses on the failure of the capital assets pricing model (CAPM). The CAPM estimates the expected stock return from risk-free interest rate, market index rate of return and the stock's systematic risk level relative to an average stock in the market. Systematic risk is how a firm is affected by market-wide economic condition changes. Ball (1978) and Joy and Jones (1979) are among the first to propose the explanation. They argue that CAPM may suffer from a variable omission problem as the model may not be able to capture all risk factors that are priced by the market. As a result, the abnormal returns from prior works may just be the risk premium for omitted risk factors that are priced by the market but not by the model. Ball (1978) and Joy and Jones (1979) call this the CAPM misspecification problem, or the proxy effect. For example, several studies use the two-parameter model to control for risk and most of them still find a positive relation between earnings surprise and subsequent market abnormal returns (Jones and Litzenberger, 1970; Litzenberger, Joy and Jones, 1971; Jones, 1973; Joy, Litzenberger and McEnally, 1977; Latane, Jones and Rieke, 1974; Basu, 1977; Peterson, 1974; Ball and Brown, 1968; Brown, 1970; Brown and Hancock, 1974; Brown and Kennelly, 1972; Foster, 1973; Beaver, 1975; Brown, 1972; Foster, 1977). The proxy effect is hard to solve as it is difficult to decide whether a risk factor is the correct one to add to the model. In addition, Roll (1977) states that CAPM is a joint-test for market efficiency and model specification. That is, if a new risk factor seems unimportant in the model, it is difficult to know whether it is because the market fails to price the factor or to the factor is not the correct risk factor.

Ball (1979) argues that the CAPM misspecification explanation is consistent with the existence of estimated abnormal returns and the predictability of the earnings announcements documented by studies mentioned above that use CAPM to control risk. He indicates that the misspecification explanation is the most likely explanation for PEAD as the explanation could explain both the sign and the magnitude of PEAD. Later studies focus on examining the specification errors in CAPM. Several works find results that are consistent with the hypothesis. For example, Foster, Olsen, and Shevlin (1984) estimate the expected earnings using several methods. They develop models that use a firm's prior years' earnings or prior stock returns to estimate its expected earnings. Foster, Olsen, and Shevlin (1984) take the difference between actual earnings from announcement day and expected earnings to form earnings surprise. Firm quarters are then divided into deciles based the magnitude of earnings surprise. Daily abnormal return on the firm is calculated as the difference between the security return and the equally weighted mean return on the NYSE firm size decile that the firm is a member of in the quarter. For each decile of earnings surprise, average size-adjusted cumulative abnormal return on the decile is calculated for the 60 trading-day period following the day of earnings announcements. They find that the post-announcement drift remains for deciles formed based on earnings surprise estimated based on prior years' earnings and that the drift disappears for deciles formed based on earnings surprise estimated based on prior stock returns. The inference from Foster, Olsen, and Shevlin (1984) is consistent with CAPM misspecification explanation. Ball, Kothari, and Watts (1993) allow the firm's beta to shift every year when calculating abnormal returns following earnings surprise, and they find the post-earnings announcements drift disappear.

2.2.2 Explanations for market underreaction phenomenon

Bernard and Thomas (1989), among others, find that the misspecification error hypothesis may not be the only explanation for post-earnings announcements drift. Bernard and Thomas (1989) argue that the post-earnings announcement drifts found by Foster, Olsen, and Shevlin (1984) may be explained if the market is just slow at processing information, the third explanation proposed in Ball (1978).

This third explanation for the predictability of earnings announcements is that security market is slow in adjusting to, or underreacts to, earnings announcements. Ball (1978) suggests that the slow adjustments may be due to high transaction costs or high information processing costs. However, Ball (1978) also points out that transaction and processing costs can explain the sign but not the magnitude of the abnormal returns for securities with the highest or lowest earnings surprise. Bernard and Thomas (1989) argue that the interpretation of results in Foster, Olsen, and Shevilin (1984) could be consistent with the delayed response hypothesis if (1) the market delays in responding to earnings news, and (2) different firms experience different levels of delay in responding to earnings news. Bernard and Thomas (1989) argument makes the preference of the second and third explanations an empirical question.

2.2.2.1 Market's incapability in processing information hypothesis

There are several hypotheses regarding the reason that the market responds to earnings news with a delay. The first hypothesis suggests that the market does not fully understand price implications contained in current earnings for future earnings. In their later work, Bernard and Thomas (1990) argue that the market does not fully understand the autocorrelation of quarterly earnings and does not adjust the price in a timely manner. Freeman and Tse (1989) investigate whether the agreement level between current earnings news and previous earnings innovation

would affect price reaction during the earnings announcement period. They find that the market underestimates the likelihood of earnings persistence and adjusts price with a delay. Abarbenell and Bernard (1992) find that analyst earnings forecasts underreact to recent earnings, though underreaction cannot fully explain the magnitude of the post-earnings announcement drift. Bartov (1992) examines whether quarterly earnings surprise explain the PEAD following quarterly earnings announcements. He finds that the market fails to fully understand earnings persistence in time. Ball and Bartov (1996) find that the market acts as if it doesn't consider the earnings' seasonal random walk nature and that it underestimates the magnitude of serial correlation at lags 1-4 in seasonally-differenced quarterly earnings. Lee and Rui (2011) generalize the Bernard and Thomas (1990) "delayed response" hypothesis by letting investors learn part of the autocorrelation of earnings. They find similar results that the market does not fully understand the autocorrelation of earnings. Results in Lee and Rui (2011) complement Ball and Bartov (1996), who argue that investors partially, but not fully, adjust for serial correlation in seasonal differences.

Although it cannot fully process information immediately, the market incorporates information into prices eventually through time. Soffer and Lys (1999) develop a model to infer the degree to which investors incorporate the information from an earnings announcement into their expectations for the subsequent earnings announcement. The results in Soffer and Lys (1999) suggest that rather than doing it immediately, investors progressively incorporate serial correlations of earnings surprise into their expectation throughout the quarter, and that the market underreacts to current earnings announcements. Shane and Brous (2001) provide evidence that investors underreact to earnings news and that they correct their underreaction in the time between the current and next earnings announcements. Chen (2011) indicates that investors progressively

process complex fundamental information that is necessary for estimating time-varying earnings persistence and that the progressive process results in PEAD.

2.2.2.2 Rational hypothesis

In addition to the inability of the market to fully understand the autocorrelation of earnings, two additional hypotheses attempt to explain the underreaction to the earnings announcements. The two hypotheses focus on how investors use new information to update their expectation of the true distribution of firm value. The difference between the two hypotheses is whether investors are fully rational or Quasi-rational. Fully rational investors follow the Bayesian rule in processing all information while Quasi-rational investors follow the Bayesian rule when processing information, but are overconfident in private information they possess.

The rational hypothesis for underreaction assumes that fully Bayesian investors cannot observe complete information structures on the distribution of their investment right after earnings announcements. Merton (1987) develops a capital market equilibrium model with incomplete information and fully Bayesian investors trading with each other. The model predicts anomalous behavior relative to a perfect-market where investors could have complete information.

It appears that when facing incomplete information, investors suffer from uncertainty when estimating the true distribution of firm value, and the uncertainty contributes to the level of PEAD. For example, Timmermann (1993) explains the PEAD with learning effects on stock price dynamics. That is, investors use historical data to learn the pattern of stock prices and attempt to estimate future stock prices. He indicates that the volatility of stock prices increases due to investors' estimation uncertainty and that dividends yield and capital gain are driven by investors' underestimation of dividends growth rate. These uncertainties and underestimations result in progressive adjustment toward correct stock prices, there by explaining the PEAD. Kurz (1994)

assumes that agents do not know the complete structural relations of the economy, such as equilibrium prices, but that they can use past economic data to form their probability beliefs and then estimate relative frequencies of possible structural relations outcomes. Kurz (1994) argues that the limit of those relative frequencies of possible outcomes induces various anomalies including post-earnings announcements drift.

In addition to the uncertainty introduced by using historical data, uncertainty can be introduced through the market learning process. In his model, Morris (1996) assumes that market traders learn the true distributions of dividends through time. He finds that traders anticipate the possible reselling of assets to another trader before the information is complete and introduce speculative premium, which could inhibit price discovery. The speculative premium could be long-lasting when the learning process is based on prior beliefs, which is helpful in explaining the post-earnings announcements drift. Lewellen and Shanken (2002) argue that when fully rational investors attempt to estimate expected cash flows, the parameter of uncertainty in estimation could affect their estimation outcome and thus the market returns. Brav and Heaton (2002) develop a structural uncertainty model where the fully Bayesian investors face uncertainty about whether there has been a shift in the distribution of their investment. The uncertainty would lead these investors to underreact to information signals that arrive right after a distribution shift has occurred, such as an earnings announcement. Francis, Lafond, Olsson, and Shipper (2007) find that information uncertainty explains the properties of and returns to PEAD, consistent with the rational hypothesis that uncertainty when estimating the true distribution of investment increases PEAD.

2.2.2.3 Behavioral hypothesis

The behavioral hypothesis assumes that investors are quasi-rational and incorporate new information following Bayesian rule. However, those investors are overconfident in their private

information and underweigh other information. For instance, Griffin and Tversky (1992) find that investors have different confidence levels on different information they possess.

There are theoretical studies in the literature that examine the market underreaction using investor overconfidence. For example, Barberis, Shleifer, and Vishny (1998) develop a model of how investors form beliefs about the future state of the economy. They use the model to explain and predict various market phenomena including underreaction to the news. Daniel, Hirshleifer, and Subrahmanyam (1998) consider investors' overconfidence to be one of the reasons that market underreacts to the news. Hong and Stein (1999) assume slowly diffusing news about future fundamentals in their model of market trading activities and predict a short run underreaction to news and a long run overreaction to news. Liang (2003) examines the relationship between PEAD and the market where investors are holding different beliefs on firm value. She documents that the level of investors' overconfidence in their private information is associated with PEAD. Zhang (2006a) investigates abnormal returns following earnings surprise in an environment with a high level of information uncertainty. He concludes that information uncertainty boosts investors' overconfidence level and thus magnifies the level of PEAD.

Brav and Heaton (2002) find that information uncertainty has a similar impact on both explanations. They argue that it is impossible to empirically distinguish between many irrational behavioral theories and rational Bayesian models because their predictions are too similar. Both explanations predict that higher uncertainty level leads to greater PEAD. Results from Francis et al. (2007) and Zhang (2006a) support the Brav and Heaton (2002) argument.

2.2.3 Informativeness of analysts' forecast revisions

2.2.3.1 Impacts of analysts' forecast revisions

One stylish fact from prior literature on analyst revised earnings forecasts is that forecast revisions contain information that is price relevant, as prior works document the association between analysts' earnings forecast revisions and contemporaneous stock price movements (Griffin, 1976; Gonedes, Dopuch, and Penman, 1976; Givoly and Lakonishok, 1979, 1980; Imhoff and Lobo, 1984; Brown, Foster and Noreen, 1985; Lys and Sohn, 1990). Moreover, Elton, Gruber, and Gultekin (1981) show that the foreknowledge of analyst revisions is more important than the foreknowledge of the reported earnings themselves in raising the abnormal returns. Stickel (1993) finds that updated earnings forecasts that are based on information in forecast revisions are less biased and are more accurate. Francis and Soffer (1997) document that forecast revisions have incremental information in addition to information about stock recommendations. Those findings show that individual analyst forecast revisions convey new information to the market.

Analyst forecast revisions affect market price discovery, a real effect, because they are informative. Stickel (1991) finds that forecast revisions affect prices, although prices do not immediately reflect all of the information contained in revisions. Gleason and Lee (2003) examine factors that help explain cross-sectional variations in the post-revision price drift. They find that although the market reacts to revisions regardless of the level of new information contained in revisions, the price adjustment process is indeed faster and more complete for revisions issued by "celebrity" analysts and for firms with greater analyst coverage. Gleason and Lee (2003) find that stock prices adjust to earnings-related news events and forecast revisions after initial forecast revisions. While Gleason and Lee (2003) find that investors react less to revisions issued by less well-known but more accurate analysts, Park and Stice (2000) document a superior impact on an

individual firm's stock price based on earnings forecasts revisions issued by a superior analyst in that firm. A superior analyst refers to an analyst that has superior past forecast performance for the specific firm.

Informativeness of forecast revisions may differ depending on the demand and supply for information, as shown by Frankel, Kothari, and Weber (2006). Frankel, Kothari, and Weber (2006) find that analyst forecast revisions contain more information when potential brokerage profits are high, and contain less information when processing costs are high. Ivkovic and Jegadeesh (2004) also show that forecast revisions issued just before quarterly earnings announcements contain more information than do forecast revisions issued shortly after the earnings announcements.

2.2.3.2 Market reaction to forecast revisions characteristics

The equity market seems to have its judgment on the informativeness of forecast revisions. Park and Stice (2000) find that the market reacts strongly to forecast revisions issued within 30 days before the quarterly earnings announcement by analysts with good prior performance. Park and Stice (2000) show that the market recognizes analysts' expertise and considers their firm-specific forecasting ability when processing forecast revisions. Cooper, Day and Lewis (2001) find that the market reacts more strongly to timely forecast revisions. Bonner, Walther, and Young (2003) find that the existence of sophisticated investors helps the market understand the factors contained in individual analyst forecast revisions. Clements and Tse (2003) find that the market also considers the revisions issued earlier in the year and revisions issued by analysts from large brokerage firms to be important in addition to the accuracy of forecast revisions. Chen et al. (2005) examine patterns in the market reaction to analyst forecast revisions. They argue that the investors' reactions to revisions suggest that investors learn about analysts' forecasting ability in a Bayesian fashion as they observe higher forecast accuracy. Bonner, Hugon, and Walther (2007) show that

the market reacts to earnings forecast revisions issued by celebrity analysts who are heavily covered by media.

2.2.3.3 Information content of forecast revisions

Another stream of literature examines the information content of analyst forecast revisions. Forecast revisions tend to incorporate information from public events into consideration. For example, results in Denis, Denis, and Sarin (1994) suggest that analyst forecast revisions following stock dividends changes reflect information about future cash flows contained in the stock dividends changes. Ettredge, Shane, and Smith (1995) find that for earnings announcements with undisclosed overstatements, forecast revisions issued around the announcements adjust for the overstatement amounts. The results imply that analysts have additional information that helps them uncover earnings manipulations. Kasznik and Lev (1995) show that analyst forecast revisions reflect the information contained in disappointing earnings announcements and accompanied warnings in the announcement. Ely and Mande (1996) document that analysts' earnings forecast revisions reflect corroborative information on dividends and earnings announcements. Ramnath (2002) finds that for firms announcing their earnings late, analyst forecast revisions partially incorporate information from the first earnings announcements in the firms' industry. Barron, Byard, and Kim (2002b) suggest that the post-earnings announcement forecast revisions contain more private information compare with forecasts issued before the same earnings announcement.

Moreover, analyst forecast revisions after an event contain additional information to the ones before the events. For instance, Ederington and Goh (1998) examine analyst's earnings forecast revisions before and after a bond rating change and suggest that the forecast revisions surrounding bond rating change reflect information other than the impact of rating change itself on the actual earnings. Results in Billings, and Morton (2001) show that analyst forecast revisions

contain information related to systematic stock price reversals. Barth and Hutton (2004) examine relations between the predictability of accounting accruals (due to a mismatch between cash transactions and recognition of revenue and expense) and the predictability of analyst earnings forecast revisions. They find that forecast revisions reflect information about accounting accruals and earnings persistence beyond the information that is contained in the level of current year accruals.

The information content of revisions may change due to several reasons. Begley and Feltham (2002) develop an improved residual income model to estimate a firm's market value. Their model suggests that analysts' implied one-year-ahead residual income forecast revisions proxy for the persistence of revenue from prior investments, and that two-year-ahead residual income forecast revisions proxy for investment opportunities. Ivkovic and Jegadeesh (2004) find a stronger market reaction to upward forecast revisions issued just before earnings announcements in both the pre- and post-Reg FD periods. Their results suggest that analysts have access to positive (but not negative) insider information before and after Reg FD.

2.2.3.4 Efficiency of forecast revisions in reflecting new information

It appears that forecast revisions reflect new information efficiently. Results in Cornell and Landsman (1989) indicate that analysts' forecast revisions provide significant explanatory power in a pooled regression of abnormal returns against forecast errors and analyst forecast revisions. Doukas, Kim, and Pantzalis (2002) examine both analyst forecast errors and forecast revisions and fail to support the argument that analysts are unduly pessimistic (optimistic) about value (glamour) stocks. Louis (2004) examines the earnings forecasts issued around merger events and finds that analysts learn earnings reversal results from merger-related abnormal accruals over time and revise their forecasts just before earnings announcements to reflect their learned results.

There are arguments that analyst forecast revisions do not contain all of the available information. Abarbanell (1991) finds that positive (negative) forecast errors are more likely to happen to firms with positive (negative) returns, and concludes that analysts do not fully incorporate information contained in price. Abarbanell and Bernard (1992) provide evidence suggesting that analysts underreact to earnings information. Results in Abarbanell and Bushee (1997) suggest that analysts ignore available non-earnings information. Shane and Brous (2001) indicate that analysts underreact to information regarding future earnings. Zhang (2006b) find positive (negative) forecast errors and forecast revisions following good (bad) news announcements when greater uncertainty, proxied by forecast dispersion, is present. The result is consistent with the analyst underreaction hypothesis. The level of informativeness of analyst revisions to the market is thus an empirical question.

2.2.4 The effects of forecast revisions and revised earnings forecasts on information asymmetry

Bonner et al. (2003) show that for firm-quarter with a high percentage of sophisticated investors trading the stock, the market seems to understand price implications in individual earnings forecast revisions better. The results suggest that sophisticated investors have information advantage relative to unsophisticated investors. The extant literature identifies information asymmetry between sophisticated and unsophisticated investors (Grossman and Stigliz, 1980; Glosten and Milgrom, 1985; Kyle, 1985; Admati and Pfleiderer, 1988; Kalay, 2015). The information asymmetry is argued to be caused by either sophisticated investors' ability to access private information that is not available to unsophisticated investors or sophisticated investors' superior processing ability concerning new information when it is released to all market participants. Kim and Verrecchia (1994) find that information that is new to both sophisticated and

unsophisticated investors would increase information asymmetry at announcement (earnings announcements, managerial forecasts) while information that is only new to unsophisticated investors would decrease information asymmetry at the announcement. The two opposite directional empirical implications predict that the net effect of an announcement on the direction of information asymmetry depends on the relative level of two types of information. Kim and Verrecchia (1994) defined two types of information contained in the announcement. Announcements refer to earnings related news events such as earnings announcements, managerial earnings forecast, and analyst earnings forecasts, etc. Amiram, Owens, and Rozenbaum (2016) find that revised analyst earnings forecasts issued after earnings announcements decrease information asymmetry at the announcement, suggesting that analysts' earnings forecasts contain relative more information that is only new to unsophisticated investors.

2.3 Hypothesis Development

2.3.1 Hypothesis 1

Prior literature indicates that market underreaction to earnings announcements reduces market efficiency in incorporating information in the price (Ball, 1978; Merton, 1989; Bernard and Thomas, 1990). Recent works show that a high level of information uncertainty prompts market underreaction level, and hence the rise of the post-earnings announcements drift (Zhang, 2006a). Brav and Heaton (2002) argue that the resolution of information uncertainty would reduce the post-earnings announcement drift. Collectively speaking, the level of information uncertainty in the market right after earnings announcements is critical in affecting the market underreaction and the drift for a firm.

Financial analysts, arguably an important information intermediary in the market, could help improve the firm information environment following earnings announcements. For instance,

Amiram, Owens, and Rozenbaum (2015) argue that the revised analyst forecasts contain relatively more information that is new to unsophisticated investors and relatively less information that is new to all investors. The information that is new to only the unsophisticated investors would result in a reduction in information asymmetry between sophisticated investors and unsophisticated investors when analysts announce their revised forecasts.

However, Amiram, Owens, and Rozenbaum (2015) don't explicitly examine how the part of information that is new to all investors would affect the information environment, especially, the information uncertainty level. Information uncertainty exists in both sophisticated and unsophisticated investors when they estimate the true distribution of firm value and has an impact on market efficiency in incorporating information into prices.

There are no direct measures for the part of the information that is new to all investors, but this portion of information should be produced by analysts and is highly related to the quality of private information (that is only known to analysts but not to the market) contained in revised forecasts. Barron et al. (1998) argue that analysts rely on both private information and public information when preparing earnings forecasts. The informativeness of analyst forecasts depends both on the precision of common information and precision of private information. The precision of those two types of information could be measured when assuming equal precision of the information among analysts. Barron et al. (1998) argue that the precision of common (private) information measures the quality of it used in preparing earnings forecasts. Information that is new to all is highly related to the precision of private information, so I can evaluate the effect of information that is new to all on information uncertainty by examining the effect of the precision of private information on information uncertainty.

It is hard to measure information uncertainty directly, but information uncertainty is positively associated with PEAD. High level of information uncertainty is associated with high level of drift and resolution of information uncertainty is associated with reduced drift (Brav and Heaton, 2002). It appears that reduced drift results from the resolution of information uncertainty.

This study examines whether the quality of private information contained in revised forecasts issued right after quarterly earnings announcement helps reduce post-earnings announcements drift. If the results show that the quality of private information contained in revised earnings forecasts could help reduce PEAD, these results provide evidence for the argument that analyst revised forecasts could help reduce information uncertainty level.

The effect of the precision of private information on reducing information uncertainty, however, may not exist. Abarbanell and Bernard (1992) find that analyst forecasts underreact to information contained in actual earnings announcements, suggesting an inefficient use of information. Abarbanell (1991) find that investors omit information from the price. Abarbanell and Bushee (1997) find that analysts ignore non-earnings information when processing financial statements. In that sense, analyst revised earnings forecasts could have no impact on the market underreaction to information and on the level of post-earnings announcement drift.

The actual effect of precision of private information on reducing information uncertainty is thus an empirical problem. As a result, I develop the Hypothesis 1:

H1: The precision of private information contained in revised earnings forecasts reduces information uncertainty.

2.3.2 Hypothesis 2

The role of financial analysts has changed dramatically since the Regulation Fair Disclosure (Reg FD) in 2000. The contents of private information in analyst forecasts have also

changed. Prior to the Reg FD, sophisticated market participants such as financial analysts and large institutional investors are able to contact managers to get insider information ("Selective Disclosure"). Therefore, most parts of private information contained in forecasts represents insider information. Revised analyst forecasts issued right after earnings announcements convey those pieces of insider information to the market and greatly reduce information uncertainty. After the Reg FD, however, selective disclosure is no longer possible. Instead, firms are required to disclose their material information publicly or not disclose at all. Private information possessed by analysts are hence obtained via their superior information processing power, industrial expertise, and other techniques and efforts. The effect of the precision of private information in reducing information uncertainty is expected to be weaker in post-Reg FD period than the effect in pre-Reg FD period. As such, I have the following hypothesis:

H2: Precision of private information in revised earnings forecasts in the post-Reg FD period has a smaller effect on post-earnings announcements drift than does precision of private information in the pre-Reg FD period.

If the effect of precision of private information on PEAD decreases, the result would be consistent with the argument that the effect of quality of private information on information uncertainty reduces after Reg FD.

2.4 Sample and Variables

2.4.1 Sample construction

I build the sample from several data sources. I collect forecasted EPS, forecasted announcement date, and actual EPS from I/B/E/S. The actual quarterly earnings announcement data and firm fundamental information are from COMPUSTAT. Stock data such as stock price and shares outstanding data are from CRSP. I also use Dr. Kenneth R. French's website to find the

monthly stock market value of equity breakthrough points and daily returns on portfolios sorted on the firm market value of equity. I build the variables based on these databases.

The sample selection method follows Liang (2003). For each firm quarter, I identify analysts that issue at least one one-year-ahead forecast within 45 days before the earnings announcement and at least one one-year-ahead forecast within 30 days after the same earnings announcement. I use two-year-ahead forecasts for the fourth quarter earnings announcements. That is, I identify analysts who actively follow a firm and who revise their one-year-ahead forecasts after receiving new information from quarterly earnings announcements. Firm quarters with less than two analysts following are excluded from the sample. The final sample has 72,165 unique firm quarters ranging from the year 1984 to 2015.

2.4.2 Key measurement construction

2.4.2.1 Precision of information

I use the precision of common (private) information to proxy the quality of respective information contained in revised earnings forecasts. The measures for the precision of private information and precision of common information are developed by Barron et al. (1998). These measures have been widely used to examine the quality of information contained in forecast revisions. For example, Mohanram and Sunder (2006) use these measures to examine the effect of the Reg FD on financial analyst operations. Barron, Byard, and Kim (2002) use the measures to examine the quality of public information and quality of private information contained in individual analysts' forecasts around earnings announcements. Botosan, Plumlee, and Xie (2004) employ these measures in examining the relationship between information precision and the cost of capital.

To calculate the measures for precision of information, I compute variables such as revised earnings forecast dispersion and squared error in the mean one-year-ahead earnings forecast right

after quarterly earnings announcement for each firm quarter. Full definitions for all variables can be found in section 4.3. If an analyst makes multiple forecasts before an earnings announcement, I take the last one issued before the quarterly earnings announcements. If an analyst makes multiple forecasts after an earnings announcement, I use the first one issued after the quarterly earnings announcements.

2.4.2.2 Quarterly Earnings Surprise

Following prior literature (Foster et al., 1984; Liang, 2003), I use a linear regression approach to examine the relationship between quarterly earnings surprise and post-earnings announcements drift. A quarterly earnings surprise is the difference between actual quarterly earnings and the mean 1-quarter ahead forecast issued within 45 trading days before the quarterly earnings announcement. If one analyst issues multiple forecasts during the period, I use the last forecast issued to calculate the mean forecast.

2.4.2.3 Cumulative abnormal returns

I use 60-trading-day risk-adjusted cumulative abnormal returns (CARRs) in the analysis. I calculate risk-adjusted cumulative abnormal returns from day one to day 60 after the quarterly earnings announcement. The daily risk-adjusted abnormal return is measured as the difference between daily realized return and the expected return estimated from market model.

$$r_i = b_0 + b_1 * r_m + \varepsilon \tag{1}$$

where r_i is the daily return for stock i and r_m is the daily return on a market portfolio.

The risk-adjusted return (CARR) controls for the firm's systematic risk, b_1, in calculating the abnormal returns.

To use the market model to estimate post-announcement 60-trading-day interval stock return, I use [-345, -45] trading days before the same announcement to estimate the b_0 and b_1. I

require data for at least 250 days within that 300-trading day period. I use market returns (r_m) on the following five portfolios: The CRSP value-weighted portfolio, CRSP equally weighted portfolio, S&P 500 index portfolio, equally weighted Fama/ French portfolio sorted on size and value-weighted Fama/ French portfolio sorted on size.

Dr. Kenneth R. French's website provides daily returns on Fama/ French stock portfolios formed on all firms listed in NYSE, AMEX, and NASDAQ with market equity data. One kind of those portfolios sorts on the firm market value of equity. At the end of each June, all firms are grouped into ten deciles based on firms' market value of equity that month. Daily decile return is the weighted average of daily returns of all firms in the decile. There are two types of weighted average decile returns, equally weighted average or value weighted average, and I develop one set of CARR on each of these two weighted averages. Dr. French's website also provides the monthly NYSE breakthrough points on market equity, which can help classify the sample firm quarters into corresponding size deciles.

I use the Fama/ French monthly breakthrough points to classify each stock into the decile the stock is a member of. Then, I use that decile's mean decile daily return as the daily market return. After estimating the intercept (b_0) and beta (b_1) for each firm quarter using market model, I apply these parameters to the daily market returns mentioned above to calculate the expected daily stock return for each stock. I do that for 60 trading days after actual announcement dates and each of five market return portfolios. The differences between realized daily stock return and these expected daily returns are referred as the risk-adjusted daily stock returns. I calculated these risk-adjusted daily abnormal returns from day 1 to day 60 after the earnings announcement and summed them up to form 60-trading days' risk-adjusted cumulative abnormal returns (CARRs).

2.4.3 Variable definitions

The following variables are used in the study.

D: This is the revised forecast dispersion for each firm quarter. The variable is calculated as the variance of annual forecasts made within 30-trading-day right after a quarterly earnings announcement.

Disp: This variable is forecast dispersion (D) scaled by the adjusted closing stock price on the 45th trading day before the quarterly earnings announcement.

SE: Squared error in the mean forecast. The variable is calculated as the square of the difference in EPS between an actual annual announcement and mean annual forecasts issued right after a quarterly earnings announcement. This is a measure of forecast accuracy for the annual forecast.

N: Number of financial analysts that make at least one forecast before and one forecast after the same quarterly earnings announcement.

h: Precision of public information defined by Barron et al. (1998). Calculated as

$$h = \frac{SE - \frac{D}{N}}{\left[\left(1 - \frac{1}{N}\right) D + SE\right]^2}.$$

s: Precision of private information defined by Barron et al. (1998). Calculated as

$$s = \frac{D}{\left[\left(1 - \frac{1}{N}\right) D + SE\right]^2}.$$

Size: Firm size is per million dollars. The product of shares outstanding and adjusted stock price on the day of the quarterly announcement.

UE6: Quarterly earnings surprise. Calculated as the difference between the actual EPS and the mean one-quarter ahead earnings forecasts issued within 45 days before the actual quarterly

earnings accouchement, scaled by the closing stock price on the 45th day before the quarterly earnings announcement.

As mentioned ahead, I develop a set of five cumulative abnormal returns as follow.

CARRv: [1, 60] trading days' cumulative abnormal returns (CARs). Daily abnormal return is calculated as the difference between daily stock return and expected stock return calculated from a market model where the market index is CRSP value-weighted index.

CARRe: [1, 60] trading days' cumulative abnormal returns (CARs). Daily abnormal return is calculated as the difference between daily stock return and expected stock return calculated from a market model where the market index is CRSP equally weighted index.

CARRsp: [1, 60] trading days' cumulative abnormal returns (CARs). Daily abnormal return is calculated as the difference between daily stock return and expected stock return calculated from a market model where the market index is S&P 500 index.

CARRszew: [1, 60] trading days' cumulative abnormal returns (CARs). Daily abnormal return is calculated as the difference between daily stock return and expected stock return calculated from a market model where the market index is equally weighted Fama French portfolios formed on size.

CARRszvw: [1, 60] trading days' cumulative abnormal returns (CARs). Daily abnormal return is calculated as the difference between daily stock return and expected stock return calculated from a market model where the market index is value-weighted Fama French portfolios formed on size.

2.5 METHODOLOGY

Prior literature describes the PEAD as the abnormal returns earned by a zero-investment portfolio constructed by taking a long position in firms with the most positive earnings surprise and a short position in firms with the most negative earnings surprise (Jones and Litzenberger,

1970; Foster et al., 1984; and Bernard and Thomas, 1989). Prior works (Liang, 2003; Bernard and Thomas, 1990; and Bhushan, 1994) replicate the portfolio by grouping firms into deciles (deciles 0 - 9) based on quarterly earnings surprise and then scale the decile numbers by 9 to form the scaled decile numbers (deciles 0, 0.1, 0.2 …, 1). They examine the existence of post-earnings announcement drift by regressing 60-day cumulative abnormal returns after quarterly earnings announcements against the scaled decile numbers of quarterly earnings surprise the firm quarters are using ordinary least square method. Liang (2003), Bernard and Thomas (1990), and Bhushan (1994) interpret the coefficient of the scaled decile numbers of quarterly earnings surprise as the abnormal return on the zero-investment portfolio or PEAD. Following this logic, I divide the sample firm quarters into deciles (0-9) based on quarterly earnings surprise (UE6) and scaled the decile numbers by 9 to form the scaled decile numbers for the analysis. I follow the same method to construct scaled decile numbers using the precision of public information contained in forecast revisions (h), and private information contained in forecast revisions (s), respectively. I then construct following interaction terms between these scaled decile numbers: quarterly earnings surprise (UE6) with precision of public information content of forecast revisions (h), quarterly earnings surprise (UE6) with precision of private information content of forecast revisions (s), quarterly earnings surprise (UE6) with firm size (size). As a result, I have the following equation:

$$\begin{aligned} CARR = b_0 + b_1 * UE6 + b_2 * UE6 * h + b_3 * UE6 * s + b_4 * UE6 * size + b_5 * h \\ + b_6 * s + b_7 * size + \varepsilon \end{aligned} \tag{2}$$

I estimated equation (2) using ordinary least square method. The coefficient of the scaled decile numbers of quarterly earnings surprise (UE6), b1, measures PEAD or the abnormal return earned by the zero-investment portfolio mentioned above. Firms in the portfolio are the ones with the lowest rank of precision of public information (h), the precision of private information (s) and

firm size (size). That is, the coefficient b1 measures PEAD for firms that are smallest, with revised earnings forecasts containing lowest precision of public information and lowest precision of private information. The coefficient b2 on the interaction term between earnings surprise (UE6) and precision of public information (h) represents the incremental changes in PEAD if the firm's revised earnings forecasts containing precision of public information (h) that is in the highest decile rather than in the lowest one. The coefficients b3 and b4 are interpreted similarly. The coefficient b3 measures difference in PEAD between firms with the highest rank of precision of private information in revised earnings forecasts (s) and otherwise similar firms with the lowest rank of precision of private information (s). The coefficient b4 measures the difference in PEAD between largest firms and smallest firms who have similar earnings surprise rank, the similar precision of information contained in analyst revised earnings forecasts. According to Hypothesis 1, I expect b3 to be negative.

The coefficient b5 and b6 are interpreted differently as those two variables are measured during the post-announcement period. These two coefficients can be interpreted as the demand for analyst services. Firms with high cumulative abnormal returns usually have inefficient price discovery and poor information environment. As a result, the demand for analyst services by the market is high, and analysts spend more effort in information acquisition activities and thus provide high-quality information. I expect both b5 and b6 are positive.

The coefficient b7 represents the relationship between firm size and abnormal returns. Large firms have better information environment and thus less abnormal returns; I expect b¬7 to be negative.

I first confirm the existence of post-earnings announcement drift (PEAD) in the sample. That is, I examine whether quarterly earnings surprise (UE6) at actual quarterly earnings

announcements are associated with post-announcement 60-day risk-adjusted abnormal returns (CARRs). To do that, I regress CARRs against quarterly earnings surprise (UE6) only using ordinary least square method and examine whether b¬1 is significantly different from 0.

Then, I examine how firm size (size), the precision of public information (h), and precision of private information (s) help explain post-earnings cumulative abnormal returns (CARR). I regress CARRs against quarterly earnings surprise (UE6), firm size (size), the precision of public information (h), and precision of private information (s) and examine whether b1 is still significantly different from 0 and the sign and significance level of b5 to b7.

Lastly, I examine how the PEAD can be affected by information precision in post-earnings announcement analysts' forecasts using the precision of public information contained in revised forecasts (h) and the precision of private information contained in revised forecasts (s) developed in Barron et al. (1998). I do that by estimate equation (2) with the ordinary least square method.

2.6 RESULTS

2.6.1 Summary statistics

Summary statistics are shown in Table 2.1 panel A. The mean quarterly earnings surprise is slightly negative at -0.01% and is significant at the 1% level (not tabulated), which is consistent with analysts being optimistic about firm performance in general. The precision of common information contained in revised earnings forecasts, h, has a mean value of 460.02. The precision of private information in revised forecasts, s, has a mean value of 861.90 These are consistent with those in Mohanram and Sunder (2006), who find that precision of private information contained in analyst forecasts is higher than the precision of common information contained in analyst forecasts. The average size of sample firms is 9,037 million dollars. The level of scaled revised forecasts dispersion (DISP) of 0.004 is significantly different from 0 (not tabulated), consistent

with the argument that markets cannot proceed all information after earnings announcements. The 60-trading day risk-adjusted cumulative abnormal returns (CARRs) are calculated after each quarterly earnings announcements for each firm quarter. I use five different measures of CARRs. The means of all CARRs are roughly similar to each other and are significantly different from zero. These statistics are in general consistent with the argument that market does not fully recognize information contained in earnings announcements.

Panel B of Table 2.1 shows the Pearson (in the lower diagonal) and Spearman (in the higher diagonal) correlations between quarterly earnings surprise (UE6), common information precision (h), private information precision (s), firm size (Size), and revised forecasts dispersion level (Disp). Earnings surprise (UE6) is positively correlated with common information precision (h), private information precision (s) and firm size (Size), and it is negatively correlated with revised earnings forecasts dispersion level (Disp). Common information precision and private information precision are positively and highly correlated with each other. Firm size is negatively correlated with common information precision but is not correlated with private information precision in Pearson correlation. But the Spearman correlation result shows that firm size is positively correlated with the precision of both types of information. Revised forecasts dispersion level, in general, is negatively correlated with other variables.

Table 2.2 shows the mean 60-trading-day risk-adjusted cumulative abnormal returns after quarterly earnings announcements for each decile. The deciles are sorted on quarterly earnings surprise (UE6). From Table 2.2, mean earnings surprise (UE6) for decile 0 is -0.0191. Mean CARRs after quarterly earnings announcements in decile 0, range from -1.51% to -0.33%. And only two out of five mean CARR in decile 0 is significantly different from 0. Mean surprise in decile 9 is 0.0137 and the corresponding CARRs after quarterly earnings announcements range

from 0.17% to 0.97%. Four of five mean CARR in decile 9 is significantly different from 0. Table 2.2 shows that only top decile (decile 9) has positive cumulative abnormal returns. From decile 0 (most negative earnings surprise) to decile 9 (most positive earnings surprise), cumulative abnormal returns are most negative at decile 4 (from -3.75% for CARRsp to -3.07% for CARRe) and become less negative as stocks move away from decile 4 for both directions (to decile 0 and to decile 9). The pattern in Table 2.2 suggests that even if properly adjust the risk of firms, the stock market has trouble understanding the true value of the firm. The market has a better understanding for firms with extreme news (group 0 and 9) but still has trouble understanding firms with low to moderate earnings surprise (group 1 through 8).

The bottom two rows show the post-earnings announcement drift, the 60-day return on a zero-investment portfolio that is long in most positive earnings surprise firms and short in most negative earnings surprise firm and the corresponding t-value. For all five CARRs, the 60-dayl return on the zero-investment portfolio is positive and statistic significant. The lowest return is 1.21% (t = 3.00) for CARRsp and highest return is 1.74% (t = 4.38) for CARRszew. The results show the existence of post-earnings announcement drift.

2.6.2 Test results on Hypothesis 1

I estimate equation (2) with ordinary least square (OLS) approach with my sample firms and report the regression results in Table 2.3. The dependent variable is the five measures of CARRs. For each measure of CARRs, I report results on three regression specifications. The first specification includes only quarterly earnings surprise (UE6) to examine whether the quarterly earnings surprise help explain PEAD after the quarterly earnings announcement. In the second specification, I then add firm size, the precision of common information, and precision of private information to the regression and examine the association between those variables and the 60-day

cumulative risk-adjusted abnormal returns. The third specification employs multivariate OLS regression to examine whether firm size (size), the precision of common information (h) or precision of private information (s) in addition to earnings surprise (UE6), has an incremental explanatory power on PEAD.

Results from column (1) in Table 2.3 show how earnings surprise are associated with PEAD where the dependent variable is CARRv. The coefficient of earnings surprise (UE6) has a value of 0.0143 with t-stat of 6.1882, which is significantly different from zero at 1% level. The coefficient of earnings surprise (UE6) is a measure of PEAD. From my result, the PEAD is 1.43% in my sample period, fits in the 1.3% PEAD over 60 trading days after earnings announcements reported in Liang (2003). The result is consistent with the argument that market underreacts to information contained in the earnings announcements. The adjusted R-square is 0.0005, which is similar to the one in Liang (2003). The result in column (4) with CARRe as a dependent variable tells a similar story. The resulting PEAD of 1.59% is higher and significant. Column (5) shows the similar result in PEAD as in column (1), which is 1.45%. The regression results with CARRs constructed from Fama/French portfolios sorted on size as the dependent variable, in general, show a smaller coefficient of quarterly earnings surprise (UE6) and a lower adjusted R-square than the other three columns. But their results are consistent with each other. Column (10) with CARRs based on equally weighted average decile returns shows the PEAD is 1.73% while column (13) with CARRs based on value-weighted average decile returns shows PEAD of 1.34%. Both columns have an adjusted R square around 0.0005, similar to the adjusted R-squares in columns (1), (4), and (7).

Columns (2), (5), (8), (11), and (14) present the regression results of additional explanatory variables. Column (2) shows an average PEAD of 1.39%. Public information precision is

positively associated with risk-adjusted cumulative abnormal returns (CARRv) at 0.012 (t = 4.97). Private information precision is positively associated with CARRv at 0.040 (t = 16.98). This result is consistent with the argument that poor information environment (low in precision of public information) prompts the demand and supply of financial analyst services. Firm size is negatively associated with CARR, consistent with large firms have better information environment and efficient price discovery process.

Columns (3), (6), (9), (12), and (12) present the regression results of the full model specification. Column (3) shows the incremental power of firm size, common information precision (h) and private information precision (s) on PEAD. PEAD now is 3.81% in the multivariate regression. The coefficient of the interaction term can be interpreted as if the variable is in its highest rank rather than lowest rank, how that variable affects PEAD, all else being constant. For example, the coefficient of interaction term between earnings surprise and firm size (UE6*size) is negative at -0.92% and significant. That is, the PEAD of the largest firms is 0.92% lower than that of the otherwise similar smaller firms. The result is consistent with prior research, who argue that firm size is inversely related to PEAD (Foster et al., 1984; Bernard and Thomas, 1989, 1990; Bhushan, 1994; Ball and Bartov, 1996; and Alford and Berger, 1997). Column (3) indicates that coefficient of the interaction term between earnings surprise and private information precision (UE6*s) is negative and is significantly different from 0, suggesting that higher private information precision contained in revised forecasts decreases the PEAD. In the extreme cases where the revised forecasts contain the highest precision of private information, the PEAD reduces by 7.62%. The result is consistent with hypothesis H1 that private information contained in forecast revisions decreases information uncertainty. Adjusted R-square of column (2) is 0.0071, which is higher than the one from the binary regression, 0.0005.

The PEAD may not be fully diminished due to following reasons: First, revised earnings forecasts may not contain the highest level of private information for all firms. This situation could be caused by analysts spending less effort acquiring information for the firm (especially when public information level is high). For those firms, the effect of revised earnings forecasts on reducing uncertainty is less pronounced than firms with the highest rank of private information precision in revised forecasts. Second, Table 2.1 shows that private information precision and public information precision in revised forecasts are positively correlated. Column (3) shows that the coefficient of the interaction between earnings surprise and common information precision (UE6*h) is positive at 3.35% and significant. Benefit from higher private information precision on reducing PEAD would be offset partially by the precision of common information.

There are several possible explanations for the positive coefficient of the precision of common information. First, Barron et al. (1998) argue that the consensus among analysts increases at the precision of common information, and higher the consensus among analysts, less likely analysts would provide different forecasts. Investors would consider the commonality among analysts as herding behavior and put less weight on the information and continue to underreact to information, hence higher level of PEAD. Secondly, Fischer and Stocken (2010) argue that high precision of public information would discourage analysts from producing private information. If analysts spend less effort for firms with high public information precision, I would expect the positive sign on b2. Lastly, Barron et al. (2003) argue that the precision measures could pertain to investors' information environment. As public information increases in the market, information asymmetry between sophisticated investors and unsophisticated investors increase and reduce the efficiency of price discovery.

Columns (6) and (9) show similar effects of common information precision and private information precision on PEAD and the magnitude of coefficients is similar as well. The effect of private information on PEAD is -7.36% and -7.73%, respectively, while the effect of public information precision on PEAD is 2.09% and 3.56%, respectively. Columns (12) and (15) show similar results in the coefficient of the precision of private information (-7.34% in column (12) and -7.16% in column (15)). The adjusted R-squares in columns (12) and (15), are again similar to the ones in columns (3), (6), and (9). In general, results shown in Table 2.3 are consistent with hypothesis H1 that precision of private information help reduces information uncertainty.

2.6.3 Test results on Hypothesis 2: Pseudo-event study: Reg FD

2.6.3.1 Reg FD and related literature

The Security and Exchange Commission (SEC) issues Regulation Fair Disclosure, also commonly referred to as Reg FD, in 2000 and fully adopted by firms in 2003. The main point of the Reg FD is to prohibit private contact between firm insiders and financial analysts. Reg FD requires firms listed in the U.S capital market to make public announcements if they want to disclose any information to outside investors or do not disclose at all.

Prior literature indicates that the information content has changed dramatically before and after the Reg FD. Several works examine the effect of regulation on analysts' forecast characteristics and have conflicting results. Several studies find that Reg FD affects the characteristics of analysts' forecast and firm information environment. For example, Bailey et al. (2003) find that both analyst forecast dispersion and quarterly earnings disclosure increase following Reg FD. Their results suggest that Reg FD increases the quantity of information available to the public and that investors' demand for professional services increases as well. Eleswarapu, Thompson, and Venkarataman (2004) examine information asymmetry using bid-ask

spreads and order flow imbalance and find that the information environment improves after Reg FD. Gintschel and Markov (2004) document a reduced absolute price impact of information disseminated by analysts after Reg FD. Their result suggests that Reg FD effectively reduces selective disclosures.

Several works examine the change of information content contained in the analysts' earnings forecasts pre- and post-Reg FD. Mohanram and Sunder (2006), for example, find that the precision of idiosyncratic information increases after Reg FD. On the other hand, Francis, Nanda, and Wang (2006) argue that analyst forecasts informativeness declines for the U.S firms relative to ADR after Reg FD.

2.6.3.2 Test results

I examine whether the impact of precision of information in revised earnings forecasts on post-earnings announcement drift changes after the Reg FD. I do so by first dividing the whole sample into two sub-samples, pre-Reg FD and post-Reg FD. I expect that the contribution of precision of information in revised earnings forecasts to post-earnings announcement drift is higher in pre-Reg FD period as the information asymmetry between firm and investors is higher before Reg FD. Since Reg FD was passed in the year 2000 and fully adopted around 2003, I drop observations in this three-year period. I define the sample period before the year 2000 as pre-Reg FD period and the sample period after 2003 as post-Reg FD period. I perform the relevant tests for the two sub-periods and use z-score (Clogg, Petkova, and Haritou, 1995; and Paternoster, Brame, Mazareolle, and Piquero, 1998) to examine the difference in contributions of precision of information contained in revised earnings forecasts between those two periods. The test results are shown in Table 2.4.

Panel A of Table 2.4 shows the regression results for the pre-Reg FD subsample and Panel B shows the result for the post-Reg FD subsample. Both subsamples give similar results and are also similar to my main results in Table 2.3. In column (3), Panel A of Table 2.4, the coefficient of the interaction term between earnings surprise and firm size (UE6*size) is negative at -2.22% (t = -1.59), which is not significant. The coefficient of the interaction term (UE6*size) is also not significant in columns (6), (9), and (15), but is significant in column (12) (-3.05% and t = -2.23), the sign of the coefficient is negative across all five dependent variables. Column (3) in panel B of Table 2.4 on the coefficient of the interaction term (UE6*size) is 0.28% and (t = 0.28), which is not significant. The coefficient of the interaction term (UE6*size) in columns (6), (9), (12), and (15) in Panel B of Table 2.4 is not significant as well.

The sign of the coefficient of interaction term between the precision of common information and quarterly earnings surprise (UE6*h) is positive, and the coefficient of interaction term between the precision of private information and quarterly earnings surprise (UE6*s) is negative across different dependent variables. Both coefficients are statistically significant. For example, column (3) in Panel A and column (3) in Panel B show that the coefficient of interaction term between private information and earnings surprise (UE6*s) are negative at -11.11% (t = -8.49) and -4.23% (t = -4.26), respectively. The coefficient of interaction term between public information and earnings surprise (UE6*h) is positive at 2.56% (t = 1.92) and 2.57% with (t = 2.44), respectively.

Next, I observe that the coefficient of the interaction term between precisions of common information and quarterly earnings surprise (UE6*h) does not vary too much in pre- and post-Reg FD subsamples. Column (3) shows that UE6*h has a coefficient of 2.56% in Panel A and 2.57% in panel B, a difference of 0.01%. But the coefficient of the interaction term between precisions of

private information and quarterly earnings surprise (UE6*s) is different across the two subsample periods. Column (3) shows that UE6*s has a coefficient of -11.11% in Panel A and of -4.23% in Panel B, a difference of 6.88%. This is also true for size-adjusted returns in columns (12) and (15). For example, column (12) reports effect of common information precision on PEAD to be 2.95% in pre-Reg FD period and 1.54% in post-Reg FD period, a difference of -1.41%. Effect of private information reported in column (12) is -10.11% in pre-Reg FD period and -4.39% in post-Reg FD period, a difference of 5.72%. To examine whether the difference is significant, I calculate Z-score proposed by Clogg, Petkova, and Haritou (1995) to compare the coefficients in Panels A and B. The Z-score is calculated as follows:

$$Z = \frac{\beta 1 - \beta 2}{\sqrt{(SE\beta 1)^2 + (SE\beta 2)^2}}$$

In my sample, β1 represents the coefficient of a variable from post-Reg FD subsample, and β2 represents the coefficient of the same variable from pre-Reg FD subsample. SE represents the associated standard error (not reported in the table).

Panel C of Table 2.4 shows the Z-scores for the coefficient of interaction term UE6*s and the coefficient of UE6*h between post- and pre-Reg FD period with the corresponding p-value in parenthesis. For the coefficient of interaction term between the precision of common information and earnings surprise (UE6*h), the difference between pre- and post-Reg FD is insignificant. When CARRv serves as the dependent variable, the difference in coefficient of UE6*h between two subsamples is 0.0015 with a p-value of 0.5, which is not significant. Results from CARRszvw and CARRszew show no significant difference between the two sub-periods. The difference is -0.8474 with a p-value of 0.80 and -0.2764 with a p-value of 0.61, respectively.

On the other hand, the difference in the coefficient of the interaction term between precisions of private information and quarterly earnings surprise (UE6*s) is statistically significant. For the same dependent variable CARRv, the difference in the coefficient of UE6*s is

4.1862 with a p-value less than 0.0001, which is significant at the 1% level. When dependent variables are size-adjusted CARRszew and CARRszvw, difference in the coefficient of UE6*s is significant as well. The differences between two sub-periods are 3.5529 (p=0.0002) and 3.51690 (p=0.0002), significant at the 1% level. The positive difference means that the precision of private information contained in revised earnings forecasts in the post-Reg FD period has a smaller effect on PAED than it does in the pre-Reg FD period. The results support hypothesis H2.

2.6.4 Robustness test: Index adjusted return

2.6.4.1 Hypothesis 1

I use index adjusted cumulative abnormal returns (CARs) in the robust analysis, following prior works (Bernard and Thomas, 1998; Liang, 2003). I calculate index-adjusted cumulative abnormal returns from day one to day 60 after a quarterly earnings announcement. Daily abnormal return (AR) is the difference between a day's stock return and the same day's market return. I use several benchmark indexes in the analysis as market index, such as CRSP value-weighted index, CRSP equal-weighted index, and S&P 500 index. I also develop size adjusted cumulative abnormal returns (CARs) based on Fama/ French portfolios sorted by size.

To calculate day 1 to day 60 cumulative abnormal return for each firm quarter with Fama/ French portfolio sorted by size, I first calculate a firm's market value of equity, which is the product of shares outstanding and the same day closing price, for each of those 60 trading days. I then compare each day's firm market value of equity with that month's market breakthrough points and classify the firm into a size decile. Each day's abnormal return is calculated as the difference between daily stock return and the same day's return on the corresponding Fama/ French size decile. I calculate [1, 60] trading days' abnormal returns and sum them up as the size-adjusted cumulative abnormal returns for each firm quarter.

I use these 60-trading-day index-adjusted cumulative abnormal returns (CARs) as the dependent variable and estimate the regression equation (2). The results are presented in Table 2.5. As in Table 2.3, I first regress index-adjusted cumulative abnormal returns (CARs) against quarterly earnings surprise (UE6). Then I run the regression with additional variables, including precision of public information (h), the precision of private information (s), and firm size (size). Lastly, I add interaction terms (UE6*s, UE6*h, and UE6*size) into the regression model.

The results are presented in Table 2.5 and are similar to the results from Table 2.3. Columns (1), (4), (7), (10), and (12) present regression of index-adjusted cumulative abnormal return (CAR) against the quarterly earnings surprise. The magnitude of the coefficient of quarterly earnings surprise is larger than the one in Table 2.3 and the coefficient remains significant. For example, column (1) in Table 2.5 shows that the PEAD is 4.60% (t = 25.83), compare with 1.43% (t = 6.19) in column (1) in Table 2.3. The PEAD or the coefficient of UE6 is 4.47% in column (4), 4.64% in column (7), 2.11% in column (10) and 2.04% in column (13). The results indicate that the drift still exists using index-adjusted returns.

Column (2) in Table 2.5 confirms the results in Table 2.3 as the coefficient of precision of public information (h) is positive at 2.41% (t = 13.38) and the coefficient of precision of private information (s) is positive at 2.86% (t = 15.84). The coefficient of firm size (size) is still negative and significant (-1.04% and t = -5.85). Columns (5), (8), (11), and (14) show the same pattern: the coefficient of s and the coefficient of h are all positive and significant, and the coefficient of size is negative and significant.

Comparing column (3) in Table 2.5 with column (3) in Table 2.3, I find that the effect of private information precision on PEAD is smaller but remains significant. The coefficient of the interaction term of quarterly earnings surprise and private information precisions (UE6*s) is -

4.60% with t-stat of -7.73 in Table 2.5, and the coefficient is -7.62% with t-stat of -9.85 in Table 2.3; both are significant at 1% level. Other columns tell the similar results. In Table 2.5, column (6) reports the coefficient of UE6*s of -4.22% (t = -7.12), and column (9) reports -4.67% (t = -7.77). Results from size-adjusted CARs are larger than the prior three CARs. In Table 2.5, columns (12) and (15) show that the coefficient of UE6*s are -8.83% (t = -13.02) and -8.77% (t = -12.85), respectively.

The coefficient of the interaction term between quarterly earnings surprise and common information precision (UE6*h) is still significant and positive in Table 2.5 across all CARs, although the magnitude is smaller than their counterparts in Table 2.3. The effects of common information precision on PEAD range from 3.20% (t = 5.19) in column (6) to 3.87% (t = 6.35) in column (9) and 3.78% (t = 5.36) to 3.96% (t = 5.59) for two size-adjusted CAR variables. Results in Table 2.5 are consistent with Hypothesis 1.

An interesting observation is the coefficient of the interaction term between quarterly earnings surprise and firm size (UE6*size). The coefficient is negative and is significant across all five sets of dependent variables in Table 2.5. These results are consistent with the argument that systematic risk is associated with firm size (Beaver, Kettler, and Scholes, 1970; Logue and Merville, 1972).

2.6.4.2 Hypothesis 2

Table 2.6 provides Reg FD sub-period regression analysis using index-adjusted returns as the dependent variable. Column (3) in Panel A of Table 2.6 reports the coefficient of the interaction term between the precision of public information and quarterly earnings surprise, UE6*h, of 3.30% (t = 3.19) and the coefficient of interaction term between the precision of private information and quarterly earnings surprise, UE6*s, of -6.44 (t = -6.38) during pre-Reg FD period.

Column (3) in Panel B of Table 2.6 uses CARv as the dependent variable and reports the coefficient of UE6*h of 4.14% (t = 5.14) and the coefficient of UE6*s of -3.10% (t = -4.07) during post-Reg FD period. The post- and pre-Reg FD difference is 0.84% for UE6*h and is 3.34% for UE6*s. Panel C of Table 2.6 shows that the Z-score for UE6*h in post-Reg FD and pre-Reg FD period is 0.64 (p=0.26), which is not significant, while the difference of UE6*s between post- and pre-Reg FD is 2.64 (p=0.004), which is highly significant. The results are consistent with Hypothesis 2.

Columns (6), (9), (12), and (15) in Panel A and B of Table 2.6 provide similar inferences as the coefficient of UE6*h is positive and significant while the coefficient of UE6*s is negative and significant. Panel C of Table 2.6 shows that effects of the precision of public information on PEAD do not change from pre- to post-Reg FD period, while effects of precision of private information on PEAD reduce from pre- to post-Reg FD period, consistent with Hypothesis 2.

2.6.5 Robustness test: with additional control variables

2.6.5.1 Measures of the additional variables

I also add additional control variables to regression equation (2) to examine if the main result holds. I use the variables proposed by Liang (2003) to control for their impacts on PEAD. For each additional variable, I create an interaction term with quarterly earnings surprise. I are more interested in the coefficient of the interaction term, as it measures the effect of the variable on PEAD.

First, I add the scaled decile numbers of level of analyst following each firm quarter, ***Nr***, to proxy for the information environment around a quarterly earnings announcement. The prior literature documents the information intermediary role of financial analysts. Brennan, Jegadeesh, and Swaminathan (1993) document that firms with high level of analyst following experience fast price adjustment to new information that is common to all firms. Lys and Soo (1995) show that

high level of analyst following is associated with a higher forecast accuracy. Schutte and Unlu (2009) find an inverse relationship between analyst following and stock price noise. I use the level of analyst following for each firm quarter to develop the measure. I divide firms into deciles from 0 (lowest) to 9 (highest), based on the level of analyst following in all firm quarters. These decile numbers are scaled by 9 to get the scaled decile numbers of the level of analyst following each firm quarter, *Nr.* I also use the level of analyst following, *N*, as an alternative measure.

Second, I control for price momentum as in Liang (2003). Price momentum strategy, documented by Jegadeesh and Titman (1993), shows that buying past winner stocks and selling past loser stocks would generate abnormal return up to 12 months. The momentum effect could affect the interpretation of PEAD, as Chan, Jegadeesh, and Lakonishok (1996) find that both past stock returns and quarterly earnings surprise help predict future large drifts in stock returns. I use the scaled decile numbers of the past 6-month compound return, ***CompRetr***, to proxy for the price momentum. The 6-month compound return is calculated as compounding individual daily stock returns from 6 months before a quarterly earnings announcement to the day before the announcement. After obtaining the compound return for each firm quarter, I divide all firms into deciles 0 (lowest) to 9 (highest) based on the compound returns. I then scale the decile numbers by 9 and denote the scaled decile numbers as *CompRetr*. The value of compound return, *CompRet,* is also used as an alternative variable.

Third, I control for trading volume with scaled decile numbers of trading volume, ***Volr***. Lee and Swaminathan (2000) find that past trading volume/ turnover ratio is positively associated with the direction of earnings surprise and the level and persistence of price momentum before a reversal happens in the long run. There is also evidence that trading volume predicts future stock abnormal returns in the short run (Gervais, Kaniel, and Mingelgrin, 2001; Chordia and

Swaminathan, 2000). The results suggest that prior trading volume contains price-relevant information and that the market recognizes the information. For each trading day, the turnover ratio is measured as the number of shares traded on that day scaled by shares outstanding on the same day. I present the trading volume in percent form. I calculate the ratio each day from 45 trading days before to one day before a quarterly earnings announcement and then calculate the mean trading volumes of those days. After finding the mean trading volume for each firm quarter in the sample, I divide all firms into ten deciles 0 (lowest) to 9 (highest) based on the mean turnover ratio. The scaled decile numbers are denoted as *Volr*. The raw trading volume calculated above in percent form, *%Vol,* is used as an alternative variable.

Fourth, Kahneman and Tversky (1979) suggest that the market may react differently to bad news than to good news. Veronesi (1999) show that the market overreacts to bad news in good times and underreacts to good news in bad times. So, I add the direction of the quarterly earnings surprise to control for potential asymmetric reaction problem. I use a sign dummy to represent the direction of the earnings surprise. The dummy variable, ***Sign***, equals 1 when the earnings surprise is positive, and 0 otherwise.

Lastly, I control for the impact of earnings levels and earnings changes on stock returns. Latane, Joy, and Jones (1970) find that sorting and ranking firms based on earnings-to-price ratio helps find firms that will outperform in next six months. Easton and Harris (1991) find that both earnings levels and changes, when deflated by stock price at the beginning of the period (E/P ratio), are associated with annual stock returns. Ali and Zarowin (1992) find that the transitory part of annual earnings contributes to the result in Easton and Harris (1991). Ali and Zarowin (1992) use P/E ratio to distinguish the permanent part from the transitory part of annual earnings. Beaver and Morse (1978) and Ou and Penman (1989) argue that extremely low (high) P/E ratio represents low

(high) transitory earnings, while a non-extreme ratio is an indicator of persistent earnings. I calculate a reversed P/E ratio, E/P ratio, for each firm quarter following Liang (2003). I first calculate the mean annual earnings forecast issued within 45 days before the upcoming actual quarterly earnings announcement and scale the mean forecast by stock price 45 days before the announcement. Following Liang (2003), I divide firms into ten groups based on this ratio. I classify firms with negative E/P ratios into group 0 and the rest into nine groups based on the E/P ratio (1-9). Then I use a dummy variable to represent whether E/P ratio is in an extreme portfolio such as the top 2 portfolios (8, 9) or the bottom two portfolios (0, 1) (Ou and Penman, 1989; and Ali and Zarowin, 1992). The dummy variable, $\boldsymbol{EPr}$, equals 1 if the observation falls into portfolio 2 to 7, and 0 otherwise.

2.6.5.2 Regression models

I add those additional variables, *Nr, CompRetr, Volr*, *Sign, and EPr* into the equation (2). Interaction terms between each of those additional variables and quarterly earnings surprise (UE6) are created to examine the additional explanatory power of those variables on PEAD. I use the same dependent variables as in Table 2.3. The regression model with these additional variables and associated interaction terms is presented below:

$$\begin{aligned} CARR = {} & b_0 + b_1 * UE6 + b_2 * UE6 * h + b_3 * UE6 * s + b_4 * UE6 * size + b_5 * h + b_6 \\ & * s + b_7 * size + b_8 * UE6 * \boldsymbol{Nr} + b_9 * UE6 * \boldsymbol{Volr} + b_{10} * UE6 \\ & * \boldsymbol{CompRetr} + b_{11} * UE6 * Sign + b_{12} * UE6 * EPr + b_{13} * \boldsymbol{Nr} + b_{14} \\ & * \boldsymbol{Volr} + b_{15} * \boldsymbol{CompRetr} + b_{16} * Sign + b_{17} * EPr + \varepsilon \end{aligned} \tag{3}$$

$$\begin{aligned} CARR = b_0 + b_1 * UE6 + b_2 * UE6 * h + b_3 * UE6 * s + b_4 * UE6 * size + b_5 * h + b_6 \\ * s + b_7 * size + b_8 * UE6 * \boldsymbol{N} + b_9 * UE6 * \%\boldsymbol{Vol} + b_{10} * UE6 \\ * \boldsymbol{CompRet} + b_{11} * UE6 * Sign + b_{12} * UE6 * EPr + b_{13} * \boldsymbol{N} + b_{14} \\ * \%\boldsymbol{Vol} + b_{15} * \boldsymbol{CompRet} + b_{16} * Sign + b_{17} * EPr + \varepsilon \end{aligned} \tag{4}$$

Equation (3) uses the scaled decile numbers of number of analysts following, of compound return and trading volume, while equation (4) uses the value of those three variables. For those additional variables, I expect that they have impacts on PEAD. I do not have a prediction for the sign of the coefficient b_8, which examines the effect of number of analysts following on PEAD. Analyst coverage is arguably negatively associated with PEAD, as more analysts following would speed up price discovery. But its effect could be absorbed by two information precision variables, h and s, the precision of public information and private information in forecast revisions. The number of analysts following is incorporated into the calculation of these two variables. Hence, the variable construction may introduce a spurious relationship between number of analysts following and PEAD. I expect b_9 to be negative, as trading volume contains price-relevant information that would reduce information uncertainty and the PEAD. I expect b_{10} to be positive, as past stock performance predicts future stock return drifts in addition to earnings surprise. I predict b_{11} to be positive. If investors underreact to good news, the underreaction would contribute to market underreaction to news due to information uncertainty and thus increase PEAD. Lastly, I expect b_{12} to be positive. Permanent earnings change represents a change of true distribution of the firm value, which results in an increased information uncertainty (Brav and Heaton, 2002).

2.6.5.3 Regression results: Hypothesis 1

The regression results from equation (3) and (4) are presented in Table 2.7. Table 2.7 shows that the results in Table 2.3 are robust to additional variables. In column (1) of Table 2.7, the

coefficient of the interaction term between earnings surprise and private information precision in revised analyst earnings forecasts (UE6*s) is -9.43% (t = -11.89), which is significantly different from 0. Columns (2) through (10) report that the coefficient of UE6*s ranges from -9.60% (t = -11.91) in column (5) to -8.68% (t = -10.55) in column (3), which are significantly different from 0. The effect of precision of private information in revised forecasts in reducing PEAD is robust to additional variables.

The effects of precision of public information in the revised earnings forecast on PEAD still exists after controlling for additional variables. In Table 2.7, the coefficient of interaction term between quarterly earnings surprise and public information precision (UE6*h) ranges from 0.88% (t = 1.02) in column (4) to 2.26% (t = 2.67) in column (5). Eight out of ten columns have a positive and significant coefficient of UE6*h in Table 2.7.

The coefficient of the interaction term between quarterly earnings surprise and firm size stays significant in Table 2.7. Collectively, the main results from Table 2.3 are robust to additional variables.

In equation (3), the signs of coefficients of variables, in general, fit my expectations. I use scaled decile numbers (0 to 1) in equation (3), except for the dummy variables. I could interpret coefficients of those interaction terms as the additional effect of a variable to PEAD if it is in the highest decile (1) rather than the lowest decile (0). For example, the coefficient of the interaction term between quarterly earnings surprise and trading volume (UE6*Volr) provides evidence for the argument that prior trading volume is inversely related to PEAD. The coefficient of (UE6*Volr) is negative and significant across all five dependent variables. The coefficient of (UE6*Volr) ranges from -3.58% (t = -4.69) in column (3) to -2.57% (t = -3.54) in column (7). That is, PEAD

after a quarterly earnings announcement could reduce by up to 3.58% if the prior trading volume of the firm is in highest decile rather than the lowest decile.

The coefficient of the interaction term between quarterly earnings surprise and number of analysts (UE6*Nr) is positive and significant in four out of five dependent variables. The results are consistent with the argument that the effect of the number of analysts on PEAD may be absorbed by the precision of public information (h) and precision of private information (s) contained in revised earnings forecasts.

The effect of price momentum on PEAD is positive, as expected. In general, price momentum increases PEAD by 2.11% to 2.32%. The results are consistent with the argument in Chan et al. (1996) that both past stock returns and quarterly earnings surprise are positively associated with future stock return drifts.

According to the coefficient of interaction term between quarterly earnings surprise and the sign of earnings surprise (UE6*Sign), the market seems to overreact to positive earnings surprise, which is inconsistent with Veronesi (1999). Positive earnings could increase the PEAD by up to 22.02% (t = 16.70 column (5)). The coefficient is significantly different from 0 at 1% level.

Results based on the E/P ratio are consistent with the argument that information uncertainty increases PEAD. The coefficient of the interaction term between quarterly earnings surprise and E/P dummy (UE6*EPr) ranges from 0.66% (t = 1.38 column (9)) to 1.36% (t = 2.69 column (4)). The results suggest that if the earnings surprise is caused by a permanent change in earnings for the firm, the market tends to experience an increase in information uncertainty and underreacts more to information, hence a stronger PEAD.

Results from equation (4) in general confirm the results from equation (3). The coefficient of the interaction term between quarterly earnings surprise and value of number of analyst following (UE6*N) is still positive across all dependent variables, suggesting variables h and s absorb the effects of analyst following. The coefficient of the interaction term between quarterly earnings surprise and value of trading volume (UE6*%Vol) is negative, although only three of them are significantly different from 0. The coefficient of the interaction term between quarterly earnings surprise and value of compound return (UE6*CompRet) are significant and positive. That is, price momentum predicts future stock return drifts.

2.6.5.4 Regression results: Hypothesis 2

I examine whether Hypothesis 2 is robust to additional variables by regression equation (3) and (4) on two sub-periods. Table 2.8 shows that the results in Table 2.4 are robust to additional variables.

In Panel A and B of Table 2.8, the coefficient of UE6*h is reducing its significance across all ten columns. In Panel A of Table 2.8, the highest t-value for the coefficient of UE6*h is 1.76, which is marginally significant at 10% level. In Panel B of Table 2.8, the largest t-value for the coefficient of UE6*h is 1.22, which is not significant.

The coefficient of UE6*s is still negative and significant across all ten columns, consistent with Hypothesis 1. In Panel A of Table 2.8, the coefficient ranges from -13.60% (t = -9.95 column (5)) to -11.77% (t = -8.92 column (10)). In Panel B of Table 2.8, the coefficient ranges from -5.91% (t = -5.72 column (5)) to -4.62% (t = -4.42 column (4)).

Hypothesis 2 appears to be robust to additional variables. Column (1) in Panel A of Table 2.8 reports a coefficient of UE6*h of 1.91% (t = 1.38) and a coefficient of UE6*s of -13.34% (t = -9.95). Column (1) in Panel B of Table 2.8 reports a coefficient of UE6*h of 1.16% (t = 1.07) and

a coefficient of UE6*s of -5.74% (t = -5.63). The difference between pre- and post-Reg FD for the coefficient of UE6*h is -0.75% while the difference between pre- and post-Reg FD for the coefficient of UE6*s is 7.60%.

Panel C of Table 2.8 reports that the coefficient of UE6*h does not change from pre- to post-Reg FD period, as all p-values are greater than 0.1. The coefficient of UE6*s, however, significantly decreased from pre- to post-Reg FD period. The results in Panel C of Table 2.8 are consistent with results in Table 2.4. The Hypothesis 2 is robust to additional variables.

Results on other variables in Panel A and B of Table 2.8, in general, confirm the results from Table 2.4. The coefficient of the interaction term between quarterly earnings surprise and firm size (UE6*size) is negative and significant in 18 out of 20 times (Is insignificant in columns (3) and (4) of Panel B). The coefficient of the interaction term between quarterly earnings surprise and number of analyst following (UE6*Nr and UE6*N) is still positive across all columns in both Panel A and B, suggesting variables h and s absorb the effects of analyst following. The coefficient of the interaction term between quarterly earnings surprise and trading volume (UE6*%Vol and UE6*Volr) is positive in pre-Reg FD period and is negative in post-Reg FD period. The coefficient of the interaction term between quarterly earnings surprise and compound return (UE6*CompRet and UE6*CompRetr) is significant and positive across all columns of Panel A and B. That is, price momentum predicts future stock return drifts. The coefficient of the interaction term between quarterly earnings surprise and sign of surprise (UE6*Sign) is positive and significant across all columns in Panel A and B, indicating the market underreacts to positive quarterly earnings surprise. The coefficient of the interaction term between quarterly earnings surprise and E/P ratio (UE6*EPr) is not significant across all columns in Panel A and B, suggesting

that the information contained in earnings persistence is captured by other variables in the regression equation.

2.7 Conclusion and Discussion

In the study, I examine how information precision in financial analysts' earnings forecast revisions is associated with post-earnings announcement drift. Prior literature shows that PEAD results from market underreaction to information and that the underreaction could be relieved if the information uncertainty level decreases. That is, the market reduces PEAD through the channel of reduced information uncertainty. Revised earnings forecasts issued right after earnings announcements contains information that is new to all investors, which is produced from analysts' private information. The high quality of private information contained in revised earnings forecasts could decrease the level of information uncertainty around the market. On the other hand, as new uncertainty presents even if old uncertainty is resolved, the effects of the precision of private information contained in revised earnings forecast may not be large enough to reduce the overall information uncertainty and PEAD. As a result, the effects of the precision of private information on PEAD is an empirical question. I hypothesize that the precision of private information contained in analysts' one-year-ahead forecasts issued right after a quarterly earnings announcement could reduce the level of PEAD, implying that the revised earnings forecasts contain high-quality private information that helps reduce information uncertainty.

I examine the effects of the precision of private information contained in revised forecasts on reducing information uncertainty and whether the market acknowledges the implications of events in a changing information environment. I conduct an event-study using Reg FD as an event that changes the information environment. In pre-Reg FD period, analysts can contact the firm's management and obtain inside information. However, in the post-Reg FD period, analysts are

restricted to their own efforts to collect price-related information without inside information. If investors do understand the private information contained in annual earnings forecast revisions and use the information to reduce information uncertainty, they would be able to learn the difference in the precision of private information in pre- and post-Reg FD periods and react differently to information. I hypothesize that the effect of private information contained in reducing information uncertainty and PEAD should be larger in pre-Reg FD period than in post-Reg FD period.

The results in the study show that precision of private information contained in the revised earnings forecasts reduce post-earnings announcement drift, though the effect is partially offset by the precision of public information contained in the revisions. The results are robust after using alternative returns or controlling for additional variables. I also find that the effects of the precision of private information contained in reducing PEAD is larger in pre-Reg FD period than in post-Reg FD period. The results are consistent with the argument that the market understands the precision of private information contained in revised analyst earnings forecasts and use this private information to reduce information uncertainty. The results suggest that the market acknowledges how legal events can impact the informativeness of information sources.

This study contributes to the literature of PEAD by showing that the precision of private information contained in the one-year-ahead earnings forecasts issued right after quarterly earnings announcements helps reduce PEAD by reducing information uncertainty on the true distribution of the firm's value. This study also contributes to the financial analyst forecast literature by showing that analysts produce private information that increases the speed of price adjustments to new information, but they underreact to public information. This study also adds to the information uncertainty literature. New information uncertainty emerges even if old uncertainty has been

resolved, which makes it hard to reduce the overall information uncertainty. The results show that high-quality private information contained in revised earnings forecasts helps reduce overall information uncertainty. Moreover, the results suggest that the market acknowledges the quality of information contained in analysts' forecasts and how legal events affect the informativeness of information sources. The results add to the growing literature of learning in the market.

Table 2.1 Descriptive Statistics

This table provides descriptive statistics for the sample. The sample period is from 1984 to 2015. Panel A provides summary statistics for quarterly earnings surprise (UE6), the precision of public information (h), the precision of private information (s), firm size (Size), Scaled forecast dispersion (Disp) and the five alternative measures of risk-adjusted cumulative abnormal return (CARR). Panel B presents the correlation matrix among key variables. Detailed information on the definitions of variables are in Appendix A.

Panel A: Summary statistics

	Mean	**Std. Dev**	**Median**	**Minimum**	**Maximum**	**N**
UE6	-0.0001	0.0099	0.0004	-0.0629	0.0349	72165
h	460.0193	2397.4730	12.1699	-3200.0000	19944.5983	72165
s	861.9043	3814.5600	6.0717	0.0000	29666.3231	72165
Size	9037.3666	20776.3298	2205.5638	61.3899	140987.6922	72165
Disp	0.0044	0.0222	0.0001	0.0000	0.1971	72165
CARRv	-0.0193	0.1974	-0.0130	-0.6417	0.5829	72165
CARRe	-0.0181	0.2042	-0.0084	-0.6640	0.5649	72165
CARRsp	-0.0195	0.2005	-0.0132	-0.6523	0.5966	72165
CARRszew	-0.0180	0.1939	-0.0102	-0.6423	0.5589	72165
CARRszvw	-0.0190	0.1952	-0.0120	-0.6401	0.5717	72165

Panel B: Correlation table (Person Correlation are shown below the diagonal with Spearman)

	UE6	**h**	**s**	**Size**	**Disp**
UE6	1	0.0238	0.0222	0.0481	-0.0140
		(<.0001)	(<.0001)	(<.0001)	(.0002)
h	0.0133	1	0.1412	0.0157	-0.5919
	(.0004)		(<.0001)	(<.0001)	(<.0001)
s	0.0088	0.1299	1	0.0838	-0.1965
	(.0176)	(<.0001)		(<.0001)	(<.0001)
Size	0.0313	-0.0077	-0.0035	1	-0.1150
	(<.0001)	(.0393)	(.3523)		(<.0001)
Disp	-0.1745	-0.0379	-0.0443	-0.0426	1
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)

Table 2.2 60-Day Risk-adjusted Cumulative Abnormal Returns by Quarterly Earnings Surprise

This table reports the 60-days risk-adjusted cumulative abnormal returns right after a quarterly earnings announcement for each decile sorted on quarterly earnings surprise (UE6). All firm quarters are sorted into ten deciles based on the quarterly earnings surprise (UE6), where decile 0 contains firms with lowest quarterly earnings surprise and decile 9 contains firms with highest quarterly earnings surprise. The mean 60-days risk-adjusted cumulative abnormal returns (CARR) are then calculated for each decile. Difference in CARR between decile 9 and decile 0 is calculated, and pooled t-test is performed to examine whether the difference is statistically different from zero. Referred to Appendix A for detailed definitions of CARRe, CARRv, CARRsp, CARRszew, and CARRszvw. The sample period is from 1984 to 2015. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Earnings surprise deciles	CARRe	CARRv	CARRsp	CARRszew	CARRszvw	UE6
Grand Mean	-0.0180***	-0.0192***	-0.0195***	-0.0180***	-0.0190***	-0.0001***
0 (Lowest)	-0.0151***	-0.0033	-0.0023	-0.0087***	-0.0042	-0.0191***
1	-0.0209***	-0.0198***	-0.0201***	-0.0203***	-0.0204***	-0.0027***
2	-0.0236***	-0.0286***	-0.0293***	-0.0250***	-0.0266***	-0.0007***
3	-0.0230***	-0.0300***	-0.0309***	-0.0274***	-0.0286***	-0.0000***
4	-0.0307***	-0.0367***	-0.0375***	-0.0335***	-0.0352***	0.0003***
5	-0.0244***	-0.0303***	-0.0307***	-0.0277***	-0.0298***	0.0006***
6	-0.0186***	-0.0240***	-0.0243***	-0.0220***	-0.0242***	0.0011***
7	-0.0144***	-0.0174***	-0.0177***	-0.0144***	-0.0168***	0.0020***
8	-0.0104***	-0.0099***	-0.0098***	-0.0082***	-0.0106***	0.0037***
9 (Highest)	0.0017	0.0091***	0.0097***	0.0086***	0.0078***	0.0137***
Diff(9-0)	0.0169	0.0126	0.0122	0.0174	0.0121	0.0328
Pooled t-test	(4.16)	(3.09)	(2.94)	(4.38)	(3.00)	(136.01)

Table 2.3 Effect of Precision of Information in Revised Earnings Forecasts on Post-Earnings Announcement Drift

This table presents results of regression equation (2). The dependent variable is the 60 trading-day risk-adjusted cumulative abnormal returns (CARR). The explanatory variables are quarterly earnings surprise (UE6), precision of public information (h), the precision of private information (s), and firm size (Size), and interaction terms between earnings surprise with public information precision (UE6*h), with private information precision (UE6*s), and with firm size (UE6*size). Detailed information on the definitions of variables are in Appendix A. *t*-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Variable	CARRv	CARRv	CARRv	CARRe	CARRe	CARRe	CARRsp	CARRsp	CARRsp	CARRszew	CARRszew	CARRszew	CARRszvw	CARRszvw	CARRszvw
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Intercept	-0.0264***	-0.0445***	-0.0556***	-0.0260***	-0.0488***	-0.0607***	-0.0267***	-0.0447***	-0.0555***	-0.0267***	-0.0472***	-0.0593***	-0.0257***	-0.0439***	-0.0542***
	(-19.3403)	(-19.6279)	(-16.4800)	(-18.3877)	(-20.7754)	(-17.3500)	(-19.2806)	(-19.4197)	(-16.1779)	(-19.8701)	(-21.1653)	(-17.8778)	(-19.0292)	(-19.5887)	(-16.2315)
UE6	0.0143***	0.0139***	0.0381***	0.0159***	0.0149***	0.0405***	0.0145***	0.0142***	0.0376***	0.0173***	0.0166***	0.0430***	0.0134***	0.0129***	0.0352***
	(6.1882)	(6.0055)	(6.5289)	(6.6377)	(6.2181)	(6.7144)	(6.1955)	(6.0609)	(6.3507)	(7.6170)	(7.3370)	(7.5088)	(5.8452)	(5.6599)	(6.1093)
UE6*h			0.0335***			0.0209**			0.0356***			0.0297***			0.0295***
			(4.1596)			(2.5033)			(4.3571)			(3.7638)			(3.7084)
UE6*s			-0.0762***			-0.0736***			-0.0773***			-0.0734***			-0.0716***
			(-9.8517)			(-9.1843)			(-9.8397)			(-9.6642)			(-9.3553)
UE6*size			-0.0115			-0.0049			-0.0106			-0.0156**			-0.0079
			(-1.5430)			(-.6351)			(-1.4062)			(-2.1385)			(-1.0670)
h		0.0116***	-0.0056		0.0132***	0.0024		0.0129***	-0.0053		0.0131***	-0.0023		0.0124***	-0.0027
		(4.9686)	(-1.2074)		(5.4753)	(.4966)		(5.4685)	(-1.1253)		(5.7155)	(-.4987)		(5.4137)	(-.5833)
s		0.0397***	0.0771***		0.0337***	0.0698***		0.0418***	0.0797***		0.0388***	0.0748***		0.0392***	0.0744***
		(16.9783)	(17.2644)		(13.9462)	(15.1099)		(17.6153)	(17.5920)		(16.9346)	(17.0677)		(16.9925)	(16.8536)
size		-0.0144***	-0.0092**		-0.0005	0.0014		-0.0181***	-0.0133***		-0.0102***	-0.0029		-0.0146***	-0.0112***
		(-6.1915)	(-2.0957)		(-.1891)	(.3081)		(-7.6856)	(-3.0017)		(-4.4650)	(-.6775)		(-6.3573)	(-2.5852)
Obs.	72,165	72,165	72,165	72,165	72,165	72,165	72,165	72,165	72,165	72,165	72,165	72,165	72,165	72,165	72,165
Adj.R^2	0.0005	0.0056	0.0070	0.0006	0.0041	0.0052	0.0005	0.0062	0.0076	0.0008	0.0058	0.0072	0.0005	0.0056	0.0069

Table 2.4 Pre- and Post- Reg FD sub-period analysis

This table presents results of regression equation (2) for the pre- and post-Reg FD periods. The dependent variable is the 60 trading-day risk-adjusted cumulative abnormal returns (CARR). The explanatory variables are quarterly earnings surprise (UE6), precision of public information (h), the precision of private information (s), and firm size (Size), and interaction terms between earnings surprise with public information precision (UE6*h), with private information precision (UE6*s), and with firm size (UE6*size). Panel A represents results for the pre-Reg FD period (1984 – 2000), and Panel B for the post-Reg FD period (2003 – 2015). Panel C presents the Z-scores of coefficients of UE6*h and UE6*s between pre- and post-Reg FD period (Post-Reg FD minus Pre-Reg FD). Refer to section 6.3.2 for details on Z-score calculation and Appendix A for detailed definitions of variables. *T-statistics* are in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Panel A: Pre Reg-FD Period

Variable	CARRv	CARRv	CARRv	CARRe	CARRe	CARRe	CARRsp	CARRsp	CARRsp	CARRszew	CARRszew	CARRszew	CARRszvw	CARRszvw	CARRszvw
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Intercept	-0.0348***	-0.0641***	-0.0835***	-0.0340***	-0.0617***	-0.0786***	-0.0342***	-0.0636***	-0.0829***	-0.0324***	-0.0610***	-0.0790***	-0.0311***	-0.0569***	-0.0728***
	(-15.27)	(-16.85)	(-15.33)	(-14.21)	(-15.44)	(-13.73)	(-14.73)	(-16.41)	(-14.93)	(-14.49)	(-16.36)	(-14.78)	(-13.87)	(-15.19)	(-13.57)
UE6	0.0350***	0.0305***	0.0794***	0.0341***	0.0299***	0.0726***	0.0359***	0.0314***	0.0800***	0.0367***	0.0324***	0.0777***	0.0313***	0.0273***	0.0675***
	(8.4782)	(7.3922)	(7.7208)	(7.8722)	(6.9001)	(6.7178)	(8.5275)	(7.4558)	(7.6276)	(9.0755)	(8.0051)	(7.7068)	(7.7031)	(6.7230)	(6.6680)
UE6*h			0.0256*			0.0248*			0.0269**			0.0295**			0.0242*
			(1.9198)			(1.7681)			(1.9761)			(2.2561)			(1.8412)
UE6*s			-0.1111***			-0.1033***			-0.1129***			-0.1011***			-0.0990***
			(-8.4874)			(-7.5045)			(-8.4563)			(-7.8790)			(-7.6778)
UE6*size			-0.0222			-0.0145			-0.0208			-0.0305**			-0.0125
			(-1.5895)			(-.9883)			(-1.4612)			(-2.2307)			(-.9120)
h		0.0086**	-0.0049		0.0098**	-0.0031		0.0091**	-0.0050		0.0104***	-0.0049		0.0079**	-0.0046
		(2.1795)	(-.6612)		(2.3539)	(-.4059)		(2.2449)	(-.6699)		(2.6716)	(-.6753)		(2.0335)	(-.6427)
s		0.0517***	0.1012***		0.0458***	0.0917***		0.0533***	0.1035***		0.0476***	0.0925***		0.0472***	0.0912***
		(12.9225)	(14.2919)		(10.8771)	(12.3301)		(13.0478)	(14.3400)		(12.1230)	(13.3409)		(11.9721)	(13.0943)
size		-0.0021	0.0072		-0.0002	0.0057		-0.0042	0.0044		-0.0008	0.0123*		-0.0042	0.0008
		(-.4828)	(.9407)		(-.0331)	(.7125)		(-.9503)	(.5720)		(-.1977)	(1.6470)		(-.9973)	(.1026)
Obs.	21,117	21,117	21,117	21,117	21,117	21,117	21,117	21,117	21,117	21,117	21,117	21,117	21,117	21,117	21,117
Adj.R^2	0.0033	0.0118	0.0152	0.0029	0.0090	0.0117	0.0034	0.0120	0.0154	0.0038	0.0115	0.0147	0.0028	0.0099	0.0127

Panel B: Post-Reg FD Period

Variable	CARRv (1)	CARRv (2)	CARRv (3)	CARRe (4)	CARRe (5)	CARRe (6)	CARRsp (7)	CARRsp (8)	CARRsp (9)	CARRszew (10)	CARRszew (11)	CARRszew (12)	CARRszvw (13)	CARRszvw (14)	CARRszvw (15)
Intercept	-0.0213***	-0.0351***	-0.0383***	-0.0145***	-0.0414***	-0.0483***	-0.0233***	-0.0360***	-0.0387***	-0.0203***	-0.0365***	-0.0425***	-0.0211***	-0.0341***	-0.0384***
	(-12.3663)	(-12.0926)	(-8.7398)	(-8.1801)	(-13.9297)	(-10.7603)	(-13.2969)	(-12.2341)	(-8.7109)	(-11.9997)	(-12.8261)	(-9.8897)	(-12.3423)	(-11.8517)	(-8.8428)
UE6	0.0056**	0.0054*	0.0119*	0.0084***	0.0075***	0.0215***	0.0055*	0.0053*	0.0109	0.0089***	0.0085***	0.0207***	0.0057**	0.0055**	0.0143**
	(1.9698)	(1.8943)	(1.6435)	(2.8954)	(2.5790)	(2.8929)	(1.9085)	(1.8633)	(1.4808)	(3.1902)	(3.0768)	(2.9193)	(2.0240)	(1.9659)	(1.9927)
UE6*h			0.0257**			0.0022			0.0282***			0.0154			0.0196*
			(2.4399)			(.1998)			(2.6425)			(1.4934)			(1.8785)
UE6*s			-0.0423***			-0.0414***			-0.0434***			-0.0439***			-0.0419***
			(-4.2619)			(-4.0757)			(-4.3106)			(-4.5029)			(-4.2630)
UE6*size			0.0026			0.0059			0.0036			0.0006			0.0026
			(.2821)			(.6345)			(.3873)			(.0674)			(.2896)
h		0.0131***	-0.0003		0.0231***	0.0219***		0.0134***	-0.0013		0.0157***	0.0076		0.0139***	0.0037
		(4.3137)	(-.0439)		(7.4164)	(3.4264)		(4.3508)	(-.2017)		(5.2557)	(1.2374)		(4.6160)	(.5932)
s		0.0267***	0.0485***		0.0286***	0.0499***		0.0277***	0.0501***		0.0282***	0.0507***		0.0267***	0.0483***
		(8.7759)	(8.1708)		(9.1704)	(8.2010)		(8.9836)	(8.3225)		(9.4416)	(8.7069)		(8.8647)	(8.2127)
size		-0.0092***	-0.0108*		0.0050*	0.0016		-0.0123***	-0.0143**		-0.0082***	-0.0088		-0.0114***	-0.0130**
		(-3.1511)	(-1.9456)		(1.6617)	(.2736)		(-4.1231)	(-2.5472)		(-2.8496)	(-1.6221)		(-3.9067)	(-2.3602)
Obs.	41,537	41,537	41,537	41,537	41,537	41,537	41,537	41,537	41,537	41,537	41,537	41,537	41,537	41,537	41,537
Ad. R^2	0.0001	0.0028	0.0032	0.0002	0.0042	0.0046	0.0001	0.0030	0.0034	0.0002	0.0035	0.0039	0.0001	0.0030	0.0034

Panel C: Coefficients Z-score comparison (After - Before)						
Variable	**Test**	**CARRv**	**CARRe**	**CARRsp**	**CARRszew**	**CARRszvw**
UE6*h	**Za-b**	0.0015	-1.2810	0.0744	-0.8474	-0.2764
	(p-value)	(.4994)	(.8999)	(.4703)	(.8016)	(.6089)
UE6*s	**Za-b**	4.1862	3.6126	4.1531	3.5529	3.5169
	(p-value)	(.0000)	(.0002)	(.0000)	(.0002)	(.0002)

Table 2.5 Index Adjusted Returns

This table presents results of regression equation (2). The dependent variable is the 60 trading-day index-adjusted cumulative abnormal returns (CAR). The explanatory variables are quarterly earnings surprise (UE6), precision of public information (h), the precision of private information (s), and firm size (Size), and interaction terms between earnings surprise with public information precision (UE6*h), with private information precision (UE6*s), and with firm size (UE6*size). Detailed information on the definitions of variables are in Appendix A. t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Variable	CARv (1)	CARv (2)	CARv (3)	CARe (4)	CARe (5)	CARe (6)	CARsp (7)	CARsp (8)	CARsp (9)	CARszew (10)	CARszew (11)	CARszew (12)	CARszvw (13)	CARszvw (14)	CARszvw (15)
Intercept	-0.0192***	-0.0399***	-0.0456***	-0.0304***	-0.0542***	-0.0596***	-0.0158***	-0.0360***	-0.0414***	-0.0145***	-0.0508***	-0.0640***	-0.0100***	-0.0416***	-0.0541***
	(-18.20)	(-22.97)	(-17.63)	(-28.83)	(-31.28)	(-23.13)	(-14.82)	(-20.54)	(-15.89)	(-12.00)	(-25.61)	(-21.75)	(-8.23)	(-20.85)	(-18.25)
UE6	0.0460***	0.0452***	0.0575***	0.0447***	0.0436***	0.0553***	0.0464***	0.0456***	0.0574***	0.0211***	0.0193***	0.0479***	0.0204***	0.0191***	0.0459***
	(25.8287)	(25.4385)	(12.9511)	(25.2121)	(24.6234)	(12.4958)	(25.7827)	(25.4224)	(12.8207)	(10.3777)	(9.5411)	(9.4649)	(9.9765)	(9.3569)	(9.0192)
UE6*h			0.0384***			0.0320***			0.0397***			0.0378***			0.0396***
			(6.1998)			(5.1936)			(6.3525)			(5.3607)			(5.5873)
UE6*s			-0.0460***			-0.0422***			-0.0467***			-0.0883***			-0.0877***
			(-7.7283)			(-7.1168)			(-7.7732)			(-13.0217)			(-12.853)
UE6*Size			-0.0207***			-0.0166***			-0.0202***			-0.0144**			-0.0128*
			(-3.6016)			(-2.9066)			(-3.4926)			(-2.1966)			(-1.9447)
h		0.0241***	0.0044		0.0218***	0.0054		0.0240***	0.0037		0.0304***	0.0109***		0.0302***	0.0098**
		(13.3810)	(1.2322)		(12.1983)	(1.5241)		(13.2412)	(1.0317)		(14.8441)	(2.6783)		(14.6601)	(2.3954)
s		0.0286***	0.0512***		0.0280***	0.0487***		0.0288***	0.0518***		0.0414***	0.0849***		0.0424***	0.0857***
		(15.8366)	(14.8409)		(15.5567)	(14.1763)		(15.8308)	(14.8793)		(20.1488)	(21.6146)		(20.4945)	(21.6578)
Size		-0.0104***	-0.0002		-0.0010	0.0072**		-0.0116***	-0.0016		0.0025	0.0092**		-0.0081***	-0.0022
		(-5.8467)	(-.0474)		(-.5572)	(2.1471)		(-6.4550)	(-.4590)		(1.2318)	(2.3855)		(-3.9515)	(-.5595)
Obs.	76，950	76，950	76，950	76，950	76，950	76，950	76，950	76，950	76，950	76，950	76，950	76，950	76，950	76，950	76，950
Adj. R^2	0.0086	0.0152	0.0165	0.0082	0.0140	0.0150	0.0086	0.0152	0.0165	0.0014	0.0109	0.0132	0.0013	0.0108	0.0131

Table 2.6 Pre- and Post- Reg FD Sub-Period Analysis with Index Adjusted Returns

This table presents results of regression equation (2) for the pre- and post-Reg FD periods. The dependent variable is the 60 trading-day index-adjusted cumulative abnormal returns (CAR). The explanatory variables are quarterly earnings surprise (UE6), precision of public information (h), the precision of private information (s), and firm size (size), and interaction terms between earnings surprise with public information precision (UE6*h), with private information precision (UE6*s), and with firm size (UE6*size). Panel a represents results for the pre-Reg FD period (1984 – 2000), and panel B for the post-Reg FD period (2003 – 2015). Panel C presents the Z-scores of coefficients of UE6*h and UE6*s between pre- and post-Reg FD period (post-Reg FD minus pre-Reg FD). Refer to section 6.3.2 for details on z-score calculation and appendix A for detailed definitions of variables. T-statistics are in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Panel A: Pre-Reg FD period

Variable	CARv (1)	CARv (2)	CARv (3)	CARe (4)	CARe (5)	CARe (6)	CARsp (7)	CARsp (8)	CARsp (9)	CARszew (10)	CARszew (11)	CARszew (12)	CARszvw (13)	CARszvw (14)	CARszvw (15)
Intercept	-0.0247***	-0.0533***	-0.0635***	-0.0350***	-0.0647***	-0.0748***	-0.0223***	-0.0508***	-0.0609***	-0.0275***	-0.0746***	-0.0911***	-0.0238***	-0.0639***	-0.0810***
	(-13.8612)	(-18.1136)	(-15.0202)	(-19.5982)	(-21.9285)	(-17.6605)	(-12.4051)	(-17.0759)	(-14.2593)	(-13.2852)	(-21.8351)	(-18.5926)	(-11.4287)	(-18.6369)	(-16.4643)
UE6	0.0440***	0.0402***	0.0657***	0.0428***	0.0389***	0.0642***	0.0435***	0.0397***	0.0650***	0.0506***	0.0445***	0.0859***	0.0499***	0.0445***	0.0872***
	(13.7558)	(12.5842)	(8.3161)	(13.3544)	(12.1449)	(8.1089)	(13.4483)	(12.2903)	(8.1474)	(13.5993)	(11.9961)	(9.3832)	(13.3554)	(11.9452)	(9.4860)
UE6*h			0.0330***			0.0281***			0.0335***			0.0512***			0.0481***
			(3.1892)			(2.7101)			(3.2087)			(4.2698)			(3.9976)
UE6*s			-0.0644***			-0.0619***			-0.0644***			-0.1162***			-0.1148***
			(-6.3750)			(-6.1140)			(-6.3061)			(-9.9190)			(-9.7557)
UE6*Size			-0.0303***			-0.0265**			-0.0307***			-0.0308**			-0.0323**
			(-2.8011)			(-2.4455)			(-2.8105)			(-2.4584)			(-2.5606)
h		0.0236***	0.0070		0.0226***	0.0084		0.0234***	0.0066		0.0351***	0.0094		0.0341***	0.0099
		(7.6756)	(1.2260)		(7.3541)	(1.4690)		(7.5465)	(1.1418)		(9.8511)	(1.4133)		(9.5449)	(1.4791)
s		0.0315***	0.0606***		0.0325***	0.0605***		0.0320***	0.0612***		0.0512***	0.1039***		0.0514***	0.1034***
		(10.1887)	(11.0028)		(10.4933)	(10.9498)		(10.2434)	(10.9771)		(14.3008)	(16.2629)		(14.2922)	(16.1155)
Size		0.0021	0.0157***		0.0047	0.0166***		0.0012	0.0151**		0.0086**	0.0223***		-0.0076**	0.0067
		(.6219)	(2.6436)		(1.4143)	(2.7860)		(.3684)	(2.5110)		(2.2227)	(3.2289)		(-1.9572)	(.9671)
Obs.	22，411	22，411	22，411	22，411	22，411	22，411	22，411	22，411	22，411	22，411	22，411	22，411	22，411	22，411	22，411
Adj. R^2	0.0083	0.0165	0.0188	0.0079	0.0162	0.0183	0.0080	0.0160	0.0183	0.0081	0.0236	0.0285	0.0079	0.0222	0.0269

Panel B: Post Reg FD period															
Variable	**CARv (1)**	**CARv (2)**	**CARv (3)**	**CARe (4)**	**CARe (5)**	**CARe (6)**	**CARsp (7)**	**CARsp (8)**	**CARsp (9)**	**CARszew (10)**	**CARszew (11)**	**CARszew (12)**	**CARszvw (13)**	**CARszvw (14)**	**CARszvw (15)**
Intercept	-0.0208***	-0.0313***	-0.0329***	-0.0259***	-0.0435***	-0.0460***	-0.0170***	-0.0264***	-0.0277***	-0.0108***	-0.0358***	-0.0426***	-0.0066***	-0.0264***	-0.0323***
	(-15.660)	(-14.144)	(-9.8912)	(-19.597)	(-19.801)	(-13.913)	(-12.719)	(-11.840)	(-8.2434)	(-7.1680)	(-14.271)	(-11.292)	(-4.3751)	(-10.455)	(-8.4830)
UE6	0.0461***	0.0458***	0.0491***	0.0446***	0.0439***	0.0490***	0.0463***	0.0461***	0.0486***	0.0087***	0.0077**	0.0214***	0.0081***	0.0075***	0.0192**
	(21.2089)	(21.1033)	(8.9444)	(20.6524)	(20.3520)	(8.9679)	(21.1066)	(21.0346)	(8.7748)	(3.5205)	(3.1287)	(3.4329)	(3.2713)	(3.0178)	(3.0568)
UE6*h			0.0414***			0.0325***			0.0429***			0.0175*			0.0222**
			(5.1407)			(4.0595)			(5.2757)			(1.9125)			(2.4088)
UE6*s			-0.0310***			-0.0266***			-0.0314***			-0.0586***			-0.0585***
			(-4.0665)			(-3.5170)			(-4.0864)			(-6.7752)			(-6.7234)
UE6*Size			-0.0147**			-0.0148**			-0.0140**			0.0092			0.0095
			(-2.1156)			(-2.1393)			(-1.9840)			(1.1694)			(1.1907)
h		0.0184***	-0.0033		0.0202***	0.0032		0.0186***	-0.0038		0.0195***	0.0104*		0.0186***	0.0071
		(7.8302)	(-.6794)		(8.6543)	(.6674)		(7.8345)	(-.7935)		(7.3349)	(1.9172)		(6.9344)	(1.2891)
s		0.0181***	0.0340***		0.0196***	0.0333***		0.0179***	0.0340***		0.0279***	0.0581***		0.0281***	0.0583***
		(7.6776)	(7.4343)		(8.3978)	(7.3269)		(7.5512)	(7.3894)		(10.4462)	(11.2065)		(10.4564)	(11.1714)
Size		-0.0122***	-0.0045		-0.0016	0.0061		-0.0143***	-0.0070		0.0054**	0.0002		-0.0039	-0.0091*
		(-5.4154)	(-1.0488)		(-.7005)	(1.4544)		(-6.3039)	(-1.6282)		(2.1175)	(.0470)		(-1.5169)	(-1.8830)
Obs.	44，293	44，293	44，293	44，293	44，293	44，293	44，293	44，293	44，293	44，293	44，293	44，293	44，293	44，293	44，293
Adj. R^2	0.0100	0.0136	0.0144	0.0095	0.0133	0.0139	0.0099	0.0136	0.0145	0.0003	0.0048	0.0057	0.0002	0.0043	0.0053

Panel C: Coefficients Z-Score Comparison (After - Before)						
Variable	**Test**	CARv	CARe	CARsp	CARszew	CARszvw
UE6*h	**Za-b**	0.6433	0.3364	0.7047	-2.2360	-1.7129
	(p-value)	(.2600)	(.3683)	(.2405)	(.9873)	(.9566)
UE6*s	**Za-b**	2.6417	2.7911	2.5817	3.9579	3.8424
	(p-value)	(.0041)	(.0026)	(.0049)	(.0000)	(.0001)

Table 2.7 Additional Control Variables

This table presents coefficient estimates of regression equation (3) with *t*-statistics in parentheses. The dependent variable is the 60 trading-day risk-adjusted cumulative abnormal returns (CARR). The explanatory variables are quarterly earnings surprise (UE6), precision of public information (h), the precision of private information (s), and firm size (Size), and interaction terms between earnings surprise with public information precision (UE 6*h), with private information precision (UE6*s), and with firm size (UE 6*Size). The additional control variables are number of analysts following (Nr), mean turnover ratio (Volr), 6-month compound return (CompRetr), sign of quarterly earnings surprise (sign), and earnings persistence (EPr). The interaction terms between earnings surprise with each of these control variables are also included in the regression: UE6*Nr, UE6*Volr, UE6*CompRetr, UE6*sign, and UE6*EPr. Refer to Appendix A for detailed definitions of variables. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Variable	**CARRv (1)**	**CARRv (2)**	**CARRe (3)**	**CARRe (4)**	**CARRsp (5)**	**CARRsp (6)**	**CARRszew (7)**	**CARRszew (8)**	**CARRszvw (9)**	**CARRszvw (10)**
Intercept	-0.0254***	-0.0311***	-0.0426***	-0.0351***	-0.0231***	-0.0302***	-0.0392***	-0.0352***	-0.0272***	-0.0323***
	(-5.3101)	(-7.5261)	(-8.6016)	(-8.2102)	(-4.7572)	(-7.1994)	(-8.3354)	(-8.6636)	(-5.7641)	(-7.9207)
Ue6	-0.0950***	-0.0925***	-0.0474***	-0.0447***	-0.1008***	-0.0979***	-0.0747***	-0.0726***	-0.0852***	-0.0821***
	(-7.5620)	(-7.7235)	(-3.6377)	(-3.6026)	(-7.9100)	(-8.0501)	(-6.0462)	(-6.1601)	(-6.8621)	(-6.9327)
UE6*h	0.0206**	0.0202**	0.0091	0.0088	0.0226***	0.0222***	0.0182**	0.0179**	0.0181**	0.0179**
	(2.4699)	(2.4323)	(1.0507)	(1.0199)	(2.6746)	(2.6347)	(2.2276)	(2.1827)	(2.2000)	(2.1737)
UE6*s	-0.0943***	-0.0939***	-0.0868***	-0.0873***	-0.0960***	-0.0953***	-0.0875***	-0.0876***	-0.0879***	-0.0880***
	(-11.8913)	(-11.8550)	(-10.5546)	(-10.6314)	(-11.9139)	(-11.8496)	(-11.2085)	(-11.2488)	(-11.2049)	(-11.2382)
UE6*Size	-0.0484***	-0.0542***	-0.0295***	-0.0344***	-0.0491***	-0.0547***	-0.0437***	-0.0497***	-0.0407***	-0.0477***
	(-5.7788)	(-6.5060)	(-3.3957)	(-3.9780)	(-5.7816)	(-6.4584)	(-5.3043)	(-6.0611)	(-4.9098)	(-5.7819)
UE6*Nr	0.0311***		0.0210**		0.0321***		0.0212**		0.0261***	
	(3.6949)		(2.4062)		(3.7599)		(2.5678)		(3.1407)	
UE6*Volr	-0.0295***		-0.0358***		-0.0280***		-0.0257***		-0.0318***	
	(-3.9945)		(-4.6859)		(-3.7366)		(-3.5385)		(-4.3552)	
UE6*CompRetr	0.0211***		0.0229***		0.0231***		0.0217***		0.0232***	
	(2.9004)		(3.0403)		(3.1245)		(3.0270)		(3.2222)	
UE6*Sign	0.2156***	0.2141***	0.1506***	0.1499***	0.2202***	0.2191***	0.1922***	0.1919***	0.2006***	0.1991***
	(16.5920)	(16.5469)	(11.1839)	(11.1743)	(16.6972)	(16.6743)	(15.0404)	(15.0762)	(15.6067)	(15.5586)
UE6*EPr	0.0098**	0.0103**	0.0125**	0.0136***	0.0095*	0.0100**	0.0068	0.0075	0.0066	0.0072
	(2.0245)	(2.1269)	(2.4853)	(2.6939)	(1.9295)	(2.0321)	(1.4334)	(1.5790)	(1.3764)	(1.4962)
h	0.0116**	0.0111**	0.0131***	0.0123**	0.0126**	0.0120**	0.0121**	0.0114**	0.0129***	0.0123***
	(2.4070)	(2.2895)	(2.6084)	(2.4481)	(2.5673)	(2.4562)	(2.5378)	(2.3913)	(2.7024)	(2.5744)
s	0.0926***	0.0921***	0.0791***	0.0785***	0.0958***	0.0954***	0.0870***	0.0866***	0.0884***	0.0881***
	(20.1321)	(20.0802)	(16.6004)	(16.4980)	(20.5302)	(20.4822)	(19.2444)	(19.2005)	(19.4407)	(19.4178)
Size	0.0220***	0.0247***	0.0194***	0.0215***	0.0189***	0.0217***	0.0197***	0.0223***	0.0171***	0.0201***
	(4.3853)	(4.9619)	(3.7366)	(4.1700)	(3.7146)	(4.2862)	(3.9972)	(4.5632)	(3.4477)	(4.0874)
Nr	-0.0041		-0.0084		-0.0029		-0.0006		-0.0022	
	(-.8319)		(-1.6361)		(-.5709)		(-.1214)		(-.4436)	
Volr	-0.0277***		-0.0231***		-0.0299***		-0.0254***		-0.0247***	
	(-6.3536)		(-5.1030)		(-6.7622)		(-5.9094)		(-5.7242)	
CompRetr	-0.0211***		0.0070		-0.0240***		-0.0011		-0.0215***	
	(-4.7222)		(1.5106)		(-5.3043)		(-.2611)		(-4.8629)	
Sign	-0.0758***	-0.0750***	-0.0568***	-0.0560***	-0.0763***	-0.0757***	-0.0706***	-0.0701***	-0.0715***	-0.0706***
	(-17.6240)	(-17.5325)	(-12.7347)	(-12.6255)	(-17.4791)	(-17.4240)	(-16.6831)	(-16.6574)	(-16.8076)	(-16.6905)
EPr	-0.0149***	-0.0169***	-0.0091***	-0.0112***	-0.0163***	-0.0183***	-0.0104***	-0.0122***	-0.0115***	-0.0135***
	(-5.0913)	(-5.7715)	(-3.0151)	(-3.6818)	(-5.4781)	(-6.1570)	(-3.6149)	(-4.2578)	(-3.9672)	(-4.6673)
UE6*N		0.0031***		0.0025**		0.0032***		0.0028***		0.0030***
		(4.2692)		(3.2889)		(4.2359)		(3.8484)		(4.1239)
UE6*Vol%		-0.0042*		-0.0086***		-0.0032		-0.0053**		-0.0058***
		(-1.8487)		(-3.7000)		(-1.4094)		(-2.3964)		(-2.6239)
UE6*CompRet		0.0391***		0.0283***		0.0415***		0.0331***		0.0397***
		(5.8732)		(4.1032)		(6.1440)		(5.0597)		(6.0277)
N		-0.0008*		-0.0010**		-0.0008*		-0.0006		-0.0007*
		(-1.9363)		(-2.2928)		(-1.7449)		(-1.3613)		(-1.7417)
Vol%		-1.4707***		-1.3700***		-1.5373***		-1.3584***		-1.3726***
		(-10.7129)		(-9.6288)		(-11.0310)		(-10.0628)		(-10.1104)
CompRet		-0.0335***		-0.0018		-0.0364***		-0.0093**		-0.0340***
		(-7.8594)		(-.3962)		(-8.4013)		(-2.2063)		(-8.0484)
Observations	70，116	70，116	70，116	70，116	70，116	70，116	70，116	70，116	70，116	70，116
Adj. R^2	0.0187	0.0215	0.0135	0.0165	0.0199	0.0225	0.0169	0.0198	0.0174	0.0206

Table 2.8 Pre- and Post- Reg FD Sub-Period with Additional Control Variables

This table presents regression results of equation (3) for the pre-Reg FD sub-period (Panel A) and post-Reg FD sub-period (Panel B). The dependent variable is the 60 trading days' risk-adjusted cumulative abnormal returns (CARR). The explanatory variables are quarterly earnings surprise (UE6), precision of public information (h), the precision of private information (s), and firm size (Size), and interaction terms between earnings surprise with public information precision (UE6*h), with private information precision (UE6*s), and with firm size (UE6*size). The additional control variables are number of analysts following (Nr), mean turnover ratio (Volr), 6-month compound return (CompRetr), sign of quarterly earnings surprise (Sign), and earnings persistence (EPr). The interaction terms between earnings surprise with each of these control variables are also included in the regression: UE6*Nr, UE6*Volr, UE6*CompRetr, UE6*Sign, and UE6*EPr. Panel C presents the Z-scores for the difference in coefficient between the two sub-periods. Refer to section 6.3.2 for details on Z-score calculation and Appendix A for detailed definitions of variables. *T-statistics* are in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Panel A: Pre-Reg FD Period

Variable	CARRv (1)	CARRv (2)	CARRe (3)	CARRe (4)	CARRsp (5)	CARRsp (6)	CARRszew (7)	CARRszew (8)	CARRszvw (9)	CARRszvw (10)
Intercept	-0.0316***	-0.0459***	-0.0395***	-0.0469***	-0.0272***	-0.0453***	-0.0383***	-0.0475***	-0.0290***	-0.0425***
	(-4.1759)	(-6.7876)	(-4.9591)	(-6.5756)	(-3.5316)	(-6.5627)	(-5.1553)	(-7.1477)	(-3.8919)	(-6.3713)
UE6	-0.1283***	-0.0993***	-0.0816***	-0.0485**	-0.1363***	-0.1078***	-0.1028***	-0.0720***	-0.1146***	-0.0838***
	(-6.0931)	(-4.8304)	(-3.6724)	(-2.2353)	(-6.3507)	(-5.1395)	(-4.9667)	(-3.5627)	(-5.5171)	(-4.1295)
UE6*h	0.0191	0.0151	0.0196	0.0176	0.0199	0.0156	0.0240*	0.0209	0.0189	0.0157
	(1.3841)	(1.0940)	(1.3432)	(1.2085)	(1.4146)	(1.1081)	(1.7668)	(1.5440)	(1.3895)	(1.1552)
UE6*s	-0.1334***	-0.1325***	-0.1208***	-0.1200***	-0.1360***	-0.1351***	-0.1194***	-0.1187***	-0.1183***	-0.1177***
	(-9.9515)	(-9.9098)	(-8.5446)	(-8.5104)	(-9.9460)	(-9.9101)	(-9.0571)	(-9.0330)	(-8.9421)	(-8.9235)
UE6*size	-0.0483***	-0.0483***	-0.0370**	-0.0354**	-0.0471***	-0.0480***	-0.0469***	-0.0464***	-0.0360**	-0.0358**
	(-2.9951)	(-3.0525)	(-2.1729)	(-2.1204)	(-2.8647)	(-2.9773)	(-2.9562)	(-2.9817)	(-2.2640)	(-2.2951)
UE6*Nr	0.0548***		0.0377**		0.0557***		0.0370**		0.0421***	
	(3.5633)		(2.3222)		(3.5541)		(2.4467)		(2.7763)	
UE6*Volr	0.0497***		0.0203		0.0585***		0.0482***		0.0351**	
	(3.3017)		(1.2812)		(3.8112)		(3.2579)		(2.3635)	
UE6*CompRetr	0.0361***		0.0516***		0.0341**		0.0446***		0.0412***	
	(2.6363)		(3.5716)		(2.4397)		(3.3101)		(3.0517)	
UE6*Sign	0.2615***	0.2523***	0.1990***	0.1912***	0.2672***	0.2577***	0.2261***	0.2169***	0.2389***	0.2286***
	(11.8560)	(11.4462)	(8.5525)	(8.2273)	(11.8831)	(11.4670)	(10.4292)	(10.0161)	(10.9775)	(10.5165)
UE6*EPr	0.0066	0.0068	0.0097	0.0103	0.0075	0.0077	0.0029	0.0031	0.0053	0.0053
	(.7769)	(.8051)	(1.0859)	(1.1466)	(.8650)	(.8827)	(.3438)	(.3708)	(.6354)	(.6301)
h	0.0137*	0.0150**	0.0101	0.0110	0.0149*	0.0163**	0.0104	0.0113	0.0117	0.0127*
	(1.8014)	(1.9779)	(1.2664)	(1.3707)	(1.9270)	(2.1120)	(1.3998)	(1.5137)	(1.5584)	(1.6904)
s	0.1226***	0.1226***	0.1081***	0.1079***	0.1261***	0.1260***	0.1109***	0.1108***	0.1107***	0.1105***
	(16.8668)	(16.9008)	(14.0982)	(14.1037)	(17.0065)	(17.0357)	(15.5189)	(15.5423)	(15.4229)	(15.4402)
Size	0.0204**	0.0223**	0.0164*	0.0171*	0.0197**	0.0216**	0.0223**	0.0223**	0.0149*	0.0150*
	(2.2816)	(2.5308)	(1.7413)	(1.8463)	(2.1642)	(2.4106)	(2.5365)	(2.5740)	(1.6954)	(1.7321)
Nr	-0.0139*		-0.0157*		-0.0139		-0.0079		-0.0103	
	(-1.6567)		(-1.7677)		(-1.6177)		(-.9553)		(-1.2434)	
Volr	-0.0744***		-0.0541***		-0.0762***		-0.0604***		-0.0588***	
	(-8.8706)		(-6.1243)		(-8.9186)		(-7.3293)		(-7.1105)	
CompRetr	-0.0169**		-0.0079		-0.0241***		-0.0112		-0.0196**	
	(-2.1292)		(-.9414)		(-2.9887)		(-1.4338)		(-2.5079)	
Sign	-0.0946***	-0.0923***	-0.0828***	-0.0804***	-0.0928***	-0.0905***	-0.0870***	-0.0842***	-0.0911***	-0.0880***
	(-12.0613)	(-11.7945)	(-10.0111)	(-9.7425)	(-11.6084)	(-11.3398)	(-11.2848)	(-10.9590)	(-11.7645)	(-11.3937)
EPr	-0.0228***	-0.0241***	-0.0166***	-0.0178***	-0.0258***	-0.0271***	-0.0180***	-0.0190***	-0.0188***	-0.0199***
	(-4.7712)	(-5.0367)	(-3.2957)	(-3.5188)	(-5.2867)	(-5.5458)	(-3.8249)	(-4.0458)	(-3.9773)	(-4.2099)
UE6*N		0.0051***		0.0035**		0.0052***		0.0036**		0.0039**
		(3.1466)		(2.0738)		(3.1534)		(2.2612)		(2.4578)
UE6*Vol%		0.0177***		0.0028		0.0221***		0.0154***		0.0101*
		(2.9014)		(.4311)		(3.5581)		(2.5768)		(1.6738)
UE6*CompRet		0.0522***		0.0560***		0.0527***		0.0559***		0.0562***
		(4.0490)		(4.1214)		(4.0103)		(4.4163)		(4.4175)
N		-0.0009		-0.0013		-0.0008		-0.0003		-0.0005
		(-1.0358)		(-1.4100)		(-.9542)		(-.4068)		(-.6349)
Vol%		-2.9706***		-2.2523***		-3.0278***		-2.5010***		-2.4231***
		(-9.0102)		(-6.4798)		(-9.0061)		(-7.7216)		(-7.4507)
CompRet		-0.0186**		-0.0073		-0.0265***		-0.0095		-0.0198**
		(-2.3183)		(-.8618)		(-3.2328)		(-1.1992)		(-2.5027)
Observation	20，499	20，499	20，499	20，499	20，499	20，499	20，499	20，499	20，499	20，499
Adj. R^2	0.0383	0.0396	0.0260	0.0281	0.0384	0.0391	0.0324	0.0347	0.0313	0.0332

Chapter 3: How Does Asymmetrical Learning in Bad Time Affect Analysts' Decision on Following a Firm?

3.1 Introduction

In the study, I examine whether professional market participants such as financial analysts suffer from pessimistic bias defined by Kuhnen (2015) in estimating the actual distribution of firm value after observing negative events during on-going economic conditions. Kuhnen (2015) argues that pessimistic bias results in a further deviation from Bayesian rules in processing information, in addition to the deviation caused by loss-aversion mentioned by Kahneman and Tversky (1979), and a domain-specific impact on forming beliefs of the future.

As a group of major players in the equity market, financial analysts preserve their importance by the widely held belief that they do a better job in forecasting earnings than a univariate time-series model (Brown and Rozeff, 1978; Collins and Hopwood, 1980; and Brown, Hagerman, Griffin, and Zmijewski, 1987). However, neuroscience shows that human brains follow a different process when facing good outcomes than when facing bad ones. (Kuhnen and Knutson, 2005; Eppinger, Herbert, and Kray, 2010; Sokol-Hessener, Camerer, and Phelps, 2012). Capital market evidence shows that market learning environment is affected by contemporary economic conditions. For instance, observing negative outcomes affect market beliefs regarding future performance significantly when estimating the true distribution of firm value (Andersen et al., 2007; Bollerslev and Todorove, 2011; and Ben-David, Graham, and Harvey, 2013). Kuhnen (2015) refers to the bias in forming belief due to the observation of continuous negative outcomes as asymmetric learning.

The asymmetric learning is different from loss-aversion proposed by Kahneman and Tversky (1979). Kahneman and Tversky (1979) show that people's different attitudes toward gain

or loss help form their valuation function of investment. Asymmetric learning suggests the valuation function developed in bad times can be different from the valuation function developed by the same person in good times. Kuhnen (2015) indicates that the investors' pessimistic bias during a bad state of economy would result in a further departure from Bayesian learning when processing new information and estimating the true distribution of firm value, compared to a good state of economy. Kuhnen (2015) helps explain investment activities during bad domains and has implications for market efficiency in incorporating new information into price.

This essay examines the implication of Kuhnen (2015) by exploring whether the professionals such as financial analysts, who have limited or no direct investment in stocks they analyze, are subject to the asymmetric learning process. This study focuses on two major activities financial analysts perform in the capital market: deciding whether to follow a firm and making accurate earnings forecasts.

The determinants of analysts following have been well explored. The literature originates from one stream of researches that examines the reasons that information contents of earnings announcements vary cross-sectionally. The researchers find that the earnings announcements informativeness and firm size are inversely related (Atiase, 1985; Freeman, 1987; and Bhushan, 1989a). Researchers attribute the inverse relationship to the number of analyst following as financial analysts often serve the role of information intermediary. Those studies argue that the inverse relationship between firm size and informativeness of firm's earnings announcements is due to larger firms attracting analyst coverage and information acquisition activities (Collins, Kothari, and Rayburn, 1987; Freeman, 1987). Bhushan (1989b) argues that firms with high level of analyst following experience relative more private information acquisition activities, resulting

in the superiority of analyst forecasts over time-series models in forecasting earnings of those firms and a reduction of informativeness of earnings announcements of these firms.

The number of analyst following or analyst coverage on firms not only relates to forecasting accuracy but also relates to firm value. Prior literature shows that financial analysts, when serving as information intermediary in the stock market, could decrease information asymmetry between firms and investors, prompt market efficiency in adjusting the price to new information and affect firm value. (Kyle, 1985; Admati and Pfleiderer, 1988; Brennan and Subrahmanyam, 1995; Chung and Jo, 1996; and Schutte and Unlu, 2009). Financial analysts also affect firm value through its monitoring ability. Prior literature finds that analysts' information acquisition activities reduce agency cost by uncovering management's misuse of a firm's assets and boosting the firm's asset utilization efficiency (Jensen and Meckling, 1976; Healy and Palepu, 2001; Yu, 2008; and Jung, and Sun and Yang, 2012). Permanently losing analysts' interest is shown to be associated with increased cost of capital and decreased future performance (Zuckerman, 1999; and Gomes, Gorton, and Madureira, 2007). Managers deem the analyst following as a critical factor in making decisions such as the level of information contained in management disclosure, and timing to issue equity (Eng and Teo, 1999; Chang, Dasgupta, and Hilary, 2006; and Bowen, Chen, and Cheng, 2008).

The critical role of financial analysts makes the literature of determinants of analyst coverage relevant. Early researchers on the determinants of analyst coverage describe the number of analyst following as an equilibrium condition between the demand for and supply of financial analyst services. The demand and supply are affected by the cost and benefit of providing analysts services (Bhushan, 1989b). As the cost and benefit of providing analysts services are not directly measurable, researchers propose to use observable firm characteristics to assess the cost and

benefit of providing analysts services to an individual firm (Bhushan, 1989b; O'Brien and Bhushan, 1990; and Shores, 1990).

In this study, I explore the determinants of analyst following by understanding whether demand for and supply of financial analysts' services are different between the good state of the economy and the bad state of the economy, and whether analysts have a bias in estimating the true value of the firm in a bad state of the economy. Answering these questions could shed light to the usefulness of financial forecasts, market pricing dynamic, and market efficiency. I use previously identified firm characteristics that are shown to affect the number of analyst following in the examination. Those firm characteristics, first proposed by O'Brien and Bhushan (1990), are firm size, shares outstanding, firm's systematic risk (Beta), stock return volatility, price momentum, and cumulative 5-year change of numbers of firms in a 3-digits SIC industry.

I examine whether the impacts of those characteristics on the number of analysts following changes from good times to bad times. During bad times, analysts affected by pessimistic bias may have pessimistic expectations on the reliability of demand/ supply implications contained in firm characteristics and underestimate the probability of getting rewards (commission) for providing services. As a result, analysts are likely to follow firms that they think are rewardable (even better firms). I hence expect that the impacts of firm characteristics on analyst following reduce in dad times. It is possible that analysts may not be able to fully and promptly recognize the impact of the bad outcomes (poor stock market performance, pessimistic press coverage) during the recession. I hence examine the determinants of analyst following in the post-bad period to explore whether analysts adjust their negative bias in the later period after they have experienced a bad time.

I then examine whether pessimistic bias is reflected in the signed analyst forecast errors. I use the method developed by Doukas, Kim, and Pantzalis (2005) to construct a measure for the

excess number of analyst following for each firm-year in good time and bad time and use it to proxy for analysts' perspective on a firm. A positive excess number of analyst following indicates that analysts are optimistic regarding the firm's performance in the future. Das, Guo, and Zhang (2006) propose that the decision of analysts to follow a firm represents their perspective on the firm's future. Analysts follow firms that they believe to have good performance in the future. Das, Guo, and Zhang (2006) show that IPO firms with an abnormally high number of analyst following tend to have favorable long-term holding abnormal returns after IPO. Doukas, Kim, and Pantzalis (2005) find that firms with an abnormally high number of analyst following have higher firm value.

I divide all firm-years in good time into three similar-sized portfolios based on the magnitude of excess analyst following (low, middle, and high). I refer these portfolios as excess analyst following portfolios. Similarly, I construct three excess analyst following portfolios for the bad time. I calculate analyst earnings forecasts errors for each firm-year in each corresponding analyst following portfolio. I then compare forecast errors across the good and bad domains for each excess analyst following group (high-to-high, middle-to-middle, low-to-low) to examine how optimism or pessimism varies across good time and bad time. I use forecast errors to measure analyst optimism or pessimism (Butler and Lang, 1991; and Easterwood and Nutt, 1999). To further examine the effect of analysts' pessimistic bias, I compare the forecast errors one period after the recession (i.e. the post-bad domain) with the forecast errors one period after a non-recession period (i.e. the post-good domain).

I find that analysts are less sensitive to firm size, shares outstanding, stock volatility, and prior stock performance, and are more sensitive to risk and industry switching during the periods of recession. Observation of recession results in analysts being less sensitive to firm size, shares outstanding, stock volatility and more sensitive to prior stock performance. The results shows that

analysts do suffer from pessimistic bias after observing negative outcomes during bad times, and the impact continues even after bad times. Moreover, analysts generally fail to fully incorporate the information of recession and tend not adjust their forecasts accordingly, which results in a more substantial forecast error during the bad domain. I do find evidence of pessimistic bias in the recession observation sample (i.e. the post-bad domain) as forecast errors are less negative during post-bad domain. The results are consistent with the implication of Kuhnen (2015) that analysts do suffer from pessimistic bias when valuing a firm after observing negative outcomes.

This study contributes to the behavioral finance literature by showing that professional market participants such as financial analysts do suffer from pessimistic bias. The pessimistic bias affects the formation of analysts' beliefs and their expectation of firms. This study also contributes to the literature of asymmetrical learning by providing empirical evidence for the implication in Kuhnen (2015), who explores how bad times contribute to the market participants' behavior. The effect of asymmetrical learning is complementary to the effect of loss-aversion proposed in Kahneman and Tversky (1979). The topic of loss-aversion has been extensively explored and the effect of bad times on investors as well as company executives have also been explored. My research differential from prior research as I focus on market participants that do not have a direct stake in firms in discussion. The study helps understand the market dynamics and the capital market learning process. Moreover, this study contributes to the literature of the efficiency of financial analysts by providing additional evidence that financial analysts fail to fully incorporate the impact of recession into their forecasts during recession.

The rest of the paper is organized as follows. Section 3.2 discusses the related literature and section 3.3 develop the hypotheses. Sample construction and variable development are in

section 3.4. Section 3.5 outlines the empirical test methods, and section 3.6 discusses the empirical results. Extra tests are presented in section 3.7. Section 3.8 concludes the paper.

3.2 Literature Review

3.2.1 Value of financial analyst coverage

3.2.1.1 Information intermediary role and monitoring role of financial analysts

The prior literature identifies two roles served by financial analysts: information intermediary role and monitoring role. The most commonly recognized role is information intermediary. That is, financial analysts acquire information of the firm and deliver information to investors and affect the price discovery. Analysts' efforts on information acquisition also play a monitoring role, reducing the agency problem. Financial analysts affect firm value via these two roles. Therefore, analysts' decision on following or stopping following a firm has real consequences.

Information intermediary role

Financial analysts serve as information intermediaries between firms and investors by conveying information to the public. Those activities improve the information environment, increase market efficiency and influence stock value. Lys and Soo (1995) document that analyst' earnings forecast accuracy increases with analyst following, suggesting that analyst following associates positively with the information environment. Brennan and Subrahmanyam (1995) find that more analyst followings reduces the information asymmetry level between informed traders and liquidity traders, hence the adverse selection cost of a security transaction. As higher adverse selection cost of security transaction implies lower liquidity or trading volume in the market (Kyle, 1985), financial analysts help improve the liquidity in the market.

Analyst coverage on a firm affects the firm's cost of capital. Bowen, Chen, and Cheng (2008) examine whether analyst coverage would affect the cost of capital in a context of seasoned equity offering (SEO) event. They argue that SEO underpricing or discount could be due to information asymmetry between the firm and market, and is a clean measure of the cost of capital. They document that higher level of analyst following is associated with reduced SEO underpricing, consistent with prior literature that analyst coverage reduces information asymmetry among investors, hence the cost of equity. Analysts also benefit firm through their effect on reducing default risk. Cheng and Subramanyam (2008) find that higher level of analyst following is associated with lower default risk (proxied by firm's credit rating) and that the association is more pronounced for firms with unfavorable information environment and weak corporate controls.

Analyst coverage also affects firm value. Chung and Jo (1996) argue that the number of analyst following exerts a significant and positive impact on a firm's market value of equity. Hong, Lim, and Stein (2000) find that a momentum strategy (buying stocks with high prior returns and selling stocks with low prior returns) produces higher abnormal returns for firms with low analyst coverage, controlling for firm size. They argue that the outperformance of momentum strategy on firms with low analyst coverage is due to the deterioration of a firm's information environment, suggesting an intermediary information role of financial analysts. Chan and Hameed (2006) find that higher analyst coverage leads to higher market information incorporation in emerging markets and that greater analyst coverage increases stock price synchronicity. Schutte and Unlu (2009) investigate the role of security analysts in reducing noise in stock price fluctuations. Using a sample of analyst coverage initiations between 1984 and 2006, they find that analyst coverage leads to less noisy price. Brennan, Jegadeesh, and Swaminathan (1993) document that higher level

of analyst following leads to a faster price adjustment to new information and that the speed of adjustment increases at an increasing rate as the level of analyst following increases.

Monitoring role

The monitoring role of analysts is first proposed by Jensen and Meckling (1976). They argue that financial analysts' information acquisition and processing activities help reduce agency costs between shareholders and management. Doukas, Kim, and Pantzalis (2000) further examine the monitoring role of security analysts from the perspective of manager-shareholder conflicts. They show that security analysis activities conducted by financial analysts reduce the agency costs between shareholders and management, confirming the argument by Jensen and Meckling (1976). Yu (2008) shows that a higher number of analyst following decreases the earnings management and that the effect is stronger if analysts come from top brokers and if they are more experienced.

The monitoring function of analysts affects the firm value and cost of capital of the firm. Jung, Sun, and Yang (2012) argue that the monitoring role of financial analysts would increase firm value by reducing agency costs for firms. They examine the association between analyst following and the firm's market value and find a positive relationship between the two. They argue their results are consistent with the monitoring role of financial analysts in reducing agency costs and increase shareholder value. Jung, Sun and Yang (2012) find that the monitoring effects are true on assets with higher agency costs or information asymmetry level, such as cash, and on preventing assets mismanagement or prompting asset utilization efficiencies, such as increases in operating performance and cash payout.

Analysts also provide a crucial role in monitoring important firm activities. Chen, Harford, and Lin (2012) examine the monitoring role of analysts under two exogenous shocks: broker closure and mergers. They find that financial analysts play an important governance role in

monitoring management behaviors. Moreover, they find that market expects an increase in expected agency problems (inappropriate management compensation and earnings management) after the loss in analyst coverage and a discount in stock price.

3.2.1.2 Management view on financial analyst coverage

Managers recognize the importance of financial analysts when making decisions. Baginski and Hassell (1997) examine the determinants of management forecast precision (whether the managerial forecast is in the format of point forecasts, range forecast, max/ min value forecast or merely qualitative forecast). Baginski and Hassell (1997) find that after controlling for firm-specific and horizon-specific earnings uncertainty, managers of firms with a higher number of analyst following produce more precise forecasts of annual earnings. Eng and Teo (1999) document that the number of analyst following associates positively with the level of annual report disclosure. Chang, Dasgupta, and Hilary (2006) examine how analyst coverage affects security issuance. They find that firms covered by fewer analysts are less likely to issue equity as opposed to debt, and issue equity at a lower frequency but more substantial amounts. In addition, firms with less analyst following are more likely to time the market when issuing equity.

Management decisions and analyst following could affect each other. Hong, Huseynov, and Zhang (2014) argue that analysts' decisions to follow firms are jointly determined with managerial decisions to manage earnings. They find that lower accrual-based earnings management leads to better information environment, which attracts more analysts to follow the firm. Analyst following has monitoring effects on managerial behaviors and is inversely related to the level of both accrual-based and real earnings management.

3.2.1.3 Consequences for completely losing analyst coverage

Several studies focus on the consequence for a firm losing the attention of analysts. Zuckerman (1999) finds that failing to gain analyst coverage decreases firm value. Gomes, Gorton, and Medureira (2007) find that the cost of capital increases for small firms when analysts shift attention. Mola, Rau, and Khorana (2012) examine long-term consequences of a complete and permanent loss in analyst coverage for a firm. They find that in the years after the loss of coverage, the firms are more likely to perform poorly and get delisted relative to a matched sample that is constructed based on the propensity for bankruptcy and potential to generate brokerage revenues.

3.2.2 Determinants of financial analyst following

Due to the crucial role of financial analyst following in producing information and in affecting firm value and managerial decisions, it is crucial to examine how financial analysts make their decision in following a firm. Bhushan (1989b) proposes a model that describes the equilibrium amount of service provided by analysts for a firm, proxies by the number of analyst following. Bhushan (1989b) argues that the equilibrium depends on the demand for and supply of analyst services as well as the cost and benefits influence demand for and supply of analyst services.

3.2.2.1 Cost and benefit for providing analyst services

High level of the financial analyst following decreases information asymmetry and increases the liquidity of the market. The reduced information asymmetry and increased liquidity of market could prompt trading volume (Kyle, 1985; Glosten and Milgrom, 1985; Admati and Pfleiderer, 1988). Analysts benefit from the increased trading volume as the commission is based on trading volume. However, financial analysts do not follow a firm free of charge. Resources are used, or costs are incurred to acquire and process price-related information (for example, managers'

misuse of the firm resource (Healy and Palepu, 2001), industrial expertise (Kadan, Madureira, Wang and Zach, 2012) when analysts follow a firm). As a result, the supply of service provided by financial analysts is determined at least partially by costs and incentives for them to acquire information. As it is impossible to direct measure cost and benefit for analysts to following a firm, researchers use proxies for benefit and cost of following and examine how financial analysts make decisions on following a firm.

3.2.2.2 Firm characteristics affecting demand and supply of analyst services

The argument of cost and benefit

Firm size is usually deemed an important determinant of analysts' decision to follow a firm (Bhushan, 1989b; and Shores, 1990). However, researchers continue to search other factors that could affect the cost and benefit for analysts to acquire information about a firm or follow a firm. Bhushan (1989b) considers several firm characteristics that could affect the demand and supply in addition to firm size. He finds that ownership structure of the firm (number of institutions, institutional ownership), firm's return variability, firm size, and the correlation between firm returns and market returns (market model R-square) are positively correlated with the level of analyst following for a firm. Moreover, insider ownership and business diversity (number of lines of business) are negatively associated with the number of analyst following. Baik, Kang, and Morton (2010) further examine the negative relationship between managerial ownership and analyst coverage. They find that greater managerial ownership result in greater agency problem and that agency problem contributes to less information disclosure and more impoverished information environment, which discourages analyst following.

Continue with Bhushan (1989b), O'Brien and Bhushan (1990) argue that an analyst's decision to follow a firm should be considered simultaneously with institutional investors' decision

to hold a firm. In addition, O'Brien and Bhushan (1990) hypothesize that analysts consider cost and benefit from information acquisition when those analysts make decisions of following. According to the hypothesis, analysts would maximize their potential reward by avoiding competition with other analysts and finding firms with higher potential trading volume generated. Moreover, analysts would minimize their cost by finding firms with relatively stable earnings, firms that provide more information beyond required by generally accepted accounting principles (GAAP), and industries with increasing numbers of similar firms, which means those analysts can apply similar information to all firm in the industry. O'Brien and Bhushan (1990) find firms experience an increasing number of analyst following if the firms are with prior low analyst following, with declining return volatility, in industries with regulated disclosures, or in industries with an increasing number of firms. O'Brien and Bhushan (1990) argue that the results are consistent with their hypothesis that analysts make a trade-off between costs and benefits.

Continued research on cost and benefit argument

Consistent with the cost and benefit argument, Brennan and Hughes (1991) find that the number of analyst following relates inversely to the share price. Brennan and Hughes (1991) argue that the brokerage commission rate on share price provides an incentive for brokers to produce research reports on the firm with low share prices. Alford and Berger (1999) use a simultaneous equations model to study relationships among forecast accuracy, analyst following, and trading volume. Their results show that forecast accuracy and analyst following are determined simultaneously, with higher accuracy associated with the higher following. Moreover, stocks that generate more trading volumes (a proxy for brokerage commissions) have higher analyst following. Using econometric models based on count distributions, Rock, Sedo, and Willenborg (2000) find that the number of institutional investors is inversely related with analyst following. Hameed,

Morck, Shen, and Yeung (2015) confirm the cost and benefit argument of O'Brien and Bhushan (1990). Hameed, Morck, Shen, and Yeung (2015) find that analysts are more likely to follow firms whose fundamental are like those of their industry peers. That is, information could have a similar impact on those similar firms. The authors argue that the coverage pattern supports the argument that profit-maximizing information intermediaries prefer to produce information that could help price many stocks.

3.2.2.3 Information environment on demand for and supply of analyst services

Firm disclosure

In addition to firm fundamentals, the firm's information environment affects the demand for and supply of analyst services, i.e., analyst following. Lang and Lundholm (1996) examine the association among firm disclosure level, analyst following, and analyst characteristics such as analysts forecast accuracy, forecast dispersion and volatility in forecast revisions. They find, with proper control variables, that higher firm disclose rating from the Report of the Financial Analysts Federation Corporation Information Committee is associated with higher number of analyst following, higher analyst earnings forecast accuracy, and less dispersion among individual analyst forecasts and less volatility in forecast revisions. Francis, Hanna, and Philbrick (1997) also examine the benefits from communication to securities analysts at corporate presentations. They find that excellent communication at presentation significantly increases in analyst following. Lehavy, Li, and Merkley (2011) find that firms with less readable 10-k filings result in higher analyst following, and more efforts devoted by analysts to generate analysts' reports, and greater informativeness of analysts' reports. Moreover, Lehavy, Li, and Merkley (2011) find that low readability of 10-k is also associated with greater forecast dispersion, lower forecast accuracy and greater overall uncertainty in analyst earnings forecasts. De Franco, Kothari, and Verdi (2011)

develop a measure of financial statement comparability. They find that their measure is positively associated with analyst following and forecasts accuracy, and is negatively related to dispersion in earnings forecasts. Their results suggest that financial statement comparability lowers the cost of acquiring information, and increases the overall quantity and quality of information available to analysts about the firm.

Information asymmetry

There is more evidence that analysts tend to follow firms when information asymmetry level is high. Gilson, Healey, Noe, and Palepu (2001) examine firm stocks generated through spin-offs, equity carve-outs, and targeted stock offering. They find that after these transactions, these newly-independent firms experience a significant increase in coverage by analysts that specialize in subsidiary firms' industries and a 30%-to-50% increase in analyst forecast accuracy for parent and subsidiary firms. Lobo, Song, and Stanford (2012) examine the association between analyst coverage and accruals quality and find that analyst coverage increases as accruals quality decreases. Lobo, Song, and Stanford (2012) argue that their result is consistent with the argument that the services of financial analysts become more valuable and in higher demand when accruals provide weaker signals about future cash flow.

3.2.2.4 Other reasons

There are other reasons for analysts' decision to follow a firm, such as regulations and locations. Gomes, Gorton, and Medureira (2007) find that the Reg FD results in analysts changing their following due to banning selective disclosure, which affect small firms the most. Irani and Karamanou (2003) find that a decrease in analyst following and an increase in forecast dispersion following Reg FD.

Geographical proximity also contributes to the decision to follow. O'Brien and Tan (2015) use hand-collected data on analyst locations to examine the relationship between analyst following and geographical proximity. They find that analysts are 80% more likely to cover local firms than non-local ones, and that nearby non-underwriter analysts initiate coverage on local firm up to 3 weeks earlier than distant analysts do. Moreover, their results show that proximity matters the most for smaller, less visible firms, for firms with less complicated operations and lower status analysts.

Bhushan and Cho (1996) document that the analyst following increase after the merger. However, they argue that analyst following changes as merger changes firm characteristics, such as firm size, expenditures on R&D, and the book to market ratio.

3.2.2.5 International evidence

Several works use international setting to examine the determinants of analyst following. Lang, Lins, and Miller (2004) investigate the association between analyst following and corporate governance in 27 countries. After controlling for country characteristics, Lang, Lins, and Miller (2004) find that analysts are less likely to follow firms with potential incentives to withhold or manipulate information, such as firm with family/ management group as being the largest control rights blockholders. They conclude that corporate governance plays a vital role in analysts' willingness to follow firms. Results in Lang, Lins, and Miller (2004) are consistent with the argument that analysts consider the cost of information acquisition when deciding to follow a firm. Chang, Khanna, and Palepu (2000) investigate the relative difficulty level for financial analysts to forecast earnings of group affiliated firms and earnings of unaffiliated firms in 47 countries. They find that the earnings of group affiliates are harder to forecast due to the complexity of the firm's business, and that group affiliates are more likely to be followed by analysts.

Hope (2003), using an international sample of 22 countries, finds that analyst following is negatively related to firm ownership concentration. Moreover, he shows that not all forms of disclosure are equally crucial to analysts. Specifically, controlling for the firm- and country-level factors, Hope (2003) documents that the number of analyst following is associated with the extent of note disclosure more strongly than the comprehensiveness of the basic financial statements. Matolcsy and Wyatt (2006) examine a group of Australian firms who capitalize intangible assets. They find that firms with a higher proportion of their intangible assets capitalized have higher analyst following, lower forecasts dispersion and more accurate earnings forecasts relative to firms that capitalize on a lower proportion of intangible assets. Chen, Weiss, and Zheng (2007) investigate that the financial analysts' power in predicting future earnings and earnings quality, using a sample of firm cross-listed in the US. They find that analyst coverage is positively related to analysts' expectations about a firm's future performance and negatively related to analysts' concern over firms' earnings quality. Eng and Teo (1999) examine the relationship between the level of firm disclosure, analyst following, and analyst forecast characteristics in Singapore. They find a higher level of corporate disclosure can lead to greater analysts' interest in the firm.

3.2.3. Asymmetrical learning during the good time and the bad time.

Prior empirical finance work shows that the on-going economic conditions may affect learnings of market participants. Several works suggest that bad times (i.e. when there is a heavy flow for negative outcomes) may have a strong impact on people when they are building their beliefs about the future. For example, Andersen et al. (2007), Bollerslev and Todorove (2011) and Ben-David, Graham, and Harvey (2013) indicate that economic downturns are characterized by stronger reactions to the negative news by equity markets, higher risk premia, and more pessimistic expectations by corporate executives. Garcia (2012) in his seminar paper finds that

disproportionately pessimistic press coverage follows firms with poor stock market outcomes. Households become reluctant to invest in equities and have pessimistic beliefs about future stock returns in economic downturns, as argued in Malmendier and Nagel (2011). Froot (2001) also find that people are more likely to buy insurance against floods or earthquakes after such an event happened, ignoring that the probability of their occurrence does not change.

Evidence from neuroscience suggests that people process negative outcomes differently from positive ones. Kuhnen and Knutson (2005) and Knutson and Bossaerts (2005) shows that when people learn from their environment, the brain process differs on whether they face with positive or negative outcomes. Eppinger, Herbert, and Kray (2010) along with Mather and Schoeke (2011) argue that memory processes are different for details related to positive contexts than for those related to negative contexts, where negative contexts lead to narrower focus than do positive ones. Sokol-Hessener, Camerer, and Phelps (2012) indicate that people's emotional reactions are stronger in the face of losses, relative to gains and that the difference is stronger when the stakes are higher.

Kuhnen (2015) in her seminar paper examines whether people indeed learn differently from gains or positive news relative to losses or negative news under an experimental setting. She finds that when people are in a negative domain, they form overly pessimistic beliefs about the available financial assets. The result is particularly true for those who actively invest. She argues that the pessimism bias is driven by an overreaction to non-favorable outcomes in the negative domain relative to the positive domain. She indicates that her findings are different from the well-known loss-aversion first proposed by Kahneman and Tversky (1979) as her result shows that gains and losses affect market participants' formation of beliefs, while Kahneman and Tversky (1979) concerns how gain and losses shape people's value function. Instead of studying how

disutility of losing an amount of money is higher, in absolute terms than the utility of winning that amount, Kuhnen (2015) examines whether this effect is different when people face negative outcomes relative to when they face positive ones.

3.3 Hypothesis Development

Kuhnen (2015) offers several implications on household finance, corporate finance, and development economics. The documented pessimism in beliefs formed during loss domain in the experiment can be related to differences between poor and good economic times in the investment behavior of economic agents, such as households and firm decision makers. Market participants who have a stake in the market, such as individual investors, are well documented in experiencing this pessimism bias in making investing decisions. Kuhnen (2015) indicates that whether professional market participants such as financial analysts, who do not directly have a stake in the market, also exhibit this pessimism bias in learning from corporate earnings announcements or the macroeconomic news is still an empirical question.

Analysts weigh costs (such as the cost of information acquisition and processing, and commonality of information to industry) and benefits (such as commission from potential high trading volume, and reputation) in providing service. Determinants of analyst following are proxies for analysts weighing process. If the asymmetrical learning applies to financial analysts, analysts would incorporate pessimism bias into their weighing process when observing negative domain such as economic downturns. Pessimistic bias suggests that analysts underestimate the probability of having benefited from providing service and that analysts could be insensitive to benefits when deciding on following a firm. That is, for the same firm with similar operating conditions, analysts may have lower expectation during bad times, which results in a lower than expected excess-analyst following. I could not directly observe the benefits and costs of providing

analyst services. However, O'Brien and Bhushan (1990) identify several observable firm characteristics that impact the costs and benefits of financial analysts' information acquisition activities. I hence argue that pessimistic bias could result in analysts underreacting or being insensitive to these firm characteristics during bad times. On the one hand, during a recession, analysts may observe negative events (such as negative market performance and news presses with a negative tone) and suffer from pessimistic bias when valuing a firm and thus become less sensitive to those firm characteristics in the current period. On the other hand, since it is usually hard to accurately predict the impact of the recession on firm performance before the actual earnings come out, it is possible that analysts fail to learn bad outcomes in time until they observe the actual earnings during the recession. In that case, the pessimistic bias may exist in the next year, and analysts become less sensitive to firm's characteristics the period after the recession. I hence formulate the first set of hypotheses as follows:

H1a: The impacts of firm characteristics on analysts' decision on following a firm are weaker in the bad domain than in the good domain.

H1b: The impacts of firm characteristics on analysts' decision on following a firm are weaker in the post-bad domain than in the post-good domain.

An analyst's decision to follow a firm contains information about the analyst's underlying expectation of a firm's prospects. (Das, Guo, and Zhang (2006). The number of analyst following is affected by several factors in addition to analysts' underlying expectations. To isolate the effect of analysts' underlying expectation of the firm's future, I employ the excess analyst coverage analysis as in Doukas, Kim, and Pantzalis (2005). Das, Guo, and Zhang (2006) argue that excess analyst coverage represents analysts' beliefs about firms' future performance. I examine how analysts' beliefs affect their ability to convey information to market by examining the subsequent

analysts reporting characteristics, such as forecast errors. I do so by grouping firms into tercile groups (Low, Middle, and High) based on the excess analyst coverage in the good domain as well as in the bad domain and examine the signed forecast errors in each group across the domains.

Forecast errors (actual earnings – mean forecast earnings) usually reflect financial analysts' optimistic level (O'Brien, 1988; Mendenhall, 1991; Brown, 1997; Dugar and Nathan, 1995; and Das, Levine, and Sivaramakrishnan, 1998). A negative forecast error indicates that analysts are overly optimistic. Asymmetrical learning suggests that analysts tend to be less optimistic, if not pessimistic, in the negative domain. I hence expect forecast errors to be less negative for each of the three groups in the bad domain than for the corresponding group in the good domain if analysts suffer from pessimistic bias.

One may argue that financial analysts have confidence in firms they follow. The confidence may still exist during bad times and result in an optimistic view on firm performance. If that was the case, I would find forecast errors in corresponding groups across the two domains to be similar to each other. However, Kuhnen (2015) suggest that asymmetric learning and pessimistic bias during bad times would cause financial analysts to better identify bad firms as bad firms. As a results, the forecast errors for analyst-identified-bad firms should be less negative as financial analysts have a more accurate perspective on a firm's future during bad times. In addition, Kuhnen (2015) suggests that the analysts suffered from pessimistic bias due to asymmetric learning would be less likely to identify good firms as good firms. As a result, the forecast errors for analyst-identified-good firms should be less negative as financial analysts are more likely following a good firm during bad time than in good time. Based on Das, Guo and Zhang (2006), excess analyst coverage could represent the analyst's expectations over the firm they follow. As a result, I could classify firms in the low group sorted on excess analyst coverage as analyst-identified-bad firms

and classify firms in the high groups as analyst-identified-good firms. Both groups of firms are predicted to have less negative forecast errors during bad times. The prediction for middle group is not clear as middle group contains bad firms misidentified as middle firms (hence a more negative forecast error) and good firms misidentified as middle firms (hence a less negative error). As a results, the actual across-domain difference in the group is an empirical problem.

Moreover, as in hypothesis 1, it is possible that analysts fail to learn from bad outcomes until they observe the actual earnings and hence the forecast errors made during the recession. In that case, the pessimistic bias may exist at the next period:

H2a: Forecast errors for firm groups in the good domain are more negative than forecast errors for the corresponding firm groups in the bad domain if the analysts are more pessimistic during the bad domain.

H2b: Forecast errors for firm groups in the post-good domain are more negative than forecast errors for the corresponding firm groups in the post-bad domain if analysts are more pessimistic in the post-bad domain.

Results that support the hypotheses would suggest the existence of pessimistic bias in financial analysts. On the one hand, the pessimistic bias could make analysts process information in a way that deviates from the Bayesian rule and decreases market efficiency in incorporate information into price. On the other hand, as analysts are optimistic in general, the pessimistic bias could offset the optimistic bias and improve the forecast accuracy.

3.4 DATA AND SAMPLE

3.4.1 Sample construction

Analyst coverage data comes from monthly I/B/E/S summary database. Share prices, trading volumes, stock returns, index returns, and other stock information are from the Center for

Research in Security Prices (CRSP) database. The firm operating segment information is from COMPUSTAT historical segment database. The U.S. business cycle information is from the National Bureau of Economic Research website (NBER).

O'Brien and Bhushan (1990) argue that the number of analyst following is settled around one month before firms' fiscal year end and remains stable during next year and actual earnings announcements. As a result, analyst forecasts information and firms' fiscal year end date are collected from monthly I/B/E/S summary surveyed a month before a firm's fiscal year-end. The final sample has 133,278 firm-years range from 1976 to 2016.

3.4.2 Variable definitions

The prior literature identifies several firm characteristics that are related to the costs and benefits of analysts' information acquisition activities. I discuss their measurements in detail in this subsection. Each of continuous variables is pooled and winsorized at the top and bottom 1%.

Dependent variable:

NUMEST: Number of analysts making 1-year ahead forecast for the firm fiscal year, obtained from monthly I/B/E/S data surveyed one month before the firm's fiscal year-end.

Explanatory variables:

LMVE: The logarithm of market value of equity of a firm at the 45 trading days before the firm's fiscal year-end.

LSHR: The logarithm of adjusted shares outstanding of the firm at 45 trading days before the firm's fiscal year-end.

BETAVW: Coefficient on market returns in a market model. This variable measures systematic risk of the firm, estimated from a market model for the firm using daily trading data around [-244, -45] days before fiscal year end of the firm:

$$r_i = b_0 + b_1 * r_m + \varepsilon$$

where r_i is the daily return for stock i, and r_m is the corresponding daily return on a market portfolio. The market returns used are the returns on the CRSP value-weighted index (VW).

BEATEW: Coefficient on market returns in a market model. It is obtained similarly as BETAVW except that the market returns used are the returns on the CRSP equally weighted index (EW).

BETASP: Coefficient on market returns in a market model. It is obtained similarly as BETAVW except that the market returns used are the returns on the S&P 500 composition index (SP).

RSEVW: Stock return volatility, measured as a residual standard error (*100) from the market model using the CRSP value-weighted index (VW). The residual standard error is calculated as the square root of the mean squared error.

RSEEW: Stock return volatility, obtained in the same way as RSEVW except that the CRSP equally weighted index (EW) is used in the market model.

RSESP: Stock return volatility, obtained in the same way as RSEVW except that the S&P 500 composition index (SP) is used in the market model.

EXVW: Market adjusted compound daily return. I first calculate compound stock daily return from 294 trading days before the firm's fiscal year end to 45 trading days before the firm's fiscal year-end. Similarly, I calculate the compound daily CRSP value-weighted index (VW) return for the same period. The market adjusted daily compound return is the difference between compound stock daily return and compound daily CRSP value-weighted index return, expressed in percent form.

EXEW: Market adjusted compound daily return. It is measured similarly as EXVW except that the CRSP equally weighted index (EW) daily returns are used in the calculation.

EXSP: Market adjusted compound daily return. It is measured similarly as EXVW except that the S&P 500 composition index (SP) daily returns are used in the calculation.

NEWFIRM5YR: Change in the number of firms in a 3-digits SIC industry in CRSP database from 5 years before the firm's fiscal year end to 1 month before the firm's fiscal year-end.

FIRM: **NEWFIRM5YR** scaled by the beginning period the number of firms in the industry.

REC: a recession dummy variable that is equal to 1 whenever there are at least (no more than) 5 months elapsed from the last peak (trough) date as determined by the NBER, and 0 otherwise.

LREC: a recession observation dummy variable that is equal to 1 when the last period of a firm is a recession (REC=1) and 0 otherwise.

3.5 Methodology

To test the hypothesis 1, I run regressions using equations (1) and (2) below with the ordinary least square (OLS) method. I am interested in the effect of pessimistic bias in the bad domain on the weight financial analysts put on each of the firm characteristics. That is, the focus is on the coefficients on interaction terms b_9 to b_{13}. If these coefficients are negative and statistically significant, the results would suggest that analyst following is affected by pessimistic bias proposed by Kuhnen (2015).

$$\begin{aligned} NUMEST = b_0 + b_1 * LMVE + b_2 * LSHR + b_3 * BETA + b_4 * RSE + b_5 * EX \\ + b_6 * FIRM + b_7 * REC + b_8 * LMVE * REC + b_9 * LSHR \\ * REC + b_{10} * BETA * REC + b_{11} * RSE * REC + b_{12} * EX \\ * REC + b_{13} * FIRM * REC + \varepsilon \end{aligned} \tag{1}$$

$$\begin{aligned} NUMEST = b_0 + b_1 * LMVE + b_2 * L + b_3 * BETA + b_4 * RSE + b_5 * EX + b_6 \\ * FIRM + b_7 * LREC + b_8 * L * LREC + b_9 * LSHR * LREC \\ + b_{10} * BETA * LREC + b_{11} * RSE * LREC + b_{12} * EX * LREC \\ + b_{13} * FIRM * LREC + \varepsilon \end{aligned} \tag{2}$$

Whereas the definition for variables can be found in section 4.2. Firm size (*LMVE*) is predicted to be positively correlated with number of analyst following as prior literature finds that the larger the firm, the analysts following it. Shares outstanding (*LSHR)* represents the trading potential of a firm, is predicted to be positively related to the number of analyst following as higher the trading potential, the higher the commission from the trading. I do not have prediction on firm's idiosyncratic risk (*RSE*) as firms with high idiosyncratic risk usually has a poor information environment, which increase the information acquisition cost. However, this kind of firms usually needs the help of financial analyst most and could generate large benefit for analysts. The prediction on stock return momentum (*EX*) is also not clear. On one hand, prior literature shows that analysts tend to follow firm with good momentum, on the other hand, firms with good momentum usually are firms with poor information environment. Firm's systematic risk is not a common determinant for number of analysts following. Boubaker and Labégorre (2008) add the beta as control variable for number of analysts. In addition, the beta of a firm is identified to influence the institutional investors' interests in the firm. I add the beta to control for a firm's systematic risk and the influence of institutional investor on the firm. Prior literature shows the beta of a firm is positively associated with institutional investor's holding of a firm and the institutional investor's holding of a firm is positively associated with number of analysts following. I predict the beta is positively associated with number of analyst following.

To test hypothesis 2, I first construct a measure for excess analyst coverage (*EXCOV*) that represents analysts' beliefs about firms' future performance. I utilize the methods in Doukas, Kim and Pantzaslis (2005) and Das, Guo, and Zhang (2006) and develop four such measures. Specifically, I first form four subsamples of firms or domains: the good domain and the bad domain based on the dummy variable, *REC,* the post-good domain and post-bad domain based on the

dummy variable, *LREC*. I assign a firm-year in the good (post-good) domain subsample if *REC (LREC)* for the firm-year equals zero, and in the bad (post-bad) domain otherwise. I then calculate the four measures of excess analyst coverage for each of the four domains.

The first measure of excess analyst coverage (*EXCOV1*) is the difference between a firm's actual analyst following and its expected analyst following, where the expected analyst following is the average number of analyst following for similar firms in the same industry. For each firm-year in the sample, I calculate industry mean analyst following-to-sales ratio using all single-segment firms in the industry that the firm is a member of in that year. I then multiply the mean following-to-sales ratio by the sales of the firm of interest in the same year to obtain the expected analyst following for the firm. As in Doukas, Kim, and Pantzaslis (2005), I require at least five single segment firms in the same 4-digits industry as the firm of interest. If the condition is not met, the range is expanded to 3-digits SIC industry, 2-digits SIC industry, and finally, 1-digit SIC industry. I also construct another version of the EXCOV1 utilizing the industry median analyst following-to-sales ratio.

The second excess analyst coverage measure, *EXCOV2,* is constructed in the same way as the *EXCOV1* except that I use Fama-French industry classification rather than SIC code in the classification.

The third measure, EXCOV3, is developed in Hong et al. (2000) model, where the excess analyst coverage is the residual from the following regression equation:

$$LN(NUMEST) = b_0 + b_1 * LMVE + \sum b_i * IND + \varepsilon \qquad (3)$$

NUMEST is the number of analyst following the firm at the month before fiscal year-end, MVE is the market value of equity for the firm 45 trading days before the fiscal year-end. IND represents a set of industries dummy variables based on the SIC division. For example, SIC code

from 0100 to 0999 belongs to the division of Agriculture, Forestry and Fishing. I estimate equation (3) with an OLS method for the pooled panel subsamples. That is, I estimate equation (3) for all firm-years in the each of the four domains and use the residuals as the excess analyst following for the firm-year in the domain.

As in Das, Guo, and Zhang (2006), I incorporate control variables in equation (1) into equation (3) and develop the fourth measure, *EXCOV4*, based on the model specification of equation (4). I estimate equation (4) for the good (bad) domain and use residuals from regression as *EXCOV4* for the good (bad) domain.

$$NUMEST = b_0 + b_1 * LMVE + b_2 * LSHR + b_3 * BETA + b_4 * RSE + b_5 * EX + b_6 * FIRM + \sum b_i * IND + \varepsilon \qquad (4)$$

For each of the four excess analyst coverage measures in each domain, I divide all firms into three groups, where firms ranked in the bottom 33.3% of the excess coverage are in the low group (Low), firm ranked in the 33.3% to 66.7% are grouped into the middle group (Middle), the rest goes to the high group (High). I calculate average forecast error for each group, then compare the forecast errors between the two same groups across the domains and examine whether analysts become less optimistic from the good domain to the bad domain, and from the post-good domain to the post-bad domain.

3.6 RESULTS

3.6.1 Summary statistics

Table 3.1 presents the summary statistics for the key variables used in this study. I have a total of 133,278 firm-years over the 1976 to 2016 sample period. The value of all variables reported here is winsorized at the top and bottom 1% to remove the impact of extreme observations.

Analysts following (NUMEST) has a mean value of 7[1]. Each firm-year has at least one analyst following, with a maximum of 55 analysts. The distribution of firm size (MVE) is skewed as the mean firm size is about \$2 billion and the median size is about \$306 million. An average firm in the sample has about 93 million shares outstanding, with a maximum outstanding of 1.5 billion shares and a minimum outstanding of 673 thousand shares.

I have three measures for firm systematic risk (BETA), calculated based on the value-weighted (VW) index, and S&P 500 composition (SP) index in a market model. The mean value of BETAVW is 0.92, and that of BETASP is 0.83. Residual standard errors (RSE, in percent form) are 2.76%and 2.78% based on the value-weighted index, and S&P 500 composition index, respectively. The corresponding mean values of the 250-day market-adjusted compound returns (EX) are 2.77% and 5.47%. The number of newly established firms in the industry for a five-year period (NEWFIRM5YR) has a mean value of 5.47 firms, with a maximum value of 601 firms increase in an industry and a minimum value of 174 firms decrease in an industry. The highest number of industry structure change happens in SIC code 999, or nonclassifiable establishments, from the year 2008 – 2016, represents the fast growth of new industries in recent years. The minimum number of industry structure change happens in SIC code 671, Holding Offices, from the year 1998 to 2001, and SIC code 737, Computer Programming, Data Processing, and Other Computer Related Services, from the year 2003 to 2007. The reduction in holding offices could occur due to the 1997 Asian financial crisis, which hurts investment companies who hold Asian financial assets. The reduction in the Computer sector in 2003 might be due to the dot-com crash in the year 2002. The dummy variable REC, which equals one if the firm-year is in recession and

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[1] The number is rounded up, the actual value of 6.85 is used in following tests.

zero otherwise, has a mean value of 0.09, which means about 9% of the sample firm-years is in recession.

Correlations among the key variables are presented in Table 3.2. For simplification purpose, I only include variables based on the CRSP value-weighted index. The level of analyst coverage (NUMEST) is positively associated with firm size (MVE), number of shares outstanding (ADSHR), firm's systematic risk (BETAVW), and past stock performance (EXVW), and is negatively associated with residual stock volatility (RSEVW), number of new firms in past five years (NEWFIRM5YR), and recession dummy (REC). Hong et al. (2000) find that number of analysts following is positively associated with firm size, and firm's systematic risk, and is negatively associated with prior stock performance. The positive correlation between the number of analysts following and prior stock performance in the sample is inconsistent with Hong et al. (2000). However, the univariate analysis result may be misleading as factors uncontrolled could affect the correlation, and the relationship between prior stock performance and the number of analyst following should be examined in a multivariate regression. O'Brien and Bhushan (1990) suggest that the number of analysts following a firm should increase as new firms entering the industry. The negative correlation might be due to new firms, which is small and attract less attention, reduce the average number of analysts per firm in the sample. High level of analysts following improves a firm's information environment and thus reduce the idiosyncratic risk of the firm, which is consistent with the finding of prior literature. A larger firm is associated with higher systematic risk, more shares outstanding, less stock volatility, higher compound return, as stated in the literature. Firms in the industry with new firms entering tend to have a smaller size, higher systematic risk, less analyst coverage, and higher residual stock volatility, as newcomers tend to be smaller firms with high level of risk and high level of information asymmetry due to the lack

of attention from analysts. The recession is associated with less analyst coverage, lower firm size, higher stock volatility, and better past stock performance. Firm's stock volatility is negatively associated with analyst following, firm size, shares outstanding, and past stock performance, and is positively associated with firm's systematic risk, recession condition and the number of the newcomers to the industry. Firms with good prior performance tend to have more analyst following, larger firm size, more shares outstanding, higher risk and lower stock volatility.

3.6.2 Test results on Hypothesis 1

I examine hypothesis 1 by estimating equations (1) and (2) with different explanatory variables using the ordinary least square method (OLS) with the panel data. Specifically, I use BETA, RSE, and EX estimated from three different indexes. For each set of variables, I estimate the equations (1) and (2) with two specifications. In the first specification, I include control variables that are previously identified to influence the number of analyst following in the model. These variables are logarithm of the market value of equity (LMVE), the logarithm of shares outstanding (LSHR), BETA, stock volatility (RSE), past stock performance (EX), the scaled net number of new firms in the past five years (FIRM) and recession dummy (REC). In the second specification, I introduce the interaction terms between control variables in equation (1) and recession dummy (RECBETA, RECLMVE, RECLSHR, RECRSE, RECEX, and RECFIRM) to examine the how recession affect the influences of those determinants on analyst following. In equation (2) I add interaction terms between control variables and recession observation dummy (LRECBETA, LRECLMVE, LRECLSHR, LRECRSE, LRECEX, and LRECFIRM) and examine the lagged effect of the recession on the relation between firm characteristics and analyst following.

3.6.2.1 The Good and Bad domain

Results of the OLS regression based on equation (1) are reported in Table 3.3. Columns (1) and (2) use BETA, RSE and EX from the value-weighted market index model, and columns (3) and (4) use the S&P 500 composition index-based variables. Column (1) reports the specification without the interaction term. The adjusted R-square for regression in column (1) is 0.50, indicating a good model fit. Most coefficients are statistically significant at 1% level. Larger firms tend to have more analyst following as the coefficient on size is significantly positive. The firm's systematic risk, BETAVW, is also significantly positive with a coefficient of 0.17 (t = 6.89), suggesting that firms that are sensitive to market condition call for more analysts. This result is consistent with Bhushan (1989) in that the cost of acquiring information reduction correlates the number of analysts following positively. The coefficient on residual stock volatility (RSEVW) is 0.087 (t = 8.53), indicating that stocks with higher volatility tend to create demands for more analysts, as suggested in Bhushan (1989). Stock past performance (EXVW) is negatively associated with analyst coverage at -0.013 (t = -48.79). The results are consistent with the gradual-information-diffusion model, which suggests that the momentum strategy works better for a firm with less analyst following and poor information environment. However, the number of new firms entering the industry in the past five years (FIRM) shows no influence on the analyst following. The result is inconsistent with O'Brien and Bhushan (1990) who argues a positive relationship. The difference may be due to the high correlation between and the recession dummy (REC) and NEWFIRM5YR.

Column (2) examines the effect of the recession on the determinants of a firm's analyst coverage by incorporating the interaction terms between recession dummy and firm characteristics. The interaction term between recession and the natural logarithm of market equity (RECLMVE)

has a coefficient of -0.35 (t = -7.99), suggesting that analysts are less sensitive to the firm size during bad times when deciding to follow a firm. The coefficient on interaction term with the logarithm of shares outstanding (RECLSHR) is -0.29 (t = -6.08), indicating that analysts are less sensitive to trading opportunities during bad times. The coefficient on the interaction term between beta and recession dummy (RECBETAV) is 0.21 (t = 2.57), showing that analysts are more likely to follow a firm with high beta, suggesting that, during bad times, analysts tend to focus on cutting the cost of information acquisition by finding firms that is sensitive to market wide shock. The coefficient on the interaction term with residual stock volatility (RECRSEV) is -0.28 (t = -9.36), indicating that analysts are avoiding poor information environment during bad times. The coefficient on the interaction term with stock momentum (RECEXV) is -0.00008 (t = -1.01). Analyst seems to treat prior performance the same during bad times as in good times. The interaction term with the five-year change of firm number in an industry (RECSFIRM) has a coefficient of 0.01 (t = 0.70), which is insignificant. Industry structure change seems will not affect the level of financial analyst coverage across domains. Columns (3) and (4) BETA, RSE, and EX based on the CRSP equally-weighted index, and (5), and (6) use S&P 500 composition indexes as the market index and provide similar insights as in columns (1) and (2). Results in Tables 3.3 show that during bad times, analysts are influenced by the pessimistic bias, which is consistent with hypothesis H1a.[2] Analysts tend to move towards the firms with "guaranteed" benefit: large in size, low in volatility, good information environment, and reduced cost of information acquisition.

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[2] I also examine the hypothesis by dropping the consecutive requirement for five-year industry firm change or deleting the variable. The results are quantitively the same. I also use firm fixed effect in regression and the results are similar, except that the coefficient of RECRSE becomes insignificant.

3.6.2.2 The Post-Good and Post-Bad domain

Table 3.4 reports the OLS regression based on equation (2) that focuses on the post-good and post-bad domains. As in Table 3.3, columns (1) and (2) use variables based on the CRSP value-weighted index, and columns (3) and (4) use variables based on the CRSP equally-weighted index and columns (5) and (6) use variable based on the S&P 500 composition index. I examine whether observing negative outcomes last fiscal year affects how analysts process this fiscal year's information hence make following decisions. As a result, firm characteristics are in the current period. The coefficients in the column (1) of Table 3.4 are similar to the corresponding coefficients in column (1) of Table 3.3. However, the coefficient of the recession observation dummy (LREC) shows that the level of analyst coverage is significantly less in bad times than in good times. The coefficient on the five-year net changes of the number of firms in an industry (FIRM) is positive and significant, which is consistent with O'Brien and Bhushan (1990).

Column (2) presents regression coefficients with interaction terms between the recession observation dummy (LREC) and the determinants of analysts following. Analysts are less sensitive to firm size, shares outstanding, and residual stock volatility after observing bad outcomes as they seek to follow firms with better information environment. The coefficient of interaction term LRECBETAV is negative and significant (Coefficient = -0.3171, t-stat = -2.60), suggesting analysts are less likely to follow firms that are sensitive to macro factors, even high beta firms could help reduce the information acquisition cost by analysts. The coefficient of LRECFIRM is insignificant, although the sign is negative. The coefficient of LRECEXV is positive and significant (Coefficient = 0.00227, t-stat = 2.60), suggesting a generally improved information environment after the recession as analysts are less reluctant to follow a firm with high prior

performance. The results in Table 3.4 are consistent with the hypothesis H1b in general.[3] Analysts are less sensitive to several firm characteristics after observing bad outcomes. The pessimistic bias exists among professional market participants such as financial analysts.

3.6.3 Test results on Hypothesis 2

Table 3.5 and Table 3.6 present the results of the portfolio examination on hypothesis 2. In Table 3.5, sample firm-years are classified into the bad domain and the good domain based on the recession dummy (REC). In Table 3.6, sample firm-years are classified into the post-bad domain and post-good domain based on the recession observation dummy (LREC). Within each domain, firm-years are further divided into three groups (Low, Middle, and High group) based on an excess coverage measure. For each group, mean excess coverage, mean forecast error (actual EPS – mean EPS forecast) and median forecast error (actual EPS – median EPS forecast) are presented. The values are then compared across domains for the corresponding group (Low to Low, Middle to Middle, and High to High). Within each domain, the differences in those values between the Low group and the High group are also compared to examine whether any of the determinants serves a different role under the good domain and bad domain.[4] Panel A of the Table 3.5 and Table 3.6 presents the results based on excess coverage measure from the relative approach and SIC (EXCOV1). Panel B presents the results based on excess coverage measure from the relative

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[3] I also examine the hypothesis by dropping the consecutive requirement for five-year industry firm change or deleting the variable. The results are quantitively the same. I also control for firm fixed effect in the regression and the results are similar, except that the coefficient of LRECBETA becomes positive and significant.

[4] The difference is tested via pooled t-test. However, in order to address the concern that the distribution of variables are different in different domains, the Wilcoxon signed-rank test is conducted in addition to pooled t-test. The results are quatitively similar.

approach and Fama-French 49 industry classification (EXCOV2). Panel C presents the results based on excess coverage measure from regression approach with equation (2) (EXCOV3) and equation (3) (EXCOV4).

3.6.3.1 The Good and Bad domain

Table 3.5, Panel A presents the results based on two types of EXCOV1. The mean EXCOV1 in the left half of Panel A uses means industry analyst coverage/ sale ratio to calculate a firm's expected analyst coverage and thus firm's excess analyst coverage, while the median EXCOV1 on the right half uses median industry analyst coverage/ sales ratio. The difference in group average of mean EXCOV1 between the low group and the high group is -2.83 (p-value = 0.00) for the good domain and is -2.97 (p-value = 0.00) for the bad domain, suggesting the excess analysts following do contain analysts' expectation on a firm. Both differences are statistically significant. Now I turn to cross-domain analysis. For the low excess analyst coverage group, the group average of EXCOV1 is -2.34 in the good domain and is -2.39 in the bad domain. The difference of 0.05 is statistically significant at the 5% level. For the middle group, the difference in group average of mean EXCOV1 between the good domain and the bad domain is 0.04 (p-value = 0.00) and is significant. The difference for the high group is 0.01 (p-value = 0.30), which is statistically insignificant.

The mean forecast error in firms sorted on EXCOV1 in Panel A Table 3.5 provides more insight regarding the pessimistic bias during bad domain. The left half of the Panel A shows that for the low group, the group average of mean forecast error is statistically more negative in the bad domain than in good domain (difference = 0.13 and p-value = 0.00). The difference in group average mean forecast error is also statistically significant for the middle (difference = 0.08 and p-value = 0.00) and high groups (difference = 0.04 and p-value = 0.00). These statistics suggest that

analysts fail to fully account for the impact of the recession on firm performance and do not adjust their forecasts timely and perform optimistically during recession.

Median forecast error portion provides similar insight. The average median forecast error in the low group is more negative in the bad domain than in good domain (difference = 0.13 and p-value = 0.00). The difference in group average of the median forecast error is also statistically significant in middle group (difference = 0.08 and p-value = 0.00), and high group (difference = 0.05 and p-value = 0.00). The results again suggest that analysts fail to fully incorporate the recession into their forecasts in a timely manner.

The right half of Panel A, Table 3.5 uses median industry analyst coverage/ sales ratio to calculate the expected analyst coverage for firms in the sample and thus excess analyst coverage (median EXCOV1). Results based on median EXCOV1 grouping are similar to those based on mean EXCOV1 grouping. In the cross-domain analysis, group average of median EXCOV1 in the low group is -1.97 in the good domain and is -2.02 in the bad domain, the difference between two domains is 0.06 and significant at 5% level. The difference in group average of median EXCOV1 between good domain and the bad domain is 0.00 (p-value = 0.80), -0.02 (p-value = 0.28) for the middle group and high group, respectively. As for the mean forecast error, the average of the mean forecast error is more negative in the bad domain than in good domain for the low group (difference = 0.11 and p-value = 0.00). The difference in group average of the mean forecast error is also statistically significant in the middle and high group. Results on median forecast error portion also provides similar insight. In a low group, group average of the median forecast error is more negative in the bad domain than in the good domain (difference = 0.11 and p-value = 0.00). The difference in group average of the median forecast error is also statistically

significant in middle and high group. I draw the same implication that analysts fail to recognize the recession on time.

Panel B of Table 3.5 uses a similar relative method as in Panel A in constructing the excess analyst coverage, EXCOV2, but Fama-French 49 industry codes rather than SIC codes are used. As in Panel A, Panel B provides results based on mean EXCOV2 and median EXCOV2. The analysis based on EXCOV2 in Panel B provides a similar result as from Panel A.

Panel C provides results based on excess analyst coverage measure developed from regression methods. EXCOV3 is the residual from the OLS regression using specification in equation (3), and EXCOV4 is the residual from the OLS regression using specification in equation (4). As the regression method controls additional factors such as firm size, stock volatility, past stock performance, shares outstanding, industry, systematic risk, and changes of the number of firms in an industry, excess analyst coverage measure developed from regression models provide a better measure for analysts' perspective on the firm.

The group average of EXCOV3 in the low group is -0.47 during good times and is -0.47 during bad times. The difference between the two average is 0.00 (p-value = 0.95), and insignificant. The difference in group average of EXCOV3 between good and bad times is 0.00 (p-value = 0.51) for the middle group, and insignificant. The difference in EXCOV3 across the domains in the High group is -0.02 (p-value = 0.00), and is significant at 1%.

The group average for the mean forecast error in the low group is -0.08 in the good domain and is -0.19 in the bad domain. The difference across the domains is 0.11 (p-value = 0.00), and significant. The difference in EXCOV3 across the domains is -0.02 (p-value = 0.00) in middle group and 0.09 (p-value = 0.00) in high group. As for the median forecast error, difference is 0.11 (p-value = 0.00) for low group, -0.02 (p-value = 0.05) for middle group and 0.10 (p-value = 0.00)

for high group. All these differences are significant. Portfolio analysis based on EXCOV4 provides similar results as the ones based on EXCOV3.

Results in Table 3.5 suggest that analysts fail to fully recognize the impact of recession and adjust their forecast before the actual earnings announcement, suggesting analysts fail to incorporate, at least not fully incorporate, on-going recession into their forecasts.

3.6.3.2 The Post-Good and Post-Bad domain

Table 3.6 presents results from the post-good and post-bad domains analysis. The layout is similar to Table 3.5. The left side of Panel A presents results from mean EXCOV1, and the right side of Panel A presents results from median EXCOV1. Within the post-good domain, the difference in group average of mean EXCOV1 between the low group and the high group is significant, and the difference in group average of mean EXCOV1 between the low group and high group in the post-bad domain is significant as well, suggesting a difference in analysts' expectations on firms. Next, I examine the cross-domain differences for each of the three groups. In the low group, the difference in mean EXCOV1 between two domains is 0.01, and is not statistically significant (p-value = 0.76). In the middle group, the difference in group average of mean EXCOV1 between post-good domain and post-bad domain is 0.00 and is not significant. The difference in group average of mean EXCOV1 between the good domain and the bad domain is -0.03 (p-value = 0.02) and is statistically significant in the high group. The result is stronger in the right half of Panel A, where I present the results based on median EXCOV1. The right half of Panel A shows the difference in median EXCOV1 between the post-good and the post-bad domain is significant at 1% level for both the middle group and high group.

The results on mean forecast error indicate that after observing bad outcomes, analysts suffer from pessimistic bias and have conservative forecasts, in the low and high groups. The

difference in group average mean forecast errors are significantly less negative in the post-bad domain than in post-good domain in the high and low group. The results in the right half of Panel A are similar to the results in the left half of Panel A in the sense of supporting hypothesis 2. The results based on EXCOV2 is similar to the results based on EXCOV1 in Panel A in the sense of supporting hypothesis 2.

Panel C provides results from EXCOV3 and EXCOV4. The left half of Panel C shows the results based on EXCOV3. The difference in mean forecast error in a low group across the domains is -0.01 (p-value = 0.60), and insignificant. The difference across the domains is -0.03 (p-value = 0.01) in middle group and -0.03 (p-value = 0.02) in high group. The median forecast error provides a similar pattern in three groups. The difference in group average for median forecast error is 0.00 (p-value = 0.78) for low group, -0.03 (p-value = 0.02) for middle group and -0.03 (p-value = 0.03) for high group. Comparison of forecast errors across domains provide evidences that is consistent with hypothesis 2, at least for firms with moderate to high expectations from analysts.

Portfolio analysis based on EXCOV4 (the right half of Panel C) provides similar results. For mean forecast error part, all three groups have less negative group average in post-bad times than in post-good times, but only the middle and the high group are significant. The across-domain difference in group average of mean forecast error is -0.02 (p-value = 0.28) for low group, -0.02 (p-value = 0.03) for middle group, and -0.03 (p-value = 0.02) for high group. The trend in median forecast error is similar to the on in mean forecast error. The across-domain difference in group average of median forecast error is -0.01 (p-value = 0.44) for low group, -0.02 (p-value = 0.06) for middle group, and -0.03 (p-value = 0.02) for high group.

Results in Table 3.6 provide support for the hypothesis H2b that after observing bad outcomes, analysts suffer from pessimistic bias and have conservative forecasts. The bias is most

significant in the group with high excess abnormal coverage. The bias still exists even after controlling for several determinants of analyst coverage.

3.7 Extra Tests

3.7.1 Firm characteristic sorted on excess analyst coverage

I further examine the firm characteristics of firms in each of three groups (Low, Middle, and High) sorted on excess analyst coverage to examine the how the favor of analyst on firm changes during bad times or during post-bad times. Specifically, for each group in each domain (Good, Bad, Post-Good, and Post Bad), I examine mean firm characteristics such as the number of analyst following, the logarithm of the market value of equity, the logarithm of shares outstanding, beta, stock volatility, past stock performance, and changes of the number of firms in the past five years. I then perform within-domain comparisons between the Low group and High group for each domain, and cross-domain comparisons (Good-Bad, Post-Good-Post-Bad) for each of three groups (Low, Middle, and High group). The examination of the difference between low and high group could help the understanding of whether a firm characteristics is important in forming analysts' expectation, while the cross-domain examination could help the understanding of whether firm characteristics for firms followed by analysts in different domains reflect the same trend as in the first set of hypothesis. I perform the analysis for each of four excess analyst coverage measures. [5]

[5] The difference is tested via pooled t-test. However, in order to address the concern that the distribution of variables are different in different domains, the Wilcoxon signed-rank test is conducted in addition to pooled t-test. The results are quatitively similar.

3.7.1.1 Good and Bad domain

Table 3.7 presents the results for the good and bad domain. As in Table 3.5, Panel A of Table 3.7 presents the results based on excess coverage measure from the relative approach and SIC (EXCOV1). Panel B of Table 3.7 presents the results based on excess coverage measure from the relative approach and Fama-French 49 industry classification (EXCOV2). Panel C of Table 3.7 presents the results based on excess coverage measure from regression approach with equation (3) (EXCOV3). Results based on excess coverage measure from regression approach with equation (4) (EXCOV4).

Panel A presents the results based on mean EXCOV1 and median EXCOV1. The left half of Panel A present results based on mean EXCOV1. Within the good domain, the difference in group average of the level of analyst coverage (NUMEST) between the Low group and the High group is 3.58 (p-value = 0.00) and is statistically significant. The difference in group average of NUMEST between the Low group and High group in the Bad domain is 2.24 (p-value = 0.00) and is statistically significant as well. The next is a cross-domain analysis. In a Low group, group average for NUMEST is 11.48 in the Good domain and is 9.95 in the Bad domain, the difference between two domains is 1.53, and the difference is statistically significant (p-value = 0.00). In a Middle group, the difference in group average of NUMEST between the Good domain and the bad domain is 0.86 (p-value = 0.00) and is statistically significant. In a High group, the difference in group average of NUMEST between the good domain and the bad domain is 0.19 (p-value = 0.14) and is not statistically significant.

Firm size (LMVE) part shows that during bad times, the size of firm analyst coverage is lower than in good times in general as the difference between the Good domain and the Bad domain is positive and significant for middle and high groups. The positive difference is likely to

relate to the loss of share price during bad times such as a recession. The argument is consistent with the results in LSHR, which shows that the number of shares outstanding is not significantly lower in the Bad domain than in the Good domain, or higher as shown in the Low (difference = -0.15 and p-value = 0.00) and High group (difference = -0.06 and p-value = 0.02). In both domains, the difference in firm size between the High and Low group is positive and significant, and the difference in shares outstanding is positive and significant. Analysts favor firms with low market value, and fewer shares outstanding in both good and bad domain.

During bad times, firms followed by analysts tend to have a higher systematic risk. The difference in group average beta (BETAVW) between the Good domain and the Bad domain are negative and significant. The difference is -0.05 (p-value = 0.00) in low excess coverage group, -0.05 (p-value = 0.00) in middle group, and -0.06 (p-value = 0.00) in high group. There is no monotonic trend from Low group to High group, and analysts tend to be less concerned about firm's Beta when analyzing the firm's future in both Good domain and Bad domain. The difference in beta between the Low and High group in the Good domain is -0.01 (p-value=0.26), which is not significant. The difference in beta between the Low and High group in the Bad domain is -0.02 (p-value=0.19), which is not significant either.

Firms during bad times, in general, have higher stock volatility than in good times as the differences in group average stock volatility (RSEVW) between the Good and Bad domain is negative and significant at all three of groups. In both the Good domain and the Bad domain, analysts tend to favor firms with high volatility as the difference between the Low group and the High group is negative and significant for both domains. The difference is -0.84 (p-value = 0.00) in Good domain and -0.87 (p-value = 0.00) in Bad domain. Moreover, there is a monotonic trend

of increase in the volatility of stock from the Low group to High group. The results suggest analysts favor growth firms, which could have considerable volatility in their stock valuation.

Analyst pays more attention to firms with higher past stock performance during bad times as the difference in past stock performance (EXVW) between the two domains is negative and significant across the three groups. The difference is -0.67 (p-value = 0.00) in low group, -0.70 (p-value = 0.00) in middle group, and -0.71 (p-value = 0.00) in high group. Firms with high analyst expectation have lower past stock performance in the Good domain as the difference in EXVW between the low group, and the high group is negative and significant in the Good domain (difference = -1.01 and p-value = 0.00). However, the analyst expects better performance for firms with relative lower past performance during Bad domain, as the difference between low group and high group in the Bad domain is 2.70 (p-value = 0.00). Moreover, analysts tend to follow firms with good performance, as all six EXVW is positive in the sample.

Differences in changes in the number of firms in the past five years (NEWFIRM5YR) between the two domains are positive and significant for all three groups. The difference is 12.18 (p-value = 0.00) in low group, 13.48 (p-value = 0.00) in middle group, and 10.64 (p-value = 0.00) in high group. Moreover, in the Bad domain, the mean number of firm changes in the past five-year period is negative, indicating bad economic condition force firms to exit the industry. Changes in the number of firms in the past five years may not be an important factor when an analyst forms the expectation of a firm, as the difference between low group and high group is not significant in both Good domain (difference = 1.07 and p-value = 0.16) and Bad domain (difference = -0.46 and p-value = 0.74). The right part of Panel A uses median EXCOV1. Sample firms grouped on median EXCOV1 give similar results as grouped on mean EXCOV1.

Panel B of Table 3.7 present analysis results based on mean EXCOV2 and median EXCOV2, which is the measure of excess analyst coverage based on Fama-French 49 industry classification rather than SIC in EXCOV1. Panel B provides similar insight as in Panel A of Table 3.7. Firm size, trading opportunities, stock volatility are still important factors analysts used when forming their expectations of a firm. Past performance and changes in the industry are not a big concern by analysts. The sign and significance level of results from the cross-domain analysis and within-domain analysis are almost similar across four measures. One difference is that the differences in group average of BETAVW between the Low and High group are positive and significant in the Good domain in Panel B, which indicate that analysts consider beta when forming their expectation in good time.

Results in Panel C of Table 3.7 are based on two excess analyst coverage from regression methods, EXCOV3 and EXCOV4. Panel C provides similar insight as in Panel A of Table 3.7. The sign and significance level of results from the cross-domain analysis and within-domain analysis are almost similar across four measures. There are several differences in results between Panel C and Panel A of Table 3.7. The first difference is the number of analysts monotonically increases from Low to High group in Panel C, which is different from the monotonically decreasing trend as in Panel A and B. The difference is probably due to the methodology difference between EXCOV1, EXCOV2 (relative method) and EXCOV3 and EXCOV4 (regression method). The second difference is the difference in the mean beta between the Low and the High group in both the Good and the Bad domain is positive and significant when the firm sample is sorted on EXCOV4. The third difference lay in how analysts treat past stock returns (EXVW). In Panel C the difference in mean past stock performance is positive and significant in both domains, rather than only in the Bad domain as in Panel A and B. The last difference is that in Panel C, analysts

appear to focus on the number of firm changes for the past five-year period (NEWFIRM5YR) in both Good and Bad domain, while in Panel A and B, the factor is not an important factor.

3.7.1.2 Post-Good and Post-Bad Domain

Table 3.8 presents the results for Post-Good and Post-Bad domain. As in Table 3.7, only the results based EXCOV1 are presented here. The variable NUMEST shows that the pessimistic bias seems to only have an impact on firms with low and middle analysts' expectations.

Firm size (LMVE) part shows that during post-bad times, the size of firm analyst coverage is no lower than the size of the firm in post-good times. The difference between the post-Good domain and the post-Bad domain is not significant in the middle and the high groups and is negative and significant in the low group. The results suggest that analysts tend to only follow larger firms after observing bad outcomes, which is consistent with the hypothesis H1b. The result is different from the result in Table 3.7, where the group average firm size is larger in good times, especially in middle and high group.

Results based on analysis of shares outstanding (LSHR) is consistent with the results based on firm size, where group average shares outstanding in post-bad time is significantly larger than in post-good time. Moreover, the middle group shows a significant difference, unlike the difference between good domain and bad domain in Table 3.7.

Results in BETA, RSE, and EX tell similar results as in Table 3.7, analysts in post-bad domain focus on firms with a higher beta, higher residual volatility, and better prior stock performance, and residual volatility affects analysts' expectation on a firm.

Differences in changes in the number of firms in the past five years (NEWFIRM5YR) between the two domains are positive and significant in all three groups, as in Table 3.7. Moreover, in the post-bad domain, the mean number of firm changes in the past five-year period is more

negative than in Table 3.7, indicating bad economic condition continues to force firms to exit industries, even after the recession. Unlike Table 3.7, Table 3.8 shows that industry structure change affects analysts' expectation of a firm in the post-good domain, but not in the post-bad domain. In addition, analysts in the post-bad domain more like to have low expectations on firms with most radical industry structure changes and analysts in bad domain tend to give high expectations to firms with most radical industry changes.

The right part of Panel A provides results based on median EXCOV1, and the results are similar to the left part of Panel A. One difference between the right part and left part of Panel A is that the beta is not a determinant for analysts' following decisions in the post-good domain as the difference between the low and the high group in post-Good is -0.01 (p-value = 0.11) and is not significant.

Results based on mean EXCOV2 and median EXCOV2 in Panel B of Table 3.8 provide similar insight as in Panel A. One difference between Panel A and Panel B is that the differences in group average of firm size (LMVE) between post-Good domain and post-Bad domain in the low group is not significant in Panel B. And the difference in firm size between two domains is significant for both the middle group and the high group in Panel B. The result is opposite to the results in Panel A, which are not significant in the middle and high group and are significant in the low group.

Results in Panel C provide similar insight as in Panel A. The sign, and the significance level of results from the cross-domain analysis and within-domain analysis are almost similar for shares outstanding (LSHR), and stock volatility (RSEVW).

The results in number of analyst following (NUMEST), firm beta (BETAVW), prior stock performance (EXVW), and changes in number of firms in the industry (NEWFIRM5YR) are very

different in Panel C than their counterparty in Panel A. The difference in NUMEST between the post-Good domain and the post-Bad domain is positive and significant at 1% level (Left side: difference = 0.38 and p-value = 0.00; Right side: difference = 0.40 and p-value = 0.06) in the high group, while in Panel A the difference is insignificant. In addition, result based on BETAVW in Panel C shows that firm beta is one of the determinants on analyst following the decision, as the difference between the low group and the high group is significant in both domains. However, results on the left side of Panel C show the difference between the low group and the high group is negative while the right side of the panel shows the difference to be positive and significant. The difference may be due to different variables added in the equation (3) and (4).

The difference in prior stock performance between the low group and the high group is positive and significant in both the post-Good domain and the post-Bad domain. The results suggest that firms with poor prior stock performance are more like to attract excess analyst followings. Also, changes in the number of firms in the industry is a determinant of analysts' expectation on a firm as the difference between the low, and the high group is positive and significant in both domains.

Collectively, I have the consistent result that firms with the relatively smaller number of shares outstanding or firms with higher stock volatility would be over-followed by analysts.

In conclusion, the results show that Firm size, shares outstanding, systematic risk, and idiosyncratic risk are important factors that an analyst consider when following a firm. Moreover, firms followed by analysts observed bad outcomes have higher shares outstanding, higher systematic risk, and idiosyncratic risk.

3.7.2 Firm characteristics sorted on excess analyst coverage based on annual mean

In section 7.1 I analyze the firm characteristics by sorting firms into three groups based on their excess analyst coverage of the year. As the number of observations is different each year, the result may be driven by certain years with a large number of observations. To avoid such issue, I calculate the mean value of firm characteristics each year in each group for both the good domain, the bad domain, the post-Good domain and the post-Bad domain. As a result, I have only one observation each year for each of three excess analyst coverage groups. I then examine firm characteristics in each group each domain based on these mean values. [6] The interpretation of the result requires caution as outliers in the small sample could drive the results.

3.7.2.1 Good and Bad domain

Table 3.9 presents the results for the good and bad domain. Panel A of Table 3.9 presents the results based on EXCOV1, Panel B presents the results based on EXCOV2, and Panel C presents the results based on EXCOV3 and EXCOV4.

The left half of Panel A present results based on mean EXCOV1. I have 40 firm-years in the good domain and eight firm-years in the bad domain. Compare with Panel A of Table 3.7, Panel A of Table 3.9 reports a similar result on the number of analyst followings (NUMEST) but reports different results on other characteristics.

Panel A of Table 3.9 shows that the difference in firm size (LMVE) and in shares outstanding (LSHR) are insignificant between the good and the bad domain across three groups.

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[6] The difference is tested via pooled t-test. However, in order to address the concern that the distribution of variables are different in different domains, the Wilcoxon signed-rank test is conducted in addition to pooled t-test. The results are quatitively similar.

However, the difference between the low and high group still has a similar sign and significance as in Table 3.7.

Firm beta (BETAVW), prior stock performance (EXVW), and changes in the number of firms in the industry (NEWFIRM5YR) now show no significant difference between Good and Bad domains across three groups and the difference between the low and the high group is not significant across domains.

Stock volatility is still one of the critical determinants for analysts to form their expectations on the firm, but the difference in stock volatility between the good and the bad domain is not significant in the high group now. The insignificance I get from five of seven firm characteristics may be due to the small sample size I have in the analysis as there are only 48 observation in each group.

Comparison between Panel B in Table 3.9 and Panel B in Table 3.7 provides similar insight as in the comparison of Panel A. Results on the number of analyst followings and stock volatility are similar to Table 3.7. Firm size and shares outstanding still are critical factors when analysts form their expectations of the firm. Moreover, analysts tend not concern firm beta, prior stock performance and changes in the number of firms in the industry when forming their expectations.

Comparison between Panel C of Table 3.9 and Panel C of Table 3.7 provides different insight as in Panel A and B of Table 3.9. Panel C of Table 3.9 shows that analysts' expectation on a firm relates to the firm's number of analyst following, firm size, shares outstanding, and firm beta in the Good domain, and to the number of analyst following only in the Bad domain.

Results from Table 3.9 shows that a firm's number for analyst following and its stock volatility are important factors that analysts use to form expectations on a firm. Moreover, the weak results in Table 3.9 may be due to the small sample size.

3.7.3.2 Post-Good and Post-Bad domain

This section compares results in Table 3.10 with results in Table 3.8. Panel A of Table 3.10 reports several similar results on the effect of firm characteristics on forming expectation by analysts. The results show that during the post-good period, analysts focus on the number of analyst following, firm size, shares outstanding, and stock volatility. Moreover, during the post-bad period, analysts focus on the number of analyst following, firm size, shares outstanding, and prior stock performance.

In Panel A of Table 3.10, the difference in the number of analyst following between the post-Good and post-Bad domain is significant across three groups, rather than just in the low group and the middle group, as in Table 3.8.

Differences in firm size (LMVE) and in shares outstanding (LSHR) are insignificant between the post-good and the post-bad domain in the low group and the high group. However, the difference between the low group and high group still has a similar sign and significance as in Table 3.8.

Firm beta (BETAVW), stock volatility (RSEVW), and changes in the number of firms in the industry (NEWFIRM5YR) now show no significant difference between the post-good domain and the post-bad domain across three groups.

Prior stock performance (EXVW) is one of the determinants for analysts to form their expectations on the firm in the post-good domain, but the difference in stock volatility between the post-Good and the post-Bad domain is significant in the high group only. The insignificance I get from firm characteristics may be due to the small sample size.

Comparison between Panel B in Table 3.10 and Panel B in Table 3.8 provides slightly different insight as in the comparison of Panel A. Number of analysts following is a factor to be

considered by analysts in forming expectation only in the post-good period. Firm beta is not a concern of analysts in both domains.

Panel C of Table 3.10 shows that analysts' expectation on a firm relates to the firm's number of analyst following, firm size, number of shares outstanding, changes in the number of firms in the industry, and firm beta in the post-Good domain, and does not relate to prior stock performance as in Table 3.8. The expectation on a firm relates to the number of analyst following, and changes in the number of firms in the industry in the post-Bad domain, and not relates to firm size, number of shares outstanding, stock volatility, firm beta, and prior stock performance as in Table 3.8.

Results from Table 3.10 shows that a firm's number for analyst following and changes in the number of firms in the industry are important factors analysts use to form expectations on a firm.

3.8 CONCLUSION

In the study, I examine whether professional market participants, more specifically, financial analysts, suffer from a pessimistic bias introduced in Kuhnen (2015). That is, the belief is different after market participants observe negative events during bad times. I argue the pessimistic bias is related to market dynamics and the capital market learning process. That is whether market participants could rationally incorporate information into their expectations on the value of their investment.

I empirically examine whether the effect of determinants of analyst coverage level on the actual analyst coverage changes after analysts observing negative economic events during an economic downturn. I explore the behavior of financial analysts during the year of economic downturn and during the year right after the economic downturn. I find that analysts are less

sensitive to firm size, shares outstanding, stock volatility, and prior stock performance during the year of recession. However, analysts tend to be more sensitive to beta and industry change during the year of recession. Observation of recession results in analysts being less sensitive to firm size, shares outstanding, stock volatility and being more sensitive to prior stock performance. The results are robust to the release of a data requirement.

I further examine whether analysts tend to be less optimistic during a recession or right after the recession by comparing their forecast errors between the good domain and the bad domain, and between the post-good and post-bad domains. I divide the sample into three groups based on the analyst's expectation of the firm's future performance, proxied by excess analyst coverage. I find that analysts fail to fully incorporate the information of recession and do not adjust their forecast accordingly, which results in a larger forecast error during bad times. I do find evidence of pessimistic bias in the recession observation sample as forecast error is less negative during post-bad domain for all three excess analyst coverage groups.

Moreover, I examine the characteristics of firms followed by analysts in different domains. I find that after observed negative outcomes during the recession, analysts tend to follow larger firms, firms with higher systematic risk, firms with higher stock volatility, firms with better prior performance, and firms in the industry with firm exiting the markets.

The results further confirm the domain-specific impact on market participants' formation of beliefs and expectation of the market, shed light on the overall impact of bad times on the behavior of market participants. In addition, the results have implication regarding the usefulness of the information that investors could draw from analysts' forecasts. The paper also contributes to the determinants of analyst following literature as I show that analysts weigh different firm characteristics differently in different domains.

One drawback of this research is that the formation of analysts' expectation of a firm based on firm characteristics is a single, exogenous decision. O'Brien and Bhushan (1990) suggest that the formation of expectation and the following decision should be examined in a multiple-decision setting to make the results more realistic. Examining the domain-specific impact on analyst behavior could yield new implication in the market dynamic and firm information environment.

Table 3.1 Summary Statistics

This table provides summary statistics for number of analysts following a firm (NUMEST), firm size (MVE), shares outstanding (ADSHR), firm beta based on market model with three different market index (BETA), residual standard error from the corresponding market model (RSE), market adjusted compound daily return based on three different market index (EX), Change in the number of firms in the 3-digits SIC industry in CRSP database from 5 years before the firm's fiscal year end to 1 month before firm's fiscal year-end (NEWFIRM5YR), and recession dummy (Rec). The value for NUMEST is rounded up, and the actual value of 6.85 is used in following tests. Detailed information on the definitions of variables is in section 4.2.

Variable	N	Mean	Median	Std. Deviation	Min	Max
NUMEST	133278	7.00	4.00	6.83	1.00	55.00
MVE (000s)	133278	2073755.78	306915.49	6035454.25	8041.25	44748304.48
ADSHR (000s)	133278	93550.45	26609.25	213794.33	673.80	1493072.00
BETAVW	133278	0.92	0.86	0.59	-0.24	2.66
BETAEW	133278	1.22	1.13	0.72	-0.13	3.50
BETASP	133278	0.83	0.77	0.56	-0.28	2.47
RSEVW	133278	2.76	2.34	1.60	0.76	8.77
RSEEW	133278	2.75	2.33	1.57	0.78	8.65
RSESP	133278	2.78	2.36	1.61	0.76	8.82
EXVW	133278	2.77	-3.46	50.62	-87.40	229.30
EXEW	133278	-9.58	-13.64	50.56	-108.25	205.16
EXSP	133278	5.47	-0.63	51.23	-86.62	232.88
NEWFIRM5YR	133278	14.61	0.00	92.32	-174.00	601.00
REC	133278	0.09	0.00	0.29	0.00	1.00

Table 3.2 Correlation Table

This table presents the correlation matrix among number of analysts following a firm (NUMEST), firm size (MVE), shares outstanding (ADSHR), firm beta based on market model with CRSP value-weighted index as market index (BETAVW), residual standard error from the market model (RSEVW), market adjusted compound daily return based on CRSP value-weighted index (EXVW), Change in the number of firms in the 3-digits SIC industry in CRSP database from 5 years before the firm's fiscal year end to 1 month before firm's fiscal year-end (NEWFIRM5YR), and recession dummy (Rec). Detailed information on the definitions of variables is in section 4.2. P-values are in parentheses.

	NUMEST	MVE	ADSHR	BETAVW	RESVW	EXVW	NEWFIRM5YR	REC
NUMEST	1	0.71455	0.63752	0.28091	-0.33815	0.07253	-0.04576	-0.01024
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.0002)
MVE	0.52412	1	0.81552	0.30914	-0.51092	0.24477	-0.15308	-0.03593
	(<.0001)		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
ADSHR	0.5555	0.76141	1	0.28843	-0.3587	0.12502	-0.14222	0.0074
	(<.0001)	(<.0001)		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.0069)
BETAVW	0.20392	0.07629	0.11253	1	0.17347	0.02888	-0.04721	0.00307
	(<.0001)	(<.0001)	(<.0001)		(<.0001)	(<.0001)	(<.0001)	(0.2619)
RSEVW	-0.29865	-0.22455	-0.20587	0.17969	1	-0.20333	0.11419	0.11054
	(<.0001)	(<.0001)	(<.0001)	(<.0001)		(<.0001)	(<.0001)	(<.0001)
EXVW	0.01417	0.046	0.03314	0.07355	-0.0816	1	-0.07629	0.02478
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)		(<.0001)	(<.0001)
NEWFIRM5YR	-0.04073	-0.04887	-0.04548	0.03005	0.14525	-0.04098	1	-0.06178
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)		(<.0001)
REC	-0.02123	-0.02193	0.00403	0.0036	0.10852	0.01892	-0.05881	1
	(<.0001)	(<.0001)	(0.1414)	(0.1885)	(<.0001)	(<.0001)	(<.0001)	

Table 3.3 Effect of Recession on Determinants of Analyst Following

This table presents the results of the regression with equation (1). The dependent variable is the number of analysts following a firm (NUMEST). The explanatory variables are the logarithm of firm size (LMVE)), the logarithm of shares outstanding (LSHR), firm beta based on market model with three different market index (BETA), residual standard error from the corresponding market model (RSE), market adjusted compound daily return based on three different market index (EX), Change in the number of firms in the 3-digits SIC industry in CRSP database from 5 years before the firm's fiscal year end to 1 month before firm's fiscal year-end, scaled by the beginning period of number of firms in the industry (FIRM), and recession dummy (REC). The interaction terms of recession dummy with each of these control variables are also included in the regression: RECLMVE, RECLSHR, RECBETA, RECRSE, RECEX, and RECFIRM Detailed information on the definitions of variables are in section 4.2. T-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dep. Var	NUMEST	NUMEST		NUMEST	NUMEST		NUMEST	NUMEST
	(1)	(2)		(3)	(4)		(5)	(6)
INTERCEPT	-28.673***	-29.654***	INTERCEPT	-28.961***	-30.079***	INTERCEPT	-28.894***	-29.874***
	(-228.30)	(-221.09)		(-237.75)	(-230.40)		(-228.02)	(-221.11)
LMVE	2.08432***	2.12643***	LMVE	2.09033***	2.15214***	LMVE	2.10991***	2.15078***
	(146.37)	(140.42)		(150.23)	(144.94)		(147.31)	(141.32)
LSHR	0.83913***	0.87350***	LSHR	0.83143***	0.85288***	LSHR	0.84734***	0.88382***
	(54.44)	(53.19)		(54.01)	(51.98)		(54.97)	(53.82)
BETAVW	0.17256***	0.14220***	BETAEW	0.29985***	0.26286***	BETASP	-0.0967***	-0.1320***
	(6.89)	(5.38)		(14.66)	(12.19)		(-3.63)	(-4.70)
RSEVW	0.08749***	0.13168***	RSEEW	0.06032***	0.11457***	RSESP	0.11530***	0.15697***
	(8.53)	(11.90)		(5.62)	(9.83)		(11.39)	(14.40)
EXVW	-0.0130***	-0.0129***	EXEW	-0.0135***	-0.0144***	EXSP	-0.0123***	-0.0122***
	(-48.79)	(-45.64)		(-50.38)	(-50.52)		(-46.83)	(-43.69)
FIRM	-0.0032	-0.0033	FIRM	-0.0018	-0.0018	FIRM	-0.0031	-0.0031
	(-1.60)	(-1.63)		(-.89)	(-.92)		(-1.53)	(-1.55)
REC	-0.4136***	7.73823***	REC	-0.4809***	8.30897***	REC	-0.4053***	7.84572***
	(-9.69)	(19.89)		(-11.25)	(22.27)		(-9.48)	(19.91)
RECLMVE		-0.3536***	RECLMVE		-0.4718***	RECLMVE		-0.3518***
		(-7.99)			(-11.16)			(-7.87)
RECLSHR		-0.2863***	RECLSHR		-0.2078***	RECLSHR		-0.3025***
		(-6.08)			(-4.44)			(-6.42)
RECBETAV		0.21469**	RECBETAE		0.36197***	RECBETASP		0.28072***
		(2.57)			(5.30)			(3.19)
RECRSEV		-0.2776***	RECRSEE		-0.3120***	RECRSESP		-0.2744***
		(-9.36)			(-10.39)			(-9.20)
RECEXV		-0.0008	RECEXE		0.00666***	RECEXSP		-0.0013
		(-1.01)			(8.04)			(-1.59)
RECFIRM		0.01143	RECFIRM		0.00713	RECFIRM		0.01234
		(.70)			(.44)			(.76)
N	133278	133278		133278	133278		133278	133278
Adj. R2	0.502385	0.504152		0.503564	0.505876		0.501634	0.503432

Table 3.4 Effect of Recession Observation on Determinants of Analyst Following

This table presents the results of the regression with equation (2). The dependent variable is the number of analysts following a firm (NUMEST). The explanatory variables are the logarithm of firm size (LMVE), the logarithm of shares outstanding (LSHR), firm beta based on market model with three different market index (BETA), residual standard error from the corresponding market model (RSE), market adjusted compound daily return based on three different market index (EX), Change in the number of firms in the 3-digits SIC industry in CRSP database from 5 years before the firm's fiscal year end to 1 month before firm's fiscal year-end, scaled by the beginning period number of firm in the industry (FIRM), and recession observation dummy (LREC). The interaction terms of recession observation dummy with each of these control variables are also included in the regression: LRECLMVE, LRECLSHR, LRECBETA, LRECRSE, LRECEX, and LRECFIRM Detailed information on the definitions of variables are in section 4.2. T-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level.

Dep. Var	NUMEST	NUMEST		NUMEST	NUMEST		NUMEST	NUMEST
	(1)	(2)		(3)	(4)		(5)	(6)
INTERCEPT	-29.884***	-30.555***	INTERCEPT	-30.098***	-30.920***	INTERCEPT	-30.189***	-30.830***
	(-212.29)	(-203.66)		(-220.87)	(-212.57)		(-212.53)	(-203.86)
LMVE	2.11938***	2.13595***	LMVE	2.11808***	2.15099***	LMVE	2.15384***	2.16645***
	(133.36)	(126.64)		(136.70)	(130.53)		(134.68)	(127.71)
LSHR	0.91330***	0.94746***	LSHR	0.90378***	0.92945***	LSHR	0.92100***	0.95795***
	(53.34)	(51.96)		(52.87)	(51.06)		(53.79)	(52.55)
BETAVW	0.13844***	0.16911***	BETAEW	0.33968***	0.36526***	BETASP	-0.1920***	-0.1576***
	(4.97)	(5.75)		(14.87)	(15.21)		(-6.52)	(-5.05)
RSEVW	0.12115***	0.15002***	RSEEW	0.08038***	0.11432***	RSESP	0.15604***	0.18227***
	(10.45)	(12.09)		(6.67)	(8.86)		(13.59)	(14.86)
EXVW	-0.0137***	-0.0141***	EXEW	-0.0143***	-0.0155***	EXSP	-0.0130***	-0.0133***
	(-45.69)	(-43.64)		(-47.54)	(-47.70)		(-43.81)	(-41.62)
FIRM	0.01120***	0.01104**	FIRM	0.01313***	0.01337***	FIRM	0.01154***	0.01138**
	(2.93)	(2.50)		(3.43)	(3.03)		(3.01)	(2.57)
LREC	-0.3470***	5.06360***	LREC	-0.5273***	5.76406***	LREC	-0.2901***	4.96393***
	(-7.61)	(11.65)		(-11.61)	(13.71)		(-6.34)	(11.30)
LRECLMVE		-0.1304***	LRECLMVE		-0.2233***	LRECLMVE		-0.1066**
		(-2.60)			(-4.61)			(-2.11)
LRECLSHR		-0.2804***	LRECLSHR		-0.2329***	LRECLSHR		-0.3008***
		(-5.31)			(-4.43)			(-5.69)
LRECBETAV		-0.3171***	LRECBETAE		-0.2389***	LRECBETASP		-0.3151***
		(-3.48)			(-3.08)			(-3.37)
LRECRSEV		-0.1792***	LRECRSEE		-0.2088***	LRECRSESP		-0.1634***
		(-5.13)			(-5.81)			(-4.68)
LRECEXV		0.00227***	LRECEXE		0.00717***	LRECEXSP		0.00159*
		(2.60)			(8.40)			(1.83)
LRECFIRM		-0.0002	LRECFIRM		-0.0019	LRECFIRM		-0.0001
		(-.02)			(-.23)			(-.02)
N	117971	117971		117971	117971		117971	117971
Adj. R2	0.498332	0.499266		0.499849	0.501202		0.497721	0.498629

Table 3.5 Analyst Forecast Errors Sorted on Excess Analyst Following for Good and Bad Domain

This table presents the portfolio examination for hypothesis H2a. Sample firm-years are classified into the bad domain and the good domain based on the recession dummy (REC). For each of the two domains, firm-years are further divided into three groups based on excess coverage measure (Low, Middle, and High group). For each group, mean excess coverage, mean forecast error (actual EPS – mean EPS forecast) and median forecast error (actual EPS – median EPS forecast) are presented. The values are then compared across domains for the corresponding group (Low to Low, Middle to Middle, And High to High). Within each domain, the differences in those values between the Low group and the High group are compared as well. Panel A presents the results based on excess coverage measure from the relative approach and SIC (EXCOV1), Panel B presents results based on excess coverage measure from the relative approach and Fama-French 49 industry classification (EXCOV2). Panel C presents the results based on excess coverage measure from regression approach with equation (2) (EXCOV3) and the results based on excess coverage measure from regression approach with equation (3) (EXCOV4). The left half of Panel A uses mean industry analyst coverage/ sale ratio to calculate a firm's expected analyst coverage and thus the firm's excess analyst coverage. The right half of Panel A uses median industry analyst coverage/ sale ratio. The left half of Panel B is based on mean industry analyst coverage/ sales ratio, and the right half is based on the median ratio. Panel C provides results from excess analyst coverage measure developed from regression method. EXCOV3 is residual from the OLS regression using specification in equation (3), and EXCOV4 is residual from the OLS regression using specification in equation (4). P-value are provided in the parentheses. Wilcoxon Test is reported with Z-score from the test and p-values are in the parentheses.

Panel A: Sorted on EXCOV1

			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
Mean EXCOV1	Low	N	15412	1892		Median EXCOV1	Low	N	15413	1893	
		Mean	-2.3353	-2.3895	0.0542 (0.04)			Mean	-1.9675	-2.0232	0.0557 (0.03)
		Wilcoxon			2.5115 (0.01)			Wilcoxon			2.4258 (0.02)
	Middle	N	16068	1998			Middle	N	16074	2007	
		Mean	-0.6957	-0.7344	0.0387 (0.00)			Mean	-0.3655	-0.3673	0.0017 (0.80)
		Wilcoxon			5.1448 (0.00)			Wilcoxon			0.3595 (0.72)
	High	N	17130	2208			High	N	17123	2198	
		Mean	0.4925	0.4795	0.0131 (0.30)			Mean	0.8222	0.8376	-0.0154 (0.28)
		Wilcoxon			1.1779 (0.09)			Wilcoxon			-0.7603 (0.45)
	Low - High	Mean	-2.8279 (0.00)	-2.8690 (0.00)			Low - High	Mean	-2.7897 (0.00)	-2.8608 (0.00)	
		Wilcoxon	-156.01 (0.00)	-55.28 (0.00)				Wilcoxon	-155.99 (0.00)	-55.23 (0.00)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
Mean Forecast error	Low	Mean	-0.0875	-0.2143	0.1267 (0.00)	Mean Forecast error	Low	Mean	-0.0901	-0.1971	0.1070 (0.00)
		Wilcoxon			4.0413 (0.00)			Wilcoxon			4.2852 (0.00)
	Middle	Mean	-0.0925	-0.1734	0.0810 (0.00)		Middle	Mean	-0.0846	-0.1808	0.0962 (0.00)
		Wilcoxon			3.2855 (0.00)			Wilcoxon			3.5799 (0.00)
	High	Mean	-0.0877	-0.1265	0.0388 (0.00)		High	Mean	-0.0928	-0.1343	0.0416 (0.00)
		Wilcoxon			-0.5807 (0.56)			Wilcoxon			-1.1809 (0.24)
	Low - High	Mean	0.0001 (0.98)	-0.0878 (0.00)			Low - High	Mean	0.0027 (0.67)	-0.0628 (0.03)	
		Wilcoxon	7.6438 (0.00))	-1.0961 (0.27)				Wilcoxon	8.5009 (0.00)	-1.3918 (0.16)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
Median Forecast error	Low	Mean	-0.0854	-0.2120	0.1265 (0.00)	Median Forecast error	Low	Mean	-0.0884	-0.1951	0.1068 (0.00)
		Wilcoxon			3.7242 (0.00)			Wilcoxon			4.1235 (0.00)
	Middle	Mean	-0.0903	-0.1716	0.0814 (0.00)		Middle	Mean	-0.0817	-0.1792	0.0974 (0.00)
		Wilcoxon			3.4065 (0.00)			Wilcoxon			3.7992 (0.00)
	High	Mean	-0.0837	-0.1290	0.0453 (0.00)		High	Mean	-0.0891	-0.1364	0.0473 (0.00)
		Wilcoxon			0.0000 (0.99)			Wilcoxon			-0.8569 (0.39)
	Low - High	Mean	-0.0017 (0.78)	-0.0829 (0.00)			Low - High	Mean	0.0008 (0.90)	-0.0587 (0.04)	
		Wilcoxon	6.8724 (0.00)	-0.7059 (0.48)				Wilcoxon	7.7245 (0.00)	-1.2893 (0.19)	

Panel B: Sorted on EXCOV2

			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
		N	24840	3123				N	24788	3105	
	Low	Mean	-2.4286	-2.5485	0.1199 (0.00)		Low	Mean	-1.9726	-1.9910	0.0185 (0.35)
		Wilcoxon			9.7775 (0.00)			Wilcoxon			2.6005 (0.01)
		N	25774	3263				N	25851	3277	
Mean	Middle	Mean	-0.8291	-0.9125	0.0834 (0.00)	Median	Middle	Mean	-0.3930	-0.3880	-0.0050 (0.38)
EXCOV2		Wilcoxon			12.5109 (0.00)	EXCOV2		Wilcoxon			-0.7560 (0.45)
		N	27465	3553				N	27440	3557	
	High	Mean	0.4006	0.3691	0.0315 (0.00)		High	Mean	0.8352	0.8821	-0.0469 (0.00)
		Wilcoxon			4.8009 (0.00)			Wilcoxon			-3.4045 (0.00)
	Low - High	Mean	-2.8292 (0.00)	-2.9176 (0.00)			Low - High	Mean	-2.8078 (0.00)	-2.8732 (0.00)	
		Wilcoxon	-197.81 (0.00)	-70.61 (0.00)				Wilcoxon	-197.66 (0.00)	-70.52 (0.00)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
	Low	Mean	-0.1049	-0.2240	0.1191 (0.00)		Low	Mean	-0.1009	-0.2252	0.1242 (0.00)
		Wilcoxon			4.9558 (0.00)			Wilcoxon			4.9525 (0.00)
Mean	Middle	Mean	-0.0991	-0.2367	0.1376 (0.00)	Mean	Middle	Mean	-0.1011	-0.2248	0.1237 (0.00)
Forecast		Wilcoxon			4.4828 (0.00)	Forecast		Wilcoxon			3.8097 (0.00)
error	High	Mean	-0.1000	-0.1703	0.0703 (0.00)	error	High	Mean	-0.1016	-0.1802	0.0786 (0.00)
		Wilcoxon			0.7009 (0.48)			Wilcoxon			1.3690 (0.00)
	Low - High	Mean	-0.0049 (0.33)	-0.0538 (0.04)			Low - High	Mean	0.0007 (0.89)	-0.0450 (0.08)	
		Wilcoxon	11.1577 (0.00)	0.1219 (0.90)				Wilcoxon	12.2521 (0.00)	0.8650 (0.39)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
	Low	Mean	-0.1027	-0.2251	0.1224 (0.00)		Low	Mean	-0.0987	-0.2256	0.1269 (0.00)
		Wilcoxon			4.4986 (0.00)			Wilcoxon			4.6080 (0.00)
Median	Middle	Mean	-0.0960	-0.2309	0.1349 (0.00)	Median	Middle	Mean	-0.0978	-0.2195	0.1216 (0.00)
Forecast		Wilcoxon			4.5649 (0.00)	Forecast		Wilcoxon			3.8244 (0.00)
error	High	Mean	-0.0963	-0.1712	0.0749 (0.00)	error	High	Mean	-0.0981	-0.1813	0.0832 (0.00)
		Wilcoxon			1.3747 (0.17)			Wilcoxon			1.9758 (0.05)
	Low - High	Mean	-0.0065 (0.19)	-0.0539 (0.03)			Low - High	Mean	-0.0007 (0.89)	-0.0444 (0.09)	
		Wilcoxon	10.3216 (0.00)	0.6255 (0.53)				Wilcoxon	11.4314 (0.00)	1.2531 (0.21)	

Panel C: Sorted on EXCOV3 and EXCOV4

			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
		N	21582	2539				N	21773	2551	
	Low	Mean	-0.4663	-0.4667	0.0004 (0.95)		Low	Mean	-0.4517	-0.4560	0.0043 (0.41)
		Wilcoxon			0.5013 (0.62)			Wilcoxon			1.3895 (0.17)
		N	31207	4047				N	31195	4006	
EXCOV3	Middle	Mean	0.0313	0.0326	-0.0013 (0.51)	EXCOV4	Middle	Mean	0.0357	0.0348	0.0008 (0.66)
		Wilcoxon			1.0429 (0.30)			Wilcoxon			0.1604 (0.87)
		N	34307	4437				N	34160	4434	
	High	Mean	0.5148	0.5307	-0.0159 (0.00)		High	Mean	0.4939	0.5107	-0.0168 (0.00)
		Wilcoxon			-4.6807 (0.00)			Wilcoxon			-4.9325 (0.00)
	Low - High	Mean	-0.9811 (0.00)	-0.9974 (0.00)			Low - High	Mean	-0.9456 (0.00)	-0.9666 (0.00)	
		Wilcoxon	-199.36 (0.00)	-69.60 (0.00)				Wilcoxon	-199.73 (0.00)	-69.69 (0.00)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
	Low	Mean	-0.0817	-0.1899	0.1081 (0.00)		Low	Mean	-0.1051	-0.2357	0.1306 (0.00)
		Wilcoxon			2.9955 (0.00)			Wilcoxon			2.9982 (0.00)
Mean Forecast error	Middle	Mean	-0.1158	-0.0935	-0.0223 (0.05)	Mean Forecast error	Middle	Mean	-0.1042	-0.2231	0.1189 (0.00)
		Wilcoxon			5.5083 (0.00)			Wilcoxon			4.3337 (0.00)
	High	Mean	-0.1427	-0.2360	0.0934 (0.00)		High	Mean	-0.1230	-0.2127	0.0897 (0.00)
		Wilcoxon			2.1068 (0.04)			Wilcoxon			3.3695 (0.00)
	Low - High	Mean	0.0610 (0.00)	0.0462 (0.11)			Low - High	Mean	0.0179 (0.00)	-0.0230 (0.43)	
		Wilcoxon	8.6453 (0.00)	1.6901 (0.09)				Wilcoxon	-0.1161 (0.91)	-0.4350 (0.66)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
	Low	Mean	-0.0811	-0.1945	0.1135 (0.00)		Low	Mean	-0.1030	-0.2402	0.1372 (0.00)
		Wilcoxon			2.9653 (0.00)			Wilcoxon			3.0765 (0.00)
Median Forecast error	Middle	Mean	-0.1121	-0.0898	-0.0222 (0.05)	Median Forecast error	Middle	Mean	-0.1008	-0.2181	0.1173 (0.00)
		Wilcoxon			5.4384 (0.00)			Wilcoxon			4.3025 (0.00)
	High	Mean	-0.1364	-0.2315	0.0951 (0.00)		High	Mean	-0.1175	-0.2078	0.0903 (0.00)
		Wilcoxon			2.2741 (0.02)			Wilcoxon			3.4178 (0.00)
	Low - High	Mean	0.0553 (0.00)	0.0369 (0.19)			Low - High	Mean	0.0145 (0.01)	-0.0324 (0.25)	
		Wilcoxon	7.7577 (0.00)	1.5236 (0.13)				Wilcoxon	-0.4187 (0.68)	-0.5839 (0.56)	

Table 3.6 Analyst Forecast Errors Sorted on Excess Analyst Following for Post-Good and Post-Bad Domain

This table presents the portfolio examination for hypothesis H2b. Sample firm-years are classified into the post-bad domain and the post-good domain based on the recession observation dummy (LREC). For each of the two domains, firm-years are further divided into three groups based on excess coverage measure (Low, Middle, and High group). For each group, mean excess coverage, mean forecast error (actual EPS – mean EPS forecast) and median forecast error (actual EPS – median EPS forecast) are presented. The values are then compared across domains for the corresponding group (Low to Low, Middle to Middle, And High to High). Within each domain, the differences in those values between the Low group and the High group are compared as well. Panel A presents the results based on excess coverage measure from the relative approach and SIC (EXCOV1), Panel B presents results based on excess coverage measure from the relative approach and Fama-French 49 industry classification (EXCOV2). Panel C presents the results based on excess coverage measure from regression approach with equation (2) (EXCOV3) and the results based on excess coverage measure from regression approach with equation (3) (EXCOV4). The left half of Panel A uses mean industry analyst coverage/ sale ratio to calculate a firm's expected analyst coverage and thus the firm's excess analyst coverage. The right half of Panel A uses median industry analyst coverage/ sale ratio. The left half of Panel B is based on mean industry analyst coverage/ sales ratio, and the right half is based on the median ratio. Panel C provides results from excess analyst coverage measure developed from regression method. EXCOV3 is residual from the OLS regression using specification in equation (3), and EXCOV4 is residual from the OLS regression using specification in equation (4). P-value are provided in the parentheses. Wilcoxon Test is reported with Z-score from the test and p-values are in the parentheses.

Panel A: Sorted on EXCOV1

			Post-Good	Post-Bad	Diff (Good - Bad)				Post-Good	Post-Bad	Diff (Good - Bad)
		N	15331	1963				N	15322	1981	
	Low	Mean	-2.3408	-2.3487	0.0079 (0.76)		Low	Mean	-1.9750	-1.9639	-0.0111 (0.66)
		Wilcoxon			0.6305 (0.53)			Wilcoxon			-0.4436 (0.66)
		N	15976	2105				N	15997	2089	
Mean EXCOV1	Middle	Mean	-0.7000	-0.7001	0.0001 (0.99)	Median EXCOV1	Middle	Mean	-0.3691	-0.3369	-0.0322 (0.00)
		Wilcoxon			0.4376 (0.66)			Wilcoxon			-4.4135 (0.00)
		N	17065	2268				N	17053	2266	
	High	Mean	0.4874	0.5173	-0.0300 (0.02)		High	Mean	0.8160	0.8812	-0.0652 (0.00)
		Wilcoxon			2.1218 (0.03)			Wilcoxon			5.0244 (0.00)
	Low - High	Mean	-2.8282 (0.00)	-2.8660 (0.00)			Low - High	Mean	-2.7910 (0.00)	-2.8451 (0.00)	
		Wilcoxon	-155.65 (0.00)	-56.17 (0.00)				Wilcoxon	-155.60 (0.00)	-56.29 (0.00)	
			Post-Good	Post-Bad	Diff (Good - Bad)				Post-Good	Post-Bad	Diff (Good - Bad)
	Low	Mean	-0.1048	-0.0597	-0.0451 (0.00)		Low	Mean	-0.1073	-0.0508	-0.0565 (0.00)
		Wilcoxon			-6.1261 (0.00)			Wilcoxon			-6.5441 (0.00)
Mean Forecast error	Middle	Mean	-0.1031	-0.0792	-0.0239 (0.09)	Mean Forecast error	Middle	Mean	-0.0949	-0.0797	-0.0152 (0.26)
		Wilcoxon			-6.0875 (0.00)			Wilcoxon			-6.0578 (0.00)
	High	Mean	-0.0952	-0.0662	-0.0290 (0.02)		High	Mean	-0.1006	-0.0736	-0.0270 (0.24)
		Wilcoxon			-5.1103 (0.00)			Wilcoxon			-4.7013 (0.00)
	Low - High	Mean	-0.010 (0.14)	0.0065 (0.71)			Low - High	Mean	-0.007 (0.32)	0.0228 (0.20)	
		Wilcoxon	5.9466 (0.00)	3.9812 (0.00)				Wilcoxon	6.5394 (0.00)	4.7162 (0.00)	
			Post-Good	Post-Bad	Diff (Good - Bad)				Post-Good	Post-Bad	Diff (Good - Bad)
	Low	Mean	-0.1031	-0.0623	-0.0408 (0.01)		Low	Mean	-0.1059	-0.0535	-0.0524 (0.00)
		Wilcoxon			-6.3301 (0.01)			Wilcoxon			-6.6111 (0.00)
Median Forecast error	Middle	Mean	-0.1007	-0.0876	-0.0131 (0.36)	Median Forecast error	Middle	Mean	-0.0918	-0.0888	-0.0030 (0.83)
		Wilcoxon			-5.9947 (0.00)			Wilcoxon			-6.0491 (0.00)
	High	Mean	-0.0919	-0.0681	-0.0239 (0.05)		High	Mean	-0.0977	-0.0748	-0.0229 (0.07)
		Wilcoxon			-5.0325 (0.00)			Wilcoxon			-4.6980 (0.00)
	Low - High	Mean	-0.011 (0.09)	0.0058 (0.75)			Low - High	Mean	-0.008 (0.22)	0.0213 (0.25)	
		Wilcoxon	5.3361 (0.00)	3.9836 (0.00)				Wilcoxon	5.8678 (0.00)	4.5367 (0.00)	

Panel B: Sorted on EXCOV2

			Post-Good	Post-Bad	Diff (Good - Bad)				Post-Good	Post-Bad	Diff (Good - Bad)
		N	24745	3222				N	24693	3203	
	Low	Mean	-2.4361	-2.4860	0.0500 (0.01)		Low	Mean	-1.9759	-1.9630	-0.0129 (0.51)
		Wilcoxon			4.7212 (0.00)			Wilcoxon			0.3504 (0.73)
		N	25691	3371				N	25761	3381	
Mean EXCOV2	Middle	Mean	-0.8347	-0.8616	0.0269 (0.00)	Median EXCOV2	Middle	Mean	-0.3927	-0.3876	-0.0051 (0.37)
		Wilcoxon			4.6627 (0.00)			Wilcoxon			-0.5437 (0.59)
		N	27388	3601				N	27370	3610	
	High	Mean	0.3970	0.4029	-0.0059 (0.54)		High	Mean	0.8354	0.8825	-0.0471 (0.00)
		Wilcoxon			0.3090 (0.76)			Wilcoxon			-4.2228 (0.00)
	Low - High	Mean	-2.8330 (0.00)	-2.8889 (0.00)			Low - High	Mean	-2.8113 (0.00)	-2.8455 (0.00)	
		Wilcoxon	-197.48 (0.00)	-71.42 (0.00)				Wilcoxon	-197.34 (0.00)	-71.35 (0.00)	
			Post-Good	Post-Bad	Diff (Good - Bad)				Post-Good	Post-Bad	Diff (Good - Bad)
	Low	Mean	-0.1202	-0.0834	-0.0368 (0.00)		Low	Mean	-0.1170	-0.0751	-0.0419 (0.00)
		Wilcoxon			-5.4117 (0.00)			Wilcoxon			-5.9068 (0.00)
Mean Forecast error	Middle	Mean	-0.1125	-0.0952	-0.0173 (0.12)	Mean Forecast error	Middle	Mean	-0.1131	-0.1005	-0.0125 (0.27)
		Wilcoxon			-5.4335 (0.00)			Wilcoxon			-5.6449 (0.00)
	High	Mean	-0.1080	-0.0895	-0.0185 (0.07)		High	Mean	-0.1105	-0.0919	-0.0186 (0.07)
		Wilcoxon			-6.8509 (0.00)			Wilcoxon			-6.1555 (0.00)
	Low - High	Mean	-0.0122 (0.02)	0.0061 (0.68)			Low - High	Mean	-0.0065 (0.22)	0.0168 (0.25)	
		Wilcoxon	9.95066 (0.00)	3.6330 (0.00)				Wilcoxon	10.8662 (0.00)	4.8018 (0.00)	
			Post-Good	Post-Bad	Diff (Good - Bad)				Post-Good	Post-Bad	Diff (Good - Bad)
	Low	Mean	-0.1189	-0.0848	-0.0341 (0.01)		Low	Mean	-0.1156	-0.0766	-0.0390 (0.00)
		Wilcoxon			-5.6064 (0.00)			Wilcoxon			-6.1676 (0.00)
Median Forecast error	Middle	Mean	-0.1100	-0.0966	-0.0134 (0.23)	Median Forecast error	Middle	Mean	-0.1102	-0.1026	-0.0076 (0.50)
		Wilcoxon			-5.6846 (0.00)			Wilcoxon			-5.7891 (0.00)
	High	Mean	-0.1052	-0.0885	-0.0168 (0.09)		High	Mean	-0.1080	-0.0900	-0.0179 (0.00)
		Wilcoxon			-6.7871 (0.00)			Wilcoxon			-6.1135 (0.00)
	Low - High	Mean	-0.0137 (0.01)	0.0037 (0.81)			Low - High	Mean	-0.0076 (0.15)	0.0135 (0.37)	
		Wilcoxon	9.3484 (0.00)	3.5726 (0.00)				Wilcoxon	10.2144 (0.00)	4.7577 (0.00)	

Panel C: Sorted on EXCOV3 and EXCOV4

			Post-Good	Post-Bad	Diff (Good - Bad)
		N	21491	2735	
	Low	Mean	-0.4642	-0.4773	0.0131 (0.00)
		Wilcoxon			2.8562 (0.00)
		N	31163	4027	
EXCOV3	Middle	Mean	0.0315	0.0323	-0.0008 (0.67)
		Wilcoxon			-0.4166 (0.68)
		N	34242	4461	
	High	Mean	0.5141	0.5239	-0.0098 (0.01)
		Wilcoxon			-2.8282 (0.00)
	Low - High	Mean	-0.9783 (0.00)	-1.0012 (0.00)	
		Wilcoxon	-197.48 (0.00)	-71.42 (0.00)	
			Post-Good	Post-Bad	Diff (Good - Bad)
	Low	Mean	-0.0921	-0.0854	-0.0067 (0.60)
		Wilcoxon			-3.1865 (0.00)
Mean Forecast error	Middle	Mean	-0.1131	-0.0844	-0.0286 (0.01)
		Wilcoxon			-7.1769 (0.00)
	High	Mean	-0.1563	-0.1275	-0.0289 (0.02)
		Wilcoxon			-7.2349 (0.00)
	Low - High	Mean	0.0642 (0.00)	0.0421 (0.02)	
		Wilcoxon	9.9506 (0.00)	3.6330 (0.00)	
			Post-Good	Post-Bad	Diff (Good - Bad)
	Low	Mean	-0.0911	-0.0877	-0.0035 (0.78)
		Wilcoxon			-2.8282 (0.00)
Median Forecast error	Middle	Mean	-0.1086	-0.0833	-0.0253 (0.02)
		Wilcoxon			-6.5991 (0.00)
	High	Mean	-0.1485	-0.1231	-0.0254 (0.03)
		Wilcoxon			-6.9887 (0.00)
	Low - High	Mean	0.0574 (0.00)	0.0355 (0.05)	
		Wilcoxon	9.3484 (0.00)	3.5726 (0.00)	

			Post-Good	Post-Bad	Diff (Good - Bad)
		N	21667	2746	
	Low	Mean	-0.4503	-0.4616	0.0113 (0.03)
		Wilcoxon			2.3578 (0.02)
		N	31111	4053	
EXCOV4	Middle	Mean	0.0356	0.0357	-0.0001 (0.96)
		Wilcoxon			-0.1289 (0.90)
		N	34118	4424	
	High	Mean	0.4933	0.5055	-0.0122 (0.00)
		Wilcoxon			-3.8090 (0.00)
	Low - High	Mean	-0.9437 (0.00)	-0.9672 (0.00)	
		Wilcoxon	-199.39 (0.00)	-71.29 (0.00)	
			Post-Good	Post-Bad	Diff (Good - Bad)
	Low	Mean	-0.1204	-0.1051	-0.0153 (0.28)
		Wilcoxon			-3.2521 (0.00)
Mean Forecast error	Middle	Mean	-0.1152	-0.0921	-0.0232 (0.03)
		Wilcoxon			-7.1439 (0.00)
	High	Mean	-0.1367	-0.1086	-0.0281 (0.02)
		Wilcoxon			-6.5930 (0.00)
	Low - High	Mean	0.0163 (0.01)	0.0035 (0.84)	
		Wilcoxon	0.0447 (0.96)	-1.2443 (0.21)	
			Post-Good	Post-Bad	Diff (Good - Bad)
	Low	Mean	-0.1176	-0.1070	-0.0106 (0.44)
		Wilcoxon			-3.3848 (0.00)
Median Forecast error	Middle	Mean	-0.1107	-0.0908	-0.0199 (0.06)
		Wilcoxon			-7.2669 (0.00)
	High	Mean	-0.1300	-0.1045	-0.0255 (0.02)
		Wilcoxon			-6.8964 (0.00)
	Low - High	Mean	0.0123 (0.04)	-0.0025 (0.89)	
		Wilcoxon	-0.2215 (0.82)	-1.3920 (0.16)	

Table 3.7 Firm Characteristics Sorted on Excess Analyst Following for Good and Bad Domain

This table presents the firm characteristics an analyst follows in good/ bad times. Sample firm-years are classified into the bad domain and the good domain based on the recession dummy (REC). For each of the two domains, firm-years are further divided into three groups based on excess coverage measure (Low, Middle, and High group). For each group, number of analyst following (NUMEST), the logarithm of the market value of equity (LMVE), the logarithm of shares outstanding (LSHR, beta (BETAVW), stock volatility (RSEVW), past stock performance (EXVW), and changes of the number of firms in the past five years (NEWFIRM5YR) are presented. The values are then compared across domains for the corresponding group (Low to Low, Middle to Middle, And High to High). Within each domain, the differences in those values between the Low group and the High group are compared as well. Panel A presents the results based on excess coverage measure from the relative approach and SIC (EXCOV1), Panel B presents results based on excess coverage measure from the relative approach and Fama-French 49 industry classification (EXCOV2). Panel C presents the results based on excess coverage measure from regression approach with equation (2) (EXCOV3) and the results based on excess coverage measure from regression approach with equation (3) (EXCOV4). The left half of Panel A uses mean industry analyst coverage/ sale ratio to calculate a firm's expected analyst coverage and thus the firm's excess analyst coverage. The right half of Panel A uses median industry analyst coverage/ sale ratio. The left half of Panel B is based on mean industry analyst coverage/ sales ratio, and the right half is based on the median ratio. Panel C provides results from excess analyst coverage measure developed from regression method. EXCOV3 is residual from the OLS regression using specification in equation (3), and EXCOV4 is residual from the OLS regression using specification in equation (4). P-values are provided in the parentheses. Wilcoxon Test is reported with Z-score from the test and p-values are in the parentheses.

Panel A: Sorted on EXCOV1

			Mean EXCOV1						Median EXCOV1		
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
		N	15412	1892				N	15413	1893	
	Low	Mean	11.4779	9.9471	1.5307 (0.00)		Low	Mean	11.5430	9.9868	1.5563 (0.00)
		Wilcoxon			4.4467 (0.00)			Wilcoxon			4.5619 (0.00)
		N	16068	1998				N	16074	2007	
NUMEST	Middle	Mean	9.0915	8.2347	0.8568 (0.00)	NUMEST	Middle	Mean	9.0970	8.0907	1.0063 (0.00)
		Wilcoxon			3.8098 (0.00)			Wilcoxon			5.09665 (0.00)
		N	17130	2208				N	17123	2198	
	High	Mean	7.9006	7.7083	0.1923 (0.14)		High	Mean	7.8362	7.8025	0.0336 (0.80)
		Wilcoxon			-0.1384 (0.89)			Wilcoxon			-1.5909 (0.11)
	Low - High	Mean	3.5773 (0.00)	2.2388 (0.00)			Low - High	Mean	3.7069 (0.00)	2.1842 (0.00)	
		Wilcoxon	27.7829 (0.00)	7.2753 (0.00)				Wilcoxon	29.9264 (0.00)	7.1320 (0.00)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
	Low	Mean	14.4209	14.3614	0.0595 (0.17)		Low	Mean	14.4136	14.3702	0.0433 (0.32)
		Wilcoxon			1.6463 (0.10)			Wilcoxon			1.2677 (0.20)
	Middle	Mean	13.4059	13.2398	0.1661 (0.00)		Middle	Mean	13.4067	13.1861	0.2205 (0.00)
LMVE		Wilcoxon			4.6220 (0.00)	LMVE		Wilcoxon			6.0090 (0.00)
	High	Mean	12.6196	12.4944	0.1251 (0.00)		High	Mean	12.6251	12.5320	0.0931 (0.00)
		Wilcoxon			3.3001 (0.00)			Wilcoxon			2.3389 (0.02)
	Low - High	Mean	1.8014 (0.00)	1.8670 (0.00)			Low - High	Mean	1.7884 (0.00)	1.8382 (0.00)	
		Wilcoxon	88.8955 (0.00)	78.8896 (0.00)				Wilcoxon	88.2230 (0.00)	33.1682 (0.00)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
	Low	Mean	11.4809	11.6274	-0.1464 (0.00)		Low	Mean	11.4751	11.6278	-0.1528 (0.00)
		Wilcoxon			-3.8898 (0.00)			Wilcoxon			-3.9732 (0.00)
	Middle	Mean	10.6760	10.7189	-0.0429 (0.16)		Middle	Mean	10.6765	10.6766	-0.0002 (1.00)
LSHR		Wilcoxon			-1.3219 (0.19)	LSHR		Wilcoxon			-0.1618 (0.87)
	High	Mean	10.1669	10.2300	-0.0631 (0.02)		High	Mean	10.1715	10.2655	-0.0940 (0.00)
		Wilcoxon			-3.1977 (0.00)			Wilcoxon			-4.1738 (0.00)
	Low - High	Mean	1.3140 (0.00)	1.3974 (0.00)			Low - High	Mean	1.3036 (0.00)	1.3623 (0.00)	
		Wilcoxon	78.8896 (0.00)	30.9503 (0.00)				Wilcoxon	78.6286 (0.00)	30.3309 (0.00)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
	Low	Mean	1.0008	1.0467	-0.0459 (0.00)		Low	Mean	1.0032	1.0387	-0.0356 (0.00)
		Wilcoxon			-2.2712 (0.02)			Wilcoxon			-1.7353 (0.08)
	Middle	Mean	0.9843	1.0301	-0.0458 (0.00)		Middle	Mean	0.9791	1.0307	-0.0516 (0.00)
BETAVW		Wilcoxon			-2.6888 (0.01)	BETAVW		Wilcoxon			-3.2281 (0.00)
	High	Mean	1.0078	1.0705	-0.0627 (0.00)		High	Mean	1.0105	1.0770	-0.0665 (0.00)
		Wilcoxon			-4.5146 (0.00)			Wilcoxon			-4.5246 (0.00)
	Low - High	Mean	-0.0071 (0.26)	-0.0239 (0.19)			Low - High	Mean	-0.0074 (0.24)	-0.0383 (0.03)	
		Wilcoxon	3.8270 (0.00)	-0.3693 (0.71)				Wilcoxon	3.5041 (0.00)	-0.8365 (0.40)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
	Low	Mean	1.9965	2.6690	-0.6725 (0.00)		Low	Mean	2.0080	2.6348	-0.6268 (0.00)
		Wilcoxon			-26.0983 (0.00)			Wilcoxon			-25.0063 (0.00)
	Middle	Mean	2.3602	3.0579	-0.6977 (0.00)		Middle	Mean	2.3423	3.0857	-0.7434 (0.00)
RSEVW		Wilcoxon			-22.5891 (0.00)	RSEVW		Wilcoxon			-23.9985 (0.00)
	High	Mean	2.8317	3.5375	-0.7058 (0.00)		High	Mean	2.8382	3.5439	-0.7056 (0.00)
		Wilcoxon			-19.3137 (0.00)			Wilcoxon			-18.9378 (0.00)
	Low - High	Mean	-0.8352 (0.00)	-0.8685 (0.00)			Low - High	Mean	-0.8302 (0.00)	-0.9091 (0.00)	
		Wilcoxon	-61.449 (0.00)	-18.617 (0.00)				Wilcoxon	-60.645 (0.00)	-18.904 (0.00)	

			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
	Low	Mean	2.6035	8.9524	-6.3489 (0.00)		Low	Mean	2.6350	8.4271	-5.7921 (0.00)
		Wilcoxon			-5.4278 (0.00)			Wilcoxon			-4.9350 (0.00)
	Middle	Mean	3.6603	10.9220	-7.2617 (0.00)		Middle	Mean	3.9707	11.3719	-7.4012 (0.00)
EXVW		Wilcoxon			-6.6176 (0.00)	EXVW		Wilcoxon			-6.5857 (0.00)
	High	Mean	3.6133	6.2533	-2.6400 (0.03)		High	Mean	3.2936	6.2746	-2.9810 (0.02)
		Wilcoxon			-3.8791 (0.00)			Wilcoxon			-4.3321 (0.00)
	Low - High	Mean	-1.0098 (0.06)	2.6991 (0.07)			Low - High	Mean	-0.6587 (0.23)	2.1525 (0.15)	
		Wilcoxon	7.9302 (0.00)	3.5540 (0.00)				Wilcoxon	8.3127 (0.00)	3.0676 (0.00)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
	Low	Mean	5.2030	-6.9725	12.1755 (0.00)		Low	Mean	4.5110	-6.7052	11.2162 (0.00)
		Wilcoxon			9.8222 (0.00)			Wilcoxon			-8.8179 (0.00)
NEWFIRM 5YR	Middle	Mean	4.5889	-8.8909	13.4798 (0.00)	NEWFIRM 5YR	Middle	Mean	3.5914	-9.6667	13.2581 (0.00)
		Wilcoxon			8.9218 (0.00)			Wilcoxon			-8.9586 (0.00)
	High	Mean	4.1307	-6.5127	10.6434 (0.00)		High	Mean	5.6898	-6.0246	11.7144 (0.00)
		Wilcoxon			7.5048 (0.00)			Wilcoxon			-8.4358 (0.00)
	Low - High	Mean	1.0723 (0.16)	-0.4598 (0.74)			Low - High	Mean	-1.1788 (0.13)	-0.6807 (0.62)	
		Wilcoxon	2.3838 (0.02)	-1.3060 (0.19)				Wilcoxon	-0.7753 (0.44)	-1.1885 (0.23)	

Panel B: Sorted on EXCOV2

			Mean EXCOV2		
			Good	Bad	Diff (Good - Bad)
NUMEST		N	24840	3123	
	Low	Mean	10.9712	9.3990	1.5722 (0.00)
		Wilcoxon			6.5515 (0.00)
		N	25774	3263	
	Middle	Mean	8.5873	7.7392	0.8481 (0.00)
		Wilcoxon			5.1770 (0.00)
		N	27465	3553	
	High	Mean	7.2376	7.1565	0.0811 (0.40)
		Wilcoxon			-0.8587 (0.39)
	Low - High	Mean	3.7336 (0.00)	2.2425 (0.00)	
		Wilcoxon	40.7152 (0.00)	10.0765 (0.00)	
			Good	Bad	Diff (Good - Bad)
LMVE	Low	Mean	14.3393	14.2496	0.0897 (0.01)
		Wilcoxon			2.9077 (0.00)
	Middle	Mean	13.3148	13.0741	0.2407 (0.00)
		Wilcoxon			8.2302 (0.00)
	High	Mean	12.4338	12.3228	0.1110 (0.00)
		Wilcoxon			4.1576 (0.00)
	Low - High	Mean	1.9055 (0.00)	1.9268 (0.00)	
		Wilcoxon	119.199 (0.00)	44.0751 (0.00)	
			Good	Bad	Diff (Good - Bad)
LSHR	Low	Mean	11.3718	11.4818	-0.1100 (0.00)
		Wilcoxon			-3.8248 (0.00)
	Middle	Mean	10.5893	10.6024	-0.0130 (0.57)
		Wilcoxon			-0.8573 (0.00)
	High	Mean	9.9762	10.0232	-0.0470 (0.02)
		Wilcoxon			-3.5667 (0.00)
	Low - High	Mean	1.3956 (0.00)	1.4586 (0.00)	
		Wilcoxon	106.909 (0.00)	40.7475 (0.00)	
			Good	Bad	Diff (Good - Bad)
BETAVW	Low	Mean	0.9751	1.0173	-0.0423 (0.00)
		Wilcoxon			-2.4831 (0.01)
	Middle	Mean	0.9626	1.0271	-0.0645 (0.00)
		Wilcoxon			-5.2224 (0.00)
	High	Mean	0.9538	1.0167	-0.0628 (0.00)
		Wilcoxon			-5.4648 (0.00)
	Low - High	Mean	0.0212 (0.00)	0.0007 (0.96)	
		Wilcoxon	9.8237 (0.00)	1.3299 (0.18)	
			Good	Bad	Diff (Good - Bad)
RSEVW	Low	Mean	1.9610	2.6155	-0.6545 (0.00)
		Wilcoxon			-32.0182 (0.00)
	Middle	Mean	2.3190	3.0628	-0.7438 (0.00)
		Wilcoxon			-31.1923 (0.00)
	High	Mean	2.7749	3.4747	-0.6998 (0.00)
		Wilcoxon			-25.9167 (0.00)
	Low - High	Mean	-0.8139 (0.00)	-0.8592 (0.00)	
		Wilcoxon	-79.740 (0.00)	-25.427 (0.00)	

			Median EXCOV2		
			Good	Bad	Diff (Good - Bad)
NUMEST		N	24788	3105	
	Low	Mean	11.0060	9.5124	1.4936 (0.00)
		Wilcoxon			6.0170 (0.00)
		N	25851	3277	
	Middle	Mean	8.6008	7.7336	0.8672 (0.00)
		Wilcoxon			5.0600 (0.00)
		N	27440	3557	
	High	Mean	7.1968	7.0717	0.1251 (0.18)
		Wilcoxon			-0.1672 (0.87)
	Low - High	Mean	3.8092 (0.00)	2.4407 (0.00)	
		Wilcoxon	41.5753 (0.00)	11.2997 (0.00)	
			Good	Bad	Diff (Good - Bad)
LMVE	Low	Mean	14.3284	14.2434	0.0850 (0.01)
		Wilcoxon			2.6231 (0.01)
	Middle	Mean	13.3187	13.0834	0.2353 (0.00)
		Wilcoxon			8.1487 (0.00)
	High	Mean	12.4411	12.3264	0.1147 (0.00)
		Wilcoxon			4.3477 (0.00)
	Low - High	Mean	1.8873 (0.00)	1.9170 (0.00)	
		Wilcoxon	118.090 (0.00)	43.690 (0.00)	
			Good	Bad	Diff (Good - Bad)
LSHR	Low	Mean	11.3665	11.4779	-0.1115 (0.00)
		Wilcoxon			-3.7793 (0.00)
	Middle	Mean	10.5985	10.6108	-0.0123 (0.59)
		Wilcoxon			-0.9874 (0.32)
	High	Mean	9.9734	10.0240	-0.0506 (0.01)
		Wilcoxon			-3.5446 (0.00)
	Low - High	Mean	1.3931 (0.00)	1.4540 (0.00)	
		Wilcoxon	106.618 (0.00)	40.300 (0.00)	
			Good	Bad	Diff (Good - Bad)
BETAVW	Low	Mean	0.9849	1.0358	-0.0509 (0.00)
		Wilcoxon			-3.5675 (0.00)
	Middle	Mean	0.9599	1.0212	-0.0614 (0.00)
		Wilcoxon			-4.7132 (0.00)
	High	Mean	0.9475	1.0059	-0.0584 (0.00)
		Wilcoxon			-5.1740 (0.00)
	Low - High	Mean	0.0374 (0.00)	0.0300 (0.03)	
		Wilcoxon	12.9375 (0.00)	3.4403 (0.00)	
			Good	Bad	Diff (Good - Bad)
RSEVW	Low	Mean	1.9884	2.6677	-0.6794 (0.00)
		Wilcoxon			-33.1226 (0.00)
	Middle	Mean	2.3187	3.0573	-0.7387 (0.00)
		Wilcoxon			-30.3446 (0.00)
	High	Mean	2.7502	3.4313	-0.6811 (0.00)
		Wilcoxon			-25.1115 (0.00)
	Low - High	Mean	-0.7618 (0.00)	-0.7636 (0.00)	
		Wilcoxon	-75.108 (0.00)	-22.308 (0.00)	

			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
EXVW	Low	Mean	2.6855	10.9232	-8.2377 (0.00)	EXVW	Low	Mean	2.7137	10.1251	-7.4114 (0.00)
		Wilcoxon			-8.6191 (0.00)			Wilcoxon			-7.9491 (0.00)
	Middle	Mean	3.5703	9.8869	-6.3166 (0.00)		Middle	Mean	3.6425	10.5270	-6.8845 (0.00)
		Wilcoxon			-7.0543 (0.00)			Wilcoxon			-7.7390 (0.00)
	High	Mean	2.9848	8.6152	-5.6304 (0.00)		High	Mean	2.8890	8.7287	-5.8397 (0.00)
		Wilcoxon			-7.1417 (0.00)			Wilcoxon			-7.1243 (0.00)
	Low - High	Mean	-0.2993 (0.47)	2.3080 (0.06)			Low - High	Mean	-0.1753 (0.67)	1.3964 (0.25)	
		Wilcoxon	10.8529 (0.00)	3.8270 (0.00)				Wilcoxon	10.0735 (0.00)	3.2111 (0.00)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
NEWFIRM 5YR	Low	Mean	4.4893	-6.5632	11.0525 (0.00)	NEWFIRM 5YR	Low	Mean	4.4613	-7.0754	11.5367 (0.00)
		Wilcoxon			13.6517 (0.00)			Wilcoxon			13.1411 (0.00)
	Middle	Mean	4.1644	-8.5507	12.7151 (0.00)		Middle	Mean	4.2439	-8.4403	12.6842 (0.00)
		Wilcoxon			12.9913 (0.00)			Wilcoxon			12.3300 (0.00)
	High	Mean	4.1666	-6.7197	10.8863 (0.00)		High	Mean	4.1176	-6.3663	10.4839 (0.00)
		Wilcoxon			10.6668 (0.00)			Wilcoxon			11.7125 (0.00)
	Low - High	Mean	0.3226 (0.58)	0.1564 (0.90)			Low - High	Mean	0.3437 (0.55)	-0.7090 (0.57)	
		Wilcoxon	-1.4080 (0.16)	-1.7024 (0.09)				Wilcoxon	-3.5421 (0.00)	-1.6681 (0.10)	

Panel C: Sorted on EXCOV3 or EXCOV4											
	Mean EXCOV3					Mean EXCOV4					
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
NUMEST	Low	N	21582	2539		NUMEST	Low	N	21773	2551	
		Mean	4.5814	4.2194	0.3620 (0.00)			Mean	4.7925	4.4010	0.3915 (0.00)
		Wilcoxon			4.1438 (0.00)			Wilcoxon			4.3625 (0.00)
	Middle	N	31239	4015			Middle	N	31195	4006	
		Mean	7.8590	6.8871	0.9718 (0.00)			Mean	7.9470	6.9546	0.9924 (0.00)
		Wilcoxon			6.3281 (0.00)			Wilcoxon			6.6367 (0.00)
	High	N	34307	4437			High	N	34160	4434	
		Mean	11.8701	10.9153	0.9548 (0.00)			Mean	11.6908	10.7598	0.9310 (0.00)
		Wilcoxon			4.1722 (0.00)			Wilcoxon			3.9184 (0.00)
	Low - High	Mean	-7.2887 (0.00)	-6.6959 (0.00)			Low - High	Mean	-6.8983 (0.00)	-6.3588 (0.00)	
		Wilcoxon	-138.87 (0.00)	-50.73 (0.00)				Wilcoxon	-133.23 (0.00)	-49.06 (0.00)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
LMVE	Low	Mean	13.5045	13.4613	0.0431 (0.18)	LMVE	Low	Mean	13.5017	13.4554	0.0464 (0.16)
		Wilcoxon			1.3793 (0.17)			Wilcoxon			1.4354 (0.15)
	Middle	Mean	13.2787	13.1035	0.1752 (0.00)		Middle	Mean	13.2747	13.0960	0.1786 (0.00)
		Wilcoxon			5.5728 (0.00)			Wilcoxon			5.7635 (0.00)
	High	Mean	13.0777	12.9574	0.1204 (0.00)		High	Mean	13.0810	12.9665	0.1145 (0.00)
		Wilcoxon			4.1622 (0.00)			Wilcoxon			3.9747 (0.00)
	Low - High	Mean	0.4267 (0.00)	0.5039 (0.00)			Low - High	Mean	0.4207 (0.00)	0.4889 (0.00)	
		Wilcoxon	24.6128 (0.00)	10.4674 (0.00)				Wilcoxon	23.7032 (0.00)	9.8516 (0.00)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
LSHR	Low	Mean	10.6704	10.7863	-0.1160 (0.00)	LSHR	Low	Mean	10.7462	10.8453	-0.0992 (0.00)
		Wilcoxon			-4.6474 (0.00)			Wilcoxon			-4.0402 (0.00)
	Middle	Mean	10.5856	10.6336	-0.0480 (0.05)		Middle	Mean	10.6005	10.6489	-0.0484 (0.05)
		Wilcoxon			-2.4826 (0.01)			Wilcoxon			-2.4835 (-0.01)
	High	Mean	10.4967	10.5756	-0.0789 (0.00)		High	Mean	10.4340	10.5274	-0.0934 (0.00)
		Wilcoxon			-3.3602 (0.00)			Wilcoxon			-4.0997 (0.00)
	Low - High	Mean	0.1737 (0.00)	0.2107 (0.00)			Low - High	Mean	0.3122 (0.00)	0.3179 (0.00)	
		Wilcoxon	9.0908 (0.00)	4.5040 (0.00)				Wilcoxon	19.9266 (0.00)	7.3821 (0.00)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
BETAVW	Low	Mean	0.9249	0.9722	-0.0474 (0.00)	BETAVW	Low	Mean	1.0169	1.0656	-0.0487 (0.00)
		Wilcoxon			-3.9111 (0.00)			Wilcoxon			-3.6419 (0.00)
	Middle	Mean	0.9393	0.9689	-0.0296 (0.00)		Middle	Mean	0.9563	0.9998	-0.0436 (0.00)
		Wilcoxon			-2.3256 (0.02)			Wilcoxon			-3.1517 (0.00)
	High	Mean	1.0146	1.0974	-0.0829 (0.00)		High	Mean	0.9408	1.0159	-0.0751 (0.00)
		Wilcoxon			7.3493 (0.00)			Wilcoxon			-7.2961 (0.00)
	Low - High	Mean	-0.0897 (0.00)	-0.1252 (0.00)			Low - High	Mean	0.0761 (0.00)	0.0497 (0.00)	
		Wilcoxon	-19.005 (0.00)	-8.460 (0.00)				Wilcoxon	14.5002 (0.00)	3.4632 (0.00)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
RSEVW	Low	Mean	2.2143	2.7537	-0.5394 (0.00)	RSEVW	Low	Mean	2.3333	2.9490	-0.6158 (0.00)
		Wilcoxon			-22.6161 (0.00)			Wilcoxon			-21.86624 (0.00)
	Middle	Mean	2.4004	3.0662	-0.6658 (0.00)		Middle	Mean	2.4258	3.1382	-0.7124 (0.00)
		Wilcoxon			-28.8043 (0.00)			Wilcoxon			-29.5947 (0.00)
	High	Mean	2.6069	3.4224	-0.8155 (0.00)		High	Mean	2.5097	3.2461	-0.7363 (0.00)
		Wilcoxon			-33.6840 (0.00)			Wilcoxon			-33.1453 (0.00)
	Low - High	Mean	-0.3926 (0.00)	-0.6688 (0.00)			Low - High	Mean	-0.1765 (0.00)	-0.2971 (0.00)	
		Wilcoxon	-36.592 (0.00)	-17.059 (0.00)				Wilcoxon	-19.586 (0.00)	-9.594 (0.00)	

			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
EXVW	Low	Mean	13.8787	20.5093	-6.6306 (0.00)	EXVW	Low	Mean	3.3512	9.2020	-5.8508 (0.00)
		Wilcoxon			-6.2918 (0.00)			Wilcoxon			-4.9717 (0.00)
	Middle	Mean	5.0299	12.5466	-7.5167 (0.00)		Middle	Mean	3.0487	10.1071	-7.0584 (0.00)
		Wilcoxon			-9.4228 (0.00)			Wilcoxon			-8.9657 (0.00)
	High	Mean	-6.4737	-0.5307	-5.9431 (0.00)		High	Mean	1.9465	8.1483	-6.2018 (0.00)
		Wilcoxon			-7.6120 (0.00)			Wilcoxon			-7.8911 (0.01)
	Low - High	Mean	20.3524 (0.00)	21.0400 (0.00)			Low - High	Mean	1.4047 (0.00)	1.0536 (0.40)	
		Wilcoxon	52.2987 (0.00)	17.5766 (0.00)				Wilcoxon	8.7746 (0.00)	1.7329 (0.08)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
NEWFIRM 5YR	Low	Mean	14.0241	-6.4419	20.4660 (0.00)	NEWFIRM 5YR	Low	Mean	14.3301	-5.4343	19.7645 (0.00)
		Wilcoxon			13.9285 (0.00)			Wilcoxon			12.6594 (0.00)
	Middle	Mean	12.2835	-6.7846	19.0680 (0.00)		Middle	Mean	12.6384	-6.7723	19.4108 (0.00)
		Wilcoxon			14.7746 (0.00)			Wilcoxon			15.0604 (0.00)
	High	Mean	10.6652	-6.9231	17.5884 (0.00)		High	Mean	10.1293	-7.5149	17.6442 (0.00)
		Wilcoxon			14.6041 (0.00)			Wilcoxon			15.1634 (0.00)
	Low - High	Mean	3.3589 (0.00)	0.4812 (0.68)			Low - High	Mean	4.2008 (0.00)	2.0805 (0.07)	
		Wilcoxon	4.1998 (0.00)	1.1972 (0.23)				Wilcoxon	5.8622 (0.00)	2.8175 (0.00)	

Table 3.8 Firm Characteristics Sorted on Excess Analyst Following for Post-Good and Post-Bad Domain

This table presents the firm characteristics an analyst follows in post-good/ post-bad times. Sample firm-years are classified into the domains based on the recession observation dummy (LREC). For each of the two domains, firm-years are further divided into three groups based on excess coverage measure (Low, Middle, and High group). For each group, number of analyst following (NUMEST), the logarithm of the market value of equity (LMVE), the logarithm of shares outstanding (LSHR, beta (BETAVW), stock volatility (RSEVW), past stock performance (EXVW), and changes of the number of firms in the past five years (NEWFIRM5YR) are presented. The values are then compared across domains for the corresponding group (Low to Low, Middle to Middle, And High to High). Within each domain, the differences in those values between the Low group and the High group are compared as well. Panel A presents the results based on excess coverage measure from the relative approach and SIC (EXCOV1), Panel B presents results based on excess coverage measure from the relative approach and Fama-French 49 industry classification (EXCOV2). Panel C presents the results based on excess coverage measure from regression approach with equation (2) (EXCOV3) and the results based on excess coverage measure from regression approach with equation (3) (EXCOV4). The left half of Panel A uses mean industry analyst coverage/ sale ratio to calculate a firm's expected analyst coverage and thus the firm's excess analyst coverage. The right half of Panel A uses median industry analyst coverage/ sale ratio. The left half of Panel B is based on mean industry analyst coverage/ sales ratio, and the right half is based on the median ratio. Panel C provides results from excess analyst coverage measure developed from regression method. EXCOV3 is residual from the OLS regression using specification in equation (3), and EXCOV4 is residual from the OLS regression using specification in equation (4). P-values are provided in the parentheses. Wilcoxon Test is reported with Z-score from the test and p-values are in the parentheses.

Panel A: Sorted on EXCOV1

			Mean EXCOV1						Median EXCOV1		
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
		N	15331	1963				N	15322	1981	
	Low	Mean	11.4086	10.6658	0.7428 (0.00)		Low	Mean	11.4764	10.6512	0.8252 (0.00)
		Wilcoxon			1.7583 (0.08)			Wilcoxon			2.0242 (0.04)
		N	15976	2105				N	15997	2089	
	Middle	Mean	9.0493	8.4979	0.5514 (0.00)		Middle	Mean	9.0220	8.5955	0.4265 (0.01)
NUMEST		Wilcoxon			2.1890 (0.03)	NUMEST		Wilcoxon			1.7554 (0.08)
		N	17065	2268				N	17053	2266	
	High	Mean	7.8652	7.9753	-0.1101 (0.39)		High	Mean	7.8304	7.8804	-0.0501 (0.70)
		Wilcoxon			-1.8381 (0.07)			Wilcoxon			-1.5443 (0.12)
	Low - High	Mean	3.5434 (0.00)	2.6905 (0.00)			Low - High	Mean	3.6460 (0.00)	2.7708 (0.00)	
		Wilcoxon	27.747 (0.00)	8.283 (0.00)				Wilcoxon	29.418 (0.00)	8.958 (0.00)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
	Low	Mean	14.4041	14.5110	-0.1069 (0.01)		Low	Mean	14.3984	14.5076	-0.1092 (0.01)
		Wilcoxon			-2.0128 (0.04)			Wilcoxon			-2.1406 (0.03)
	Middle	Mean	13.3915	13.3537	0.0378 (0.29)		Middle	Mean	13.3848	13.3448	0.0400 (0.27)
LMVE		Wilcoxon			1.2115 (0.23)	LMVE		Wilcoxon			1.0860 (0.28)
	High	Mean	12.6038	12.6094	-0.0056 (0.85)		High	Mean	12.6152	12.6108	0.0044 (0.88)
		Wilcoxon			-0.3042 (0.76)			Wilcoxon			-0.0977 (0.92)
	Low - High	Mean	1.8004 (0.00)	1.9016 (0.00)			Low - High	Mean	1.7832 (0.00)	1.8968 (0.00)	
		Wilcoxon	88.479 (0.00)	35.166 (0.00)				Wilcoxon	87.641 (0.00)	35.122 (0.00)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
	Low	Mean	11.4796	11.6426	-0.1630 (0.00)		Low	Mean	11.4739	11.6392	-0.1653 (0.00)
		Wilcoxon			-4.4146 (0.00)			Wilcoxon			-4.3758 (0.00)
	Middle	Mean	10.6747	10.7232	-0.0485 (0.11)		Middle	Mean	10.6698	10.7291	-0.0592 (0.05)
LSHR		Wilcoxon			-2.2468 (0.02)	LSHR		Wilcoxon			-2.6561 (0.01)
	High	Mean	10.1616	10.2645	-0.1029 (0.00)		High	Mean	10.1714	10.2543	-0.0829 (0.00)
		Wilcoxon			-4.3880 (0.00)			Wilcoxon			-3.9003 (0.00)
	Low - High	Mean	1.3180 (0.00)	1.3781 (0.00)			Low - High	Mean	1.3025 (0.00)	1.3850 (0.00)	
		Wilcoxon	78.952 (0.00)	30.926 (0.00)				Wilcoxon	78.069 (0.00)	31.062 (0.00)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
	Low	Mean	0.9960	1.0779	-0.0820 (0.00)		Low	Mean	1.0003	1.0526	-0.0522 (0.00)
		Wilcoxon			-6.1340 (0.00)			Wilcoxon			-3.7918 (0.00)
	Middle	Mean	0.9796	1.0645	-0.0849 (0.00)		Middle	Mean	0.9725	1.0860	-0.1135 (0.00)
BETAVW		Wilcoxon			-7.1269 (0.00)	BETAVW		Wilcoxon			-9.3848 (0.00)
	High	Mean	1.0078	1.0725	-0.0647 (0.00)		High	Mean	1.0105	1.0747	-0.0642 (0.00)
		Wilcoxon			-6.6030 (0.00)			Wilcoxon			-6.3885 (0.00)
	Low - High	Mean	-0.0118 (0.06)	0.0054 (0.74)			Low - High	Mean	-0.0102 (0.11)	-0.0221 (0.17)	
		Wilcoxon	3.5815 (0.00)	0.1761 (0.86)				Wilcoxon	3.565 (0.00)	-1.292 (0.20)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
	Low	Mean	2.0450	2.2574	-0.2124 (0.00)		Low	Mean	2.0565	2.2234	-0.1670 (0.00)
		Wilcoxon			-8.6781 (0.00)			Wilcoxon			-7.5693 (0.00)
	Middle	Mean	2.4086	2.6443	-0.2357 (0.00)		Middle	Mean	2.3937	2.6738	-0.2802 (0.00)
RSEVW		Wilcoxon			-7.4766 (0.00)	RSEVW		Wilcoxon			-8.8205 (0.00)
	High	Mean	2.8895	3.1002	-0.2107 (0.00)		High	Mean	2.8933	3.1062	-0.2128 (0.00)
		Wilcoxon			-5.7794 (0.00)			Wilcoxon			-5.7079(0.00)
	Low - High	Mean	-0.8445 (0.00)	-0.8428 (0.00)			Low - High	Mean	-0.8369 (0.00)	-0.8827 (0.00)	
		Wilcoxon	-60.052 (0.00)	-21.284 (0.00)				Wilcoxon	-59.186 (0.00)	-21.765 (0.00)	

			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
EXVW	Low	Mean	2.5680	8.9017	-6.3337 (0.00)	EXVW	Low	Mean	2.6675	8.3140	-5.6464 (0.00)
		Wilcoxon			-7.1297 (0.00)			Wilcoxon			-6.5215 (0.00)
	Middle	Mean	3.2371	13.9165	-10.6794 (0.00)		Middle	Mean	3.3771	15.4651	-12.0880 (0.00)
		Wilcoxon			-11.1819 (0.00)			Wilcoxon			-11.9087 (0.00)
	High	Mean	2.9258	11.2952	-8.3694 (0.00)		High	Mean	2.7045	10.4189	-7.7144 (0.00)
		Wilcoxon			-8.6091 (0.00)			Wilcoxon			-8.4750(0.00)
	Low - High	Mean	-0.3578 (0.51)	-2.3935 (0.11)			Low - High	Mean	-0.0370 (0.95)	-2.1049 (0.16)	
		Wilcoxon	8.8854 (0.00)	0.8641 (0.39)				Wilcoxon	9.1550 (0.00)	0.6651 (0.51)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
NEWFIRM 5YR	Low	Mean	5.8871	-12.2700	18.1571 (0.00)	NEWFIRM 5YR	Low	Mean	5.2515	-12.8269	18.0783 (0.00)
		Wilcoxon			18.1527 (0.00)			Wilcoxon			18.1473 (0.00)
	Middle	Mean	5.7201	-16.5078	22.2280 (0.00)		Middle	Mean	4.5959	-16.1125	20.7084 (0.00)
		Wilcoxon			18.7150 (0.00)			Wilcoxon			17.9112 (0.00)
	High	Mean	5.3130	-15.0459	20.3588 (0.00)		High	Mean	6.9385	-14.9559	21.8944 (0.00)
		Wilcoxon			18.0332 (0.00)			Wilcoxon			18.8018 (0.00)
	Low - High	Mean	0.5741 (0.45)	2.7759 (0.06)			Low - High	Mean	-1.6871 (0.03)	2.1290 (0.14)	
		Wilcoxon	1.8733 (0.06)	-0.2876 (0.77)				Wilcoxon	-1.1179 (0.26)	-0.9235 (0.25)	

Panel B: Sorted on EXCOV2											
			Mean EXCOV2						Median EXCOV2		
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
		N	24745	3222				N	24693	3203	
	Low	Mean	10.9128	9.8883	1.0245 (0.00)		Low	Mean	10.9464	10.0181	0.9283 (0.00)
		Wilcoxon			4.5433 (0.00)			Wilcoxon			3.5441 (0.00)
		N	25691	3371				N	25761	3381	
	Middle	Mean	8.5262	8.2014	0.3248 (0.01)		Middle	Mean	8.5500	8.1334	0.4166 (0.00)
NUMEST		Wilcoxon			1.3521 (0.18)	NUMEST		Wilcoxon			2.3486 (0.02)
		N	27388	3601				N	27370	3610	
	High	Mean	7.2113	7.3799	-0.1686 (0.08)		High	Mean	7.1623	7.3393	-0.1771 (0.06)
		Wilcoxon			-3.3228 (0.00)			Wilcoxon			-3.1746 (0.00)
	Low - High	Mean	3.7014 (0.00)	2.5084 (0.00)			Low - High	Mean	3.7841 (0.00)	2.6788 (0.00)	
		Wilcoxon	40.786 (0.00)	9.984 (0.00)				Wilcoxon	41.6506 (0.00)	11.3769 (0.00)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
	Low	Mean	14.3287	14.3356	-0.0069 (0.84)		Low	Mean	14.3164	14.3388	-0.0224 (0.51)
		Wilcoxon			0.2970 (0.77)			Wilcoxon			-0.1260 (0.90)
	Middle	Mean	13.2932	13.2367	0.0565 (0.04)		Middle	Mean	13.3000	13.2274	0.0726 (0.01)
		Wilcoxon			2.0556 (0.04)			Wilcoxon			2.5911 (0.01)
LMVE	High	Mean	12.4156	12.4617	-0.0462 (0.04)	LMVE	High	Mean	12.4216	12.4753	-0.0537 (0.02)
		Wilcoxon			-2.4126 (0.02)			Wilcoxon			-2.6920 (0.01)
	Low - High	Mean	1.9132 (0.00)	1.8739 (0.00)			Low - High	Mean	1.8948 (0.00)	1.8635 (0.00)	
		Wilcoxon	119.149 (0.00)	44.200 (0.00)				Wilcoxon	118.007 (0.00)	43.937 (0.00)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
	Low	Mean	11.3725	11.4644	-0.0919 (0.00)		Low	Mean	11.3669	11.4686	-0.1017 (0.00)
		Wilcoxon			-2.9215 (0.00)			Wilcoxon			-3.1882 (0.00)
	Middle	Mean	10.5854	10.6364	-0.0511 (0.02)		Middle	Mean	10.5931	10.6330	-0.0399 (0.08)
		Wilcoxon			-2.9981 (0.00)			Wilcoxon			-2.6933 (0.00)
LSHR	High	Mean	9.9702	10.0664	-0.0962 (0.00)	LSHR	High	Mean	9.9690	10.0716	-0.1026 (0.00)
		Wilcoxon			-5.7435 (0.00)			Wilcoxon			-5.9899 (0.00)
	Low - High	Mean	1.4023 (0.00)	1.3980 (0.00)			Low - High	Mean	1.3979 (0.00)	1.3970 (0.00)	
		Wilcoxon	107.143 (0.00)	39.790 (0.00)				Wilcoxon	106.687 (0.00)	39.519 (0.00)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
	Low	Mean	0.9712	1.0449	-0.0737 (0.00)		Low	Mean	0.9808	1.0625	-0.0817 (0.00)
		Wilcoxon			-6.6644 (0.00)			Wilcoxon			-7.5157 (0.00)
BETAVW	Middle	Mean	0.9575	1.0593	-0.1018 (0.00)		Middle	Mean	0.9563	1.0436	-0.0873 (0.00)
		Wilcoxon			-10.4876 (0.00)	BETAVW		Wilcoxon			-9.0695 (0.00)
	High	Mean	0.9538	1.0207	-0.0668 (0.00)		High	Mean	0.9463	1.0198	-0.0735 (0.00)
		Wilcoxon			-7.8817 (0.00)			Wilcoxon			-8.5429 (0.00)
	Low - High	Mean	0.0174 (0.00)	0.0242 (0.06)			Low - High	Mean	0.0344 (0.00)	0.0427 (0.00)	
		Wilcoxon	9.4703 (0.00)	2.0143 (0.00)				Wilcoxon	12.7186 (0.00)	3.4760 (0.00)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
	Low	Mean	2.0079	2.2351	-0.2271 (0.00)		Low	Mean	2.0364	2.2709	-0.2345 (0.00)
		Wilcoxon			-10.7485 (0.00)			Wilcoxon			-11.5716 (0.00)
	Middle	Mean	2.3680	2.6608	-0.2928 (0.00)		Middle	Mean	2.3683	2.6486	-0.2802 (0.00)
		Wilcoxon			-12.1981 (0.00)			Wilcoxon			-11.3735 (0.00)
RSEVW	High	Mean	2.8393	2.9833	-0.1440 (0.00)	RSEVW	High	Mean	2.8130	2.9600	-0.1470 (0.00)
		Wilcoxon			-6.2689 (0.00)			Wilcoxon			-6.3435 (0.00)
	Low - High	Mean	-0.8314 (0.00)	-0.7483 (0.00)			Low - High	Mean	-0.7765 (0.00)	-0.6890 (0.00)	
		Wilcoxon	-78.205 (0.00)	-27.271 (0.00)				Wilcoxon	-73.501 (0.00)	-24.941 (0.00)	

			Post-Good	Post-Bad	Diff (Gd - Bd)
EXVW	Low	Mean	2.6675	10.9898	-8.3223 (0.00)
		Wilcoxon			-10.9333 (0.00)
	Middle	Mean	2.9909	14.0193	-11.0284 (0.00)
		Wilcoxon			-14.0084 (0.00)
	High	Mean	2.6366	11.0979	-8.4613 (0.00)
		Wilcoxon			-10.6082 (0.00)
	Low - High	Mean	0.0309 (0.94)	-0.1082 (0.93)	
		Wilcoxon	11.4485 (0.00)	2.1724 (0.00)	
			Post-Good	Post-Bad	Diff (Gd - Bd)
NEWFIRM 5YR	Low	Mean	5.0794	-10.6862	15.7656 (0.00)
		Wilcoxon			20.8533 (0.00)
	Middle	Mean	4.9334	-14.0347	18.9681 (0.00)
		Wilcoxon			20.9585 (0.00)
	High	Mean	5.2485	-14.8375	20.0861 (0.00)
		Wilcoxon			21.2075 (0.00)
	Low - High	Mean	-0.1691 (0.77)	4.1513 (0.00)	
		Wilcoxon	-2.3155 (0.00)	0.6580 (0.00)	

			Post-Good	Post-Bad	Diff (Gd - Bd)
EXVW	Low	Mean	2.5942	10.6809	-8.0867 (0.00)
		Wilcoxon			-10.3594 (0.00)
	Middle	Mean	3.1767	14.0669	-10.8902 (0.00)
		Wilcoxon			-13.7666 (0.00)
	High	Mean	2.5271	11.3187	-8.7917 (0.00)
		Wilcoxon			-11.2420 (0.00)
	Low - High	Mean	0.0672 (0.87)	-0.6379 (0.60)	
		Wilcoxon	10.7009 (0.00)	1.1278 (0.26)	
			Post-Good	Post-Bad	Diff (Gd - Bd)
NEWFIRM 5YR	Low	Mean	5.1664	-12.0924	17.2589 (0.00)
		Wilcoxon			21.4344 (0.00)
	Middle	Mean	4.9560	-13.8619	18.8179 (0.00)
		Wilcoxon			20.5544 (0.00)
	High	Mean	5.1493	-13.7321	18.8814 (0.00)
		Wilcoxon			21.0631 (0.00)
	Low - High	Mean	0.0172 (0.98)	1.6397 (0.21)	
		Wilcoxon	-3.9996 (0.00)	-1.1421 (0.25)	

Panel C: Sorted on EXCOV3 or EXCOV4											
	Mean EXCOV3					Mean EXCOV4					
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
		N	21491	2735				N	21667	2746	
	Low	Mean	4.5763	4.3715	0.2048 (0.02)		Low	Mean	4.7674	4.6326	0.1348 (0.15)
		Wilcoxon			2.1100 (0.03)			Wilcoxon			1.5449 (0.12)
		N	31163	4027				N	31111	4053	
	Middle	Mean	7.7835	7.5317	0.2518 (0.02)		Middle	Mean	7.8780	7.6084	0.2695 (0.01)
NUMEST		Wilcoxon			-1.0044 (0320)	NUMEST		Wilcoxon			-0.1518 (0.88)
		N	34242	4461				N	34118	4424	
	High	Mean	11.8058	11.4234	0.3824 (0.00)		High	Mean	11.6294	11.2315	0.3980 (0.00)
		Wilcoxon			0.1332 (0.89)			Wilcoxon			0.1823 (0.86)
	Low - High	Mean	-7.2295 (0.00)	-7.0520 (0.00)			Low - High	Mean	-6.8620 (0.00)	-6.5989 (0.00)	
		Wilcoxon	-138.19 (0.00)	-51.37 (0.00)				Wilcoxon	-133.06 (0.00)	-49.10 (0.00)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
	Low	Mean	13.4972	13.5099	-0.0128 (0.68)		Low	Mean	13.4890	13.5350	-0.0459 (0.15)
		Wilcoxon			-0.2958 (0.77)			Wilcoxon			-1.3035 (0.19)
	Middle	Mean	13.2527	13.2996	-0.0470 (0.12)		Middle	Mean	13.2530	13.2836	-0.0306 (0.31)
LMVE		Wilcoxon			-1.9477 (0.05)	LMVE		Wilcoxon			-1.2851 (0.20)
	High	Mean	13.0603	13.0971	-0.0368 (0.19)		High	Mean	13.0632	13.0941	-0.0309 (0.27)
		Wilcoxon			-1.1386 (0.25)			Wilcoxon			-1.0237 (0.31)
	Low - High	Mean	0.4369 (0.00)	0.4128 (0.00)			Low - High	Mean	0.4258 (0.00)	0.4409 (0.00)	
		Wilcoxon	25.2038 (0.00)	8.7861 (0.00)				Wilcoxon	23.9454 (0.00)	9.1748 (0.00)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
	Low	Mean	10.6687	10.7883	-0.1196 (0.00)		Low	Mean	10.7428	10.8562	-0.1134 (0.00)
		Wilcoxon			-5.0247 (0.00)			Wilcoxon			-4.8432 (0.00)
	Middle	Mean	10.5769	10.6950	-0.1181 (0.00)		Middle	Mean	10.5947	10.6924	-0.0977 (0.00)
LSHR		Wilcoxon			-5.4400 (0.00)	LSHR		Wilcoxon			-4.8157 (0.00)
	High	Mean	10.4969	10.5780	-0.0811 (0.00)		High	Mean	10.4329	10.5370	-0.1042 (0.00)
		Wilcoxon			-3.4450 (0.00)			Wilcoxon			-4.3575 (0.00)
	Low - High	Mean	0.1718 (0.00)	0.2103 (0.00)			Low - High	Mean	0.3099 (0.00)	0.3191 (0.00)	
		Wilcoxon	8.9011 (0.00)	4.6548 (0.00)				Wilcoxon	19.5959 (0.00)	7.8739 (0.00)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
	Low	Mean	0.9206	1.0072	-0.0866 (0.00)		Low	Mean	1.0156	1.0715	-0.0559 (0.00)
		Wilcoxon			-7.6707 (0.00)			Wilcoxon			-5.1126 (0.00)
	Middle	Mean	0.9341	1.0088	-0.0747 (0.00)		Middle	Mean	0.9519	1.0295	-0.0776 (0.00)
BETAVW		Wilcoxon			-8.1152 (0.00)	BETAVW		Wilcoxon			-8.6659 (0.00)
	High	Mean	1.0153	1.0896	-0.0742 (0.00)		High	Mean	0.9391	1.0314	-0.0923 (0.00)
		Wilcoxon			-9.2661 (0.00)			Wilcoxon			-11.1497 (0.00)
	Low - High	Mean	-0.0947 (0.00)	-0.0824 (0.00)			Low - High	Mean	0.0765 (0.00)	0.0402 (0.00)	
		Wilcoxon	-19.399 (0.00)	-7.025 (0.00)				Wilcoxon	14.7940 (0.00)	2.4601 (0.01)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
	Low	Mean	2.2566	2.3994	-0.1429 (0.00)		Low	Mean	2.3825	2.5206	-0.1381 (0.00)
		Wilcoxon			-6.7796 (0.00)			Wilcoxon			-5.2299 (0.00)
	Middle	Mean	2.4551	2.6470	-0.1919 (0.00)		Middle	Mean	2.4792	2.7133	-0.2341 (0.00)
RSEVW		Wilcoxon			-8.7058 (0.00)	RSEVW		Wilcoxon			-9.8873 (0.00)
	High	Mean	2.6713	2.9138	-0.2425 (0.00)		High	Mean	2.5712	2.7806	-0.2095 (0.00)
		Wilcoxon			-10.9296 (0.00)			Wilcoxon			-11.0149 (0.00)
	Low - High	Mean	-0.4148 (0.00)	-0.5144 (0.00)			Low - High	Mean	-0.1886 (0.00)	-0.2600 (0.00)	
		Wilcoxon	-36.799 (0.00)	-15.810 (0.00)				Wilcoxon	-19.731 (0.00)	-10.450 (0.00)	

			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
EXVW	Low	Mean	13.4017	22.2376	-8.8359 (0.00)	EXVW	Low	Mean	2.7381	12.7218	-9.9837 (0.00)
		Wilcoxon			-11.1044 (0.00)			Wilcoxon			-12.0876 (0.00)
	Middle	Mean	4.7299	14.3991	-9.6692 (0.00)		Middle	Mean	2.9221	11.9444	-9.0223 (0.00)
		Wilcoxon			-13.6411 (0.00)			Wilcoxon			-12.5769 (0.00)
	High	Mean	-6.8579	3.4221	-10.2800 (0.00)		High	Mean	1.4758	11.4662	-9.9904 (0.00)
		Wilcoxon			-13.8702 (0.00)			Wilcoxon			-13.7631 (0.00)
	Low - High	Mean	20.2596 (0.00)	18.8155 (0.00)			Low - High	Mean	1.2623 (0.00)	1.2557 (0.31)	
		Wilcoxon	51.9452 (0.00)	16.7196 (0.00)				Wilcoxon	8.2902 (0.00)	2.2463 (0.02)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
NEWFIRM 5YR	Low	Mean	14.5357	-10.0764	24.6121 (0.00)	NEWFIRM 5YR	Low	Mean	14.9530	-10.2414	25.1945 (0.00)
		Wilcoxon			19.7607 (0.00)			Wilcoxon			19.5417 (0.00)
	Middle	Mean	13.0176	-12.3598	25.3774 (0.00)		Middle	Mean	13.4010	-12.0671	25.4681 (0.00)
		Wilcoxon			23.1742 (0.00)			Wilcoxon			23.6148 (0.00)
	High	Mean	11.8008	-14.9827	26.7836 (0.00)		High	Mean	11.1740	-15.1761	26.3501 (0.00)
		Wilcoxon			26.8570 (0.00)			Wilcoxon			26.6137 (0.00)
	Low - High	Mean	2.7349 (0.00)	4.9063 (0.00)			Low - High	Mean	3.7790 (0.00)	4.9346 (0.00)	
		Wilcoxon	2.7818 (0.01)	5.1677 (0.00)				Wilcoxon	4.9264 (0.00)	5.2907 (0.00)	

Table 3.9 Annual Mean Firm Characteristics Sorted on Excess Analyst Following for Good and Bad Domain

This table presents the annual mean firm characteristics an analyst follows in good/ bad times. The annual mean firm characteristics are calculated as the mean value of firm characteristics in a fiscal year. Sample firm-years are classified into the bad domain and the good domain based on the recession dummy (REC). For each of the two domains, firm-years are further divided into three groups based on excess coverage measure (Low, Middle, and High group). For each group, annual mean for number of analyst following (NUMEST), the logarithm of the market value of equity (LMVE), the logarithm of shares outstanding (LSHR, beta (BETAVW), stock volatility (RSEVW), past stock performance (EXVW), and changes of the number of firms in the past five years (NEWFIRM5YR) are calculated for each fiscal year and presented. The values are then compared across domains for the corresponding group (Low to Low, Middle to Middle, And High to High). Within each domain, the differences in those values between the Low group and the High group are compared as well. Panel A presents the results based on excess coverage measure from the relative approach and SIC (EXCOV1), Panel B presents results based on excess coverage measure from the relative approach and Fama-French 49 industry classification (EXCOV2). Panel C presents the results based on excess coverage measure from regression approach with equation (2) (EXCOV3) and the results based on excess coverage measure from regression approach with equation (3) (EXCOV4). The left half of Panel A uses mean industry analyst coverage/ sale ratio to calculate a firm's expected analyst coverage and thus the firm's excess analyst coverage. The right half of Panel A uses median industry analyst coverage/ sale ratio. The left half of Panel B is based on mean industry analyst coverage/ sales ratio, and the right half is based on the median ratio. Panel C provides results from excess analyst coverage measure developed from regression method. EXCOV3 is residual from the OLS regression using specification in equation (3), and EXCOV4 is residual from the OLS regression using specification in equation (4). P-values are provided in the parentheses. Wilcoxon Test is reported with Z-score from the test and p-values are in the parentheses.

Panel A: Sorted on EXCOV1

			Mean EXCOV1						Median EXCOV1		
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
NUMEST	Low	N	40	8		NUMEST	Low	N	40	8	
		Mean	11.2144	9.5434	1.6710 (0.08)			Mean	11.2632	9.7107	1.5525 (0.09)
		Wilcoxon			2.1440 (0.03)			Wilcoxon			2.2823 (0.02)
	Middle	N	40	8			Middle	N	40	8	
		Mean	9.2201	8.3457	0.8744 (0.07)			Mean	9.2045	7.8477	1.3568 (0.01)
		Wilcoxon			2.1716 (0.03)			Wilcoxon			2.9462 (0.00)
	High	N	40	8			High	N	40	8	
		Mean	7.9740	7.6108	0.3632 (0.24)			Mean	7.9435	7.9338	0.0097 (0.98)
		Wilcoxon			1.3417 (0.18)			Wilcoxon			0.0968 (0.93)
	Low - High	Mean	3.2404 (0.00)	1.9326 (0.02)			Low - High	Mean	3.3197 (0.00)	1.7769 (0.01)	
		Wilcoxon	6.7117 (0.00)	2.3630 (0.01)				Wilcoxon	6.7406 (0.00)	2.3630 (0.18)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
LMVE	Low	Mean	14.2170	13.6661	0.5510 (0.10)	LMVE	Low	Mean	14.2083	13.7081	0.5001 (0.13)
		Wilcoxon			1.5907 (0.11)			Wilcoxon			1.5907 (0.11)
	Middle	Mean	13.2629	12.7819	0.4810 (0.09)		Middle	Mean	13.2540	12.6691	0.5849 (0.04)
		Wilcoxon			1.8397 (0.07)			Wilcoxon			1.8950 (0.06)
	High	Mean	12.5247	12.1323	0.3923 (0.07)		High	Mean	12.5388	12.1961	0.3427 (0.12)
		Wilcoxon			1.7290 (0.08)			Wilcoxon			1.6460 (0.10)
	Low - High	Mean	1.6924 (0.00)	1.5337 (0.00)			Low - High	Mean	1.6694 (0.00)	1.5120 (0.00)	
		Wilcoxon	7.0677 (0.00)	2.7831 (0.01)				Wilcoxon	7.0292 (0.00)	2.8881 (0.00)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
LSHR	Low	Mean	11.4172	11.2550	0.1622 (0.31)	LSHR	Low	Mean	11.4073	11.2957	0.1116 (0.47)
		Wilcoxon			0.4841 (0.63)			Wilcoxon			0.5671 (0.57)
	Middle	Mean	10.6656	10.4937	0.1719 (0.24)		Middle	Mean	10.6647	10.3647	0.3000 (0.04)
		Wilcoxon			1.4800 (0.14)			Wilcoxon			1.9780 (0.05)
	High	Mean	10.1687	10.0275	0.1412 (0.25)		High	Mean	10.1768	10.1012	0.0755 (0.50)
		Wilcoxon			0.7608 (0.45)			Wilcoxon			0.4841 (0.63)
	Low - High	Mean	1.2485 (0.00)	1.2274 (0.00)			Low - High	Mean	1.2305 (0.00)	1.1945 (0.00)	
		Wilcoxon	7.3949 (0.00)	3.3082 (0.00)				Wilcoxon	7.4238 (0.00)	3.3082 (0.00)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
BETAVW	Low	Mean	1.0521	1.0077	0.0444 (0.67)	BETAVW	Low	Mean	1.0519	1.0176	0.0343 (0.74)
		Wilcoxon			0.4841 (0.63)			Wilcoxon			0.0692 (0.94)
	Middle	Mean	1.0170	1.0049	0.0121 (0.92)		Middle	Mean	1.0158	0.9712	0.0447 (0.71)
		Wilcoxon			-0.1245 (0.90)			Wilcoxon			0.2351 (0.81)
	High	Mean	1.0228	1.0134	0.0094 (0.92)		High	Mean	1.0233	1.0319	-0.0086 (0.93)
		Wilcoxon			-0.2075 (0.84)			Wilcoxon			-0.3458 (0.73)
	Low - High	Mean	0.0293 (0.62)	-0.0057 (0.94)			Low - High	Mean	0.0286 (0.63)	-0.0143 (0.86)	
		Wilcoxon	0.8227 (0.41)	-0.0525 (0.96)				Wilcoxon	0.6979 (0.49)	-0.1575 (0.87)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
RSEVW	Low	Mean	1.9959	2.4906	-0.4947 (0.01)	RSEVW	Low	Mean	2.0014	2.4661	-0.4646 (0.02)
		Wilcoxon			-2.5315 (0.01)			Wilcoxon			-2.5589 (0.01)
	Middle	Mean	2.3368	2.7894	-0.4526 (0.06)		Middle	Mean	2.3322	2.8033	-0.4712 (0.05)
		Wilcoxon			-1.6184 (0.11)			Wilcoxon			-1.6184 (0.11)
	High	Mean	2.7477	3.1973	-0.4496 (0.15)		High	Mean	2.7460	3.2046	-0.4585 (0.15)
		Wilcoxon			-0.8991 (0.37)			Wilcoxon			-0.8714 (0.38)
	Low - High	Mean	-0.752 (0.00)	-0.7066 (0.09)			Low - High	Mean	-0.7446 (0.00)	-0.7385 (0.07)	
		Wilcoxon	-5.1817 (0.00)	-1.4178 (0.16)				Wilcoxon	-5.1529 (0.00)	-1.4178 (0.16)	

			Good	Bad	Diff (Good - Bad)
EXVW	Low	Mean	6.7742	7.0835	-0.3093 (0.97)
		Wilcoxon			-0.2075 (0.84)
	Middle	Mean	3.3264	9.4854	-6.1590 (0.28)
		Wilcoxon			-1.2034 (0.23)
	High	Mean	4.1387	6.3202	-2.1814 (0.65)
		Wilcoxon			-0.8997 (0.37)
	Low - High	Mean	2.6355 (0.49)	0.7634 (0.87)	
		Wilcoxon	0.6399 (0.52)	-0.0525 (0.96)	
			Good	Bad	Diff (Good - Bad)
NEWFIRM 5YR	Low	Mean	4.0705	-0.2685	4.3390 (0.67)
		Wilcoxon			0.3735 (0.71)
	Middle	Mean	3.7485	-2.4879	6.2365 (0.56)
		Wilcoxon			0.2075 (0.84)
	High	Mean	3.4986	-0.0483	3.5469 (0.75)
		Wilcoxon			0.2075 (0.84)
	Low - High	Mean	0.5719 (0.93)	-0.2202 (0.98)	
		Wilcoxon	0.1010 (0.92)	0.0000 (1.00)	

			Good	Bad	Diff (Good - Bad)
EXVW	Low	Mean	6.6291	7.5770	-0.9479 (0.90)
		Wilcoxon			-0.4288 (0.67)
	Middle	Mean	3.7701	8.6140	-4.8439 (0.42)
		Wilcoxon			-0.8991 (0.37)
	High	Mean	3.9292	6.8791	-2.9499 (0.54)
		Wilcoxon			-0.9237 (0.35)
	Low - High	Mean	2.6999 (0.47)	0.6978 (0.89)	
		Wilcoxon	0.5918 (0.55)	-0.0525 (0.96)	
			Good	Bad	Diff (Good - Bad)
NEWFIRM 5YR	Low	Mean	3.4086	-0.1643	3.5729 (0.74)
		Wilcoxon			0.1798 (0.86)
	Middle	Mean	3.0474	-2.5872	5.6347 (0.58)
		Wilcoxon			0.3181 (0.75)
	High	Mean	4.6888	-0.0409	4.7297 (0.67)
		Wilcoxon			0.2351 (0.81)
	Low - High	Mean	-1.2802 (0.85)	-0.1233 (0.99)	
		Wilcoxon	-0.1588 (0.87)	-0.0525 (0.96)	

Panel B: Sorted on EXCOV2

	Mean EXCOV2					Median EXCOV2					
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
NUMEST		N	40	8		NUMEST		N	40	8	
	Low	Mean	10.7226	9.3811	1.3416 (0.04)		Low	Mean	10.881	9.3126	1.5226 (0.02)
		Wilcoxon			2.3100 (0.02)			Wilcoxon			2.4483 (0.01)
		N	40	8				N	40	8	
	Middle	Mean	8.4549	7.7080	0.7469 (0.08)		Middle	Mean	8.4241	7.8774	0.5467 (0.24)
		Wilcoxon			2.0333 (0.04)			Wilcoxon			1.4524 (0.15)
		N	40	8				N	40	8	
	High	Mean	7.3677	7.2555	0.1122 (0.73)		High	Mean	7.3365	7.1356	0.2009 (0.52)
		Wilcoxon			0.5118 (0.61)			Wilcoxon			0.6224 (0.53)
	Low - High	Mean	3.3550 (0.00)	2.1256 (0.00)			Low - High	Mean	3.4987 (0.00)	2.1770 (0.00)	
		Wilcoxon	7.0966 (0.00)	3.0981 (0.00)				Wilcoxon	7.2458 (0.00)	2.9931 (0.00)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
LMVE	Low	Mean	14.1611	13.5993	0.5618 (0.10)	LMVE	Low	Mean	14.1854	13.5716	0.6138 (0.06)
		Wilcoxon			1.6737 (0.09)			Wilcoxon			1.8673 (0.06)
	Middle	Mean	13.1663	12.6172	0.5490 (0.05)		Middle	Mean	13.1553	12.6378	0.5175 (0.07)
		Wilcoxon			1.8673 (0.06)			Wilcoxon			1.7567 (0.08)
	High	Mean	12.3771	12.0192	0.3579 (0.09)		High	Mean	12.3852	12.0210	0.3642 (0.09)
		Wilcoxon			1.4800 (0.14)			Wilcoxon			1.5630 (0.12)
	Low - High	Mean	1.7840 (0.00)	1.5801 (0.00)			Low - High	Mean	1.8002 (0.00)	1.5506 (0.00)	
		Wilcoxon	7.2987 (0.00)	2.9931 (0.00)				Wilcoxon	7.4141 (0.00)	2.8881 (0.00)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
LSHR	Low	Mean	11.2830	11.0830	0.2000 (0.29)	LSHR	Low	Mean	11.2962	11.0637	0.2325 (0.18)
		Wilcoxon			1.3417 (0.18)			Wilcoxon			1.3417 (0.18)
	Middle	Mean	10.5565	10.3778	0.1787 (0.16)		Middle	Mean	10.5464	10.3980	0.1483 (0.28)
		Wilcoxon			1.1481 (0.25)			Wilcoxon			0.9544 (0.34)
	High	Mean	10.0074	9.8659	0.1415 (0.27)		High	Mean	10.0198	9.8567	0.1631 (0.27)
		Wilcoxon			0.7054 (0.48)			Wilcoxon			0.7884 (0.43)
	Low - High	Mean	1.2756 (0.00)	1.2171 (0.00)			Low - High	Mean	1.2764 (0.00)	1.2070 (0.00)	
		Wilcoxon	7.2698 (0.00)	3.2031 (0.00)				Wilcoxon	7.3468 (0.00)	3.2031 (0.00)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
BETAVW	Low	Mean	0.9727	0.9679	0.0048 (0.93)	BETAVW	Low	Mean	0.9860	0.9832	0.0028 (0.96)
		Wilcoxon			0.5948 (0.55)			Wilcoxon			0.4288 (0.67)
	Middle	Mean	0.9659	0.9796	-0.0137 (0.86)		Middle	Mean	0.9558	0.9700	-0.0142 (0.85)
		Wilcoxon			-0.2075 (0.84)			Wilcoxon			-0.3458 (0.73)
	High	Mean	0.9598	1.0007	-0.0409 (0.56)		High	Mean	0.9603	0.9959	-0.0355 (0.61)
		Wilcoxon			-0.6501 (0.52)			Wilcoxon			-0.5948 (0.55)
	Low - High	Mean	0.0129 (0.72)	-0.0328 (0.62)			Low - High	Mean	0.0256 (0.47)	-0.0127 (0.85)	
		Wilcoxon	0.7361 (0.46)	-0.4726 (0.64)				Wilcoxon	0.8805 (0.38)	-0.2626 (0.79)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
RSEVW	Low	Mean	1.9406	2.4104	-0.4698 (0.02)	RSEVW	Low	Mean	1.9627	2.4614	-0.4987 (0.01)
		Wilcoxon			-2.4759 (0.01)			Wilcoxon			-2.6696 (0.01)
	Middle	Mean	2.2969	2.8605	-0.5636 (0.02)		Middle	Mean	2.2889	2.8476	-0.5587 (0.03)
		Wilcoxon			-1.9780 (0.05)			Wilcoxon			-1.7290 (0.08)
	High	Mean	2.6953	3.1914	-0.4960 (0.08)		High	Mean	2.6819	3.1614	-0.4795 (0.08)
		Wilcoxon			-1.0927 (0.27)			Wilcoxon			-1.1481 (0.25)
	Low - High	Mean	-0.7547 (0.00)	-0.7810 (0.05)			Low - High	Mean	-0.7192 (0.00)	-0.7000 (0.06)	
		Wilcoxon	-5.4511 (0.00)	-1.5228 (0.13)				Wilcoxon	-5.3453 (0.00)	-1.4178 (0.16)	

			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
	Low	Mean	3.8402	7.3304	-3.4902 (0.32)		Low	Mean	4.0241	6.5351	-2.5110 (0.49)
		Wilcoxon			-0.2628 (0.79)			Wilcoxon			-0.1245 (0.90)
	Middle	Mean	5.4311	8.1874	-2.7563 (0.58)		Middle	Mean	5.0934	8.2591	-3.1657 (0.48)
EXVW		Wilcoxon			-0.7054 (0.48)	EXVW		Wilcoxon			-0.7608 (0.45)
	High	Mean	3.4937	7.3695	-3.8758 (0.42)		High	Mean	3.5974	7.7626	-4.1652 (0.39)
		Wilcoxon			-1.1757 (0.24)			Wilcoxon			-1.2311 (0.22)
	Low - High	Mean	0.3465 (0.89)	-0.0390 (0.99)			Low - High	Mean	0.4267 (0.87)	-1.2275 (0.80)	
		Wilcoxon	0.2358 (0.81)	-0.3676 (0.71)				Wilcoxon	0.3031 (0.76)		
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
	Low	Mean	4.9544	-1.6993	6.6537 (0.49)		Low	Mean	5.6761	-1.6332	7.3093 (0.53)
		Wilcoxon			0.5118 (0.61)			Wilcoxon			0.5118 (0.61)
	Middle	Mean	3.4362	-2.9753	6.4115 (0.48)		Middle	Mean	3.6675	-2.9287	6.5961 (0.46)
NEWFIRM 5YR		Wilcoxon			0.5671 (0.57)	NEWFIRM 5YR		Wilcoxon			0.4565 (0.65)
	High	Mean	2.6670	-0.8055	3.4725 (0.74)		High	Mean	2.7204	-0.8008	3.5212 (0.72)
		Wilcoxon			0.3458 (0.73)			Wilcoxon			0.4011 (0.69)
	Low - High	Mean	2.2874 (0.71)	-0.8938 (0.89)			Low - High	Mean	2.9557 (0.66)	-0.8324 (0.89)	
		Wilcoxon	0.3705 (0.71)	-0.3676 (0.71)				Wilcoxon	0.2165 (0.83)	-0.2626 (0.79)	

Panel C: Sorted on EXCOV3 or EXCOV4

			Mean EXCOV3						Mean EXCOV4		
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
NUMEST	Low	N	40	8		NUMEST	Low	N	40	8	
		Mean	4.5917	4.2565	0.3352 (0.26)			Mean	4.8035	4.4724	0.3311 (0.32)
		Wilcoxon			1.5354 (0.12)			Wilcoxon			1.3970 (0.16)
	Middle	N	40	8			Middle	N	40	8	
		Mean	7.8131	7.1293	0.6837 (0.12)			Mean	7.8951	7.1176	0.7775 (0.07)
		Wilcoxon			1.5077 (0.13)			Wilcoxon			2.1716 (0.03)
	High	N	40	8			High	N	40	8	
		Mean	11.7456	10.5060	1.2396 (0.01)			Mean	11.5676	10.4250	1.1425 (0.01)
		Wilcoxon			2.4759 (0.01)			Wilcoxon			2.2823 (0.02)
	Low - High	Mean	-7.1539 (0.00)	-6.2495 (0.00)			Low - High	Mean	-6.7641 (0.00)	-5.9527 (0.00)	
		Wilcoxon	-7.6932 (0.00)	-3.3082 (0.00)				Wilcoxon	-7.6932 (0.00)	-3.3082 (0.00)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
LMVE	Low	Mean	13.3770	12.9702	0.4067 (0.14)	LMVE	Low	Mean	13.3666	12.9555	0.4111 (0.13)
		Wilcoxon			1.4524 (0.15)			Wilcoxon			1.4524 (0.15)
	Middle	Mean	13.1498	12.6911	0.4587 (0.07)		Middle	Mean	13.1458	12.6749	0.4709 (0.06)
		Wilcoxon			1.7843 (0.07)			Wilcoxon			1.8397 (0.07)
	High	Mean	12.9590	12.4592	0.4998 (0.07)		High	Mean	12.9643	12.4784	0.4859 (0.07)
		Wilcoxon			1.6737 (0.10)			Wilcoxon			1.6184 (0.11)
	Low - High	Mean	0.4180 (0.01)	0.5110 (0.20)			Low - High	Mean	0.4023 (0.01)	0.4770 (0.23)	
		Wilcoxon	2.7953 (0.01)	1.3128 (0.19)				Wilcoxon	2.8050 (0.01)	1.2077 (0.23)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
LSHR	Low	Mean	10.6325	10.5001	0.1324 (0.34)	LSHR	Low	Mean	10.7132	10.5685	0.1446 (0.27)
		Wilcoxon			1.0097 (0.31)			Wilcoxon			1.0651 (0.29)
	Middle	Mean	10.5611	10.4088	0.1523 (0.22)		Middle	Mean	10.5832	10.4150	0.1682 (0.18)
		Wilcoxon			1.3140 (0.19)			Wilcoxon			1.5354 (0.12)
	High	Mean	10.4791	10.2854	0.1937 (0.20)		High	Mean	10.4086	10.2426	0.1660 (0.26)
		Wilcoxon			1.2864 (0.20)			Wilcoxon			1.1204 (0.26)
	Low - High	Mean	0.1534 (0.06)	0.2147 (0.35)			Low - High	Mean	0.3046 (0.00)	0.3259 (0.16)	
		Wilcoxon	2.3046 (0.02)	1.1027 (0.27)				Wilcoxon	3.5170 (0.00)	1.5228 (0.13)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
BETAVW	Low	Mean	0.9297	0.9157	0.0139 (0.85)	BETAVW	Low	Mean	1.0221	1.0206	0.0015 (0.98)
		Wilcoxon			-0.1522 (0.88)			Wilcoxon			-0.0692 (0.94)
	Middle	Mean	0.9425	0.9366	0.0059 (0.93)		Middle	Mean	0.9571	0.9697	-0.0127 (0.84)
		Wilcoxon			0.1797 (0.86)			Wilcoxon			-0.2351 (0.81)
	High	Mean	1.0253	1.0484	-0.0231 (0.74)		High	Mean	0.9523	0.9675	-0.0151 (0.82)
		Wilcoxon			-0.2905 (0.77)			Wilcoxon			-0.3458 (0.73)
	Low - High	Mean	-0.0957 (0.03)	-0.1327 (0.09)			Low - High	Mean	0.0698 (0.09)	0.0532 (0.44)	
		Wilcoxon	-2.1795 (0.03)	-1.9429 (0.05)				Wilcoxon	1.7465 (0.08)	0.8927 (0.37)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
RSEVW	Low	Mean	2.1983	2.5777	-0.3794 (0.09)	RSEVW	Low	Mean	2.3111	2.7079	-0.3968 (0.09)
		Wilcoxon			-2.0333 (0.04)			Wilcoxon			-1.6184 (0.11)
	Middle	Mean	2.3564	2.7781	-0.4217 (0.07)		Middle	Mean	2.3799	2.8304	-0.4505 (0.06)
		Wilcoxon			1.5077 (0.13)			Wilcoxon			-1.5354 (0.12)
	High	Mean	2.5550	3.1703	-0.6152 (0.02)		High	Mean	2.4639	3.0509	-0.5870 (0.02)
		Wilcoxon			-1.6737 (0.09)			Wilcoxon			-1.7013 (0.09)
	Low - High	Mean	-0.3568 (0.01)	-0.5926 (0.12)			Low - High	Mean	-0.1528 (0.25)	-0.3430 (0.35)	
		Wilcoxon	-3.0840 (0.00)	-1.6278 (0.10)				Wilcoxon	-1.6503 (0.10)	-1.3128 (0.19)	

			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
EXVW	Low	Mean	15.0166	19.5068	-4.4902 (0.33)	EXVW	Low	Mean	5.0660	8.2254	-3.1594 (0.42)
		Wilcoxon			-0.8714 (0.38)			Wilcoxon			-1.1481 (0.25)
	Middle	Mean	6.0211	8.9869	-2.9658 (0.47)		Middle	Mean	4.2675	7.8804	-3.6130 (0.38)
		Wilcoxon			-0.6501 (0.52)			Wilcoxon			-1.0651 (0.29)
	High	Mean	-4.2129	-1.1014	-3.1115 (0.47)		High	Mean	3.4345	5.8583	-2.4238 (0.57)
		Wilcoxon			-1.1481 (0.25)			Wilcoxon			-0.6778 (0.50)
	Low - High	Mean	19.2295 (0.00)	20.6082 (0.00)			Low - High	Mean	1.6315 (0.50)	2.3671 (0.61)	
		Wilcoxon	6.2017 (0.00)	2.7831 (0.01)				Wilcoxon	0.9093 (0.36)	0.2626 (0.79)	
			Good	Bad	Diff (Good - Bad)				Good	Bad	Diff (Good - Bad)
NEWFIRM 5YR	Low	Mean	10.5812	-1.9067	12.4878 (0.18)	NEWFIRM 5YR	Low	Mean	10.7585	-0.5652	11.3238 (0.23)
		Wilcoxon			1.4247 (0.15)			Wilcoxon			1.1481 (0.25)
	Middle	Mean	9.5535	-1.3741	10.9276 (0.28)		Middle	Mean	10.2845	-2.1699	12.4544 (0.21)
		Wilcoxon			1.0651 (0.29)			Wilcoxon			1.2034 (0.23)
	High	Mean	9.0371	-1.0868	10.1239 (0.32)		High	Mean	8.2884	-1.0727	9.3611 (0.35)
		Wilcoxon			0.9544 (0.34)			Wilcoxon			0.9544 (0.34)
	Low - High	Mean	1.5440 (0.79)	-0.8199 (0.89)			Low - High	Mean	2.4701 (0.68)	0.5075 (0.93)	
		Wilcoxon	0.1973 (0.84)	0.0000 (1.00)				Wilcoxon	0.2935 (0.77)	0.0525 (0.96)	

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Table 3.10 Annual Mean Firm Characteristics Sorted on Excess Analyst Following for Post-Good and Post-Bad Domain

This table presents the annual mean firm characteristics an analyst follows in post-good/ post-bad times. The annual mean firm characteristics are calculated as the mean value of firm characteristics in a fiscal year. Sample firm-years are classified into the bad domain and the good domain based on the recession observation dummy (LREC). For each of the two domains, firm-years are further divided into three groups based on excess coverage measure (Low, Middle, and High group). For each group, annual mean for number of analyst following (NUMEST), the logarithm of the market value of equity (LMVE), the logarithm of shares outstanding (LSHR, beta (BETAVW), stock volatility (RSEVW), past stock performance (EXVW), and changes of the number of firms in the past five years (NEWFIRM5YR) are calculated for each fiscal year and presented. The values are then compared across domains for the corresponding group (Low to Low, Middle to Middle, And High to High). Within each domain, the differences in those values between the Low group and the High group are compared as well. Panel A presents the results based on excess coverage measure from the relative approach and SIC (EXCOV1), Panel B presents results based on excess coverage measure from the relative approach and Fama-French 49 industry classification (EXCOV2). Panel C presents the results based on excess coverage measure from regression approach with equation (2) (EXCOV3) and the results based on excess coverage measure from regression approach with equation (3) (EXCOV4). The left half of Panel A uses mean industry analyst coverage/ sale ratio to calculate a firm's expected analyst coverage and thus the firm's excess analyst coverage. The right half of Panel A uses median industry analyst coverage/ sale ratio. The left half of Panel B is based on mean industry analyst coverage/ sales ratio, and the right half is based on the median ratio. Panel C provides results from excess analyst coverage measure developed from regression method. EXCOV3 is residual from the OLS regression using specification in equation (3), and EXCOV4 is residual from the OLS regression using specification in equation (4). P-values are provided in the parentheses. Wilcoxon Test is reported with Z-score from the test and p-values are in the parentheses.

Panel A: Sorted on EXCOV1											
	Mean EXCOV1					Median EXCOV1					
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
		N	40	16				N	40	13	
	Low	Mean	11.1508	8.4379	2.7130 (0.02)		Low	Mean	11.2009	8.4545	2.7464 (0.00)
		Wilcoxon			2.4947 (0.01)			Wilcoxon			2.2740 (0.02)
		N	40	16				N	40	13	
	Middle	Mean	9.1149	5.6527	3.4622 (0.00)		Middle	Mean	9.0616	6.4095	2.6521 (0.00)
NUMEST		Wilcoxon			4.1807 (0.00)	NUMEST		Wilcoxon			3.2766 (0.00)
		N	40	16				N	40	13	
	High	Mean	7.8839	5.3648	2.5191 (0.00)		High	Mean	7.8776	5.9424	1.9351 (0.00)
		Wilcoxon			2.7117 (0.01)			Wilcoxon			2.3050 (0.02)
	Low - High	Mean	3.2670 (0.00)	3.0731 (0.07)			Low - High	Mean	3.3233 (0.00)	2.5120 (0.07)	
		Wilcoxon	6.5192 (0.00)	1.6293 (0.10)				Wilcoxon	6.5962 (0.00)	2.1799 (0.03)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
	Low	Mean	14.1829	13.7573	0.4256 (0.15)		Low	Mean	14.1792	13.7789	0.4003 (0.17)
		Wilcoxon			1.5326 (0.13)			Wilcoxon			1.7262 (0.08)
	Middle	Mean	13.2266	12.5027	0.7240 (0.00)		Middle	Mean	13.2050	12.6365	0.5685 (0.02)
		Wilcoxon			2.9472 (0.00)			Wilcoxon			2.2430 (0.02)
LMVE	High	Mean	12.4986	12.1442	0.3544 (0.06)	LMVE	High	Mean	12.5175	12.2545	0.2630 (0.15)
		Wilcoxon			1.5144 (0.13)			Wilcoxon			1.3954 (0.16)
	Low - High	Mean	1.6843 (0.00)	1.6131 (0.00)			Low - High	Mean	1.6617 (0.00)	1.5244 (0.00)	
		Wilcoxon	7.1351 (0.00)	3.4485 (0.00)				Wilcoxon	7.1158 (0.00)	3.5897 (0.00)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
	Low	Mean	11.4040	11.0448	0.3592 (0.12)		Low	Mean	11.4005	11.1469	0.2537 (0.21)
		Wilcoxon			1.6051 (0.11)			Wilcoxon			1.4367 (0.15)
	Middle	Mean	10.6597	10.0621	0.5976 (0.00)		Middle	Mean	10.6385	10.1846	0.4539 (0.00)
		Wilcoxon			3.2374 (0.00)			Wilcoxon			2.2016 (0.03)
LSHR	High	Mean	10.1532	9.9418	0.2114 (0.08)	LSHR	High	Mean	10.1717	10.0293	0.1424 (0.23)
		Wilcoxon			0.9703 (0.33)			Wilcoxon			1.0233 (0.31)
	Low - High	Mean	1.2508 (0.00)	1.1030 (0.00)			Low - High	Mean	1.2289 (0.00)	1.1176 (0.00)	
		Wilcoxon	7.4038 (0.00)	3.3355 (0.00)				Wilcoxon	7.4141 (0.00)	3.0769 (0.00)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
	Low	Mean	1.0386	1.1447	-0.1061 (0.30)		Low	Mean	1.0439	1.0429	0.0010 (0.99)
		Wilcoxon			-0.4806(0.63)			Wilcoxon			-0.6098 (0.54)
	Middle	Mean	1.0183	0.9246	0.0936 (0.38)		Middle	Mean	1.0098	1.0461	-0.0363 (0.73)
		Wilcoxon			0.5894 (0.56)			Wilcoxon			-0.6098 (0.54)
BETAVW	High	Mean	1.0129	0.9386	0.0743 (0.31)	BETAVW	High	Mean	1.0153	0.9993	0.0160 (0.83)
		Wilcoxon			0.7708 (0.44)			Wilcoxon			-0.0310 (0.98)
	Low - High	Mean	0.0257 (0.66)	0.2061 (0.12)			Low - High	Mean	0.0286 (0.63)	0.0436 (0.70)	
		Wilcoxon	0.8035 (0.42)	0.9234 (0.36)				Wilcoxon	0.7361 (0.46)	0.5641 (0.57)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
	Low	Mean	2.0242	2.3880	-0.3637 (0.14)		Low	Mean	2.0328	2.1382	-0.1054 (0.51)
		Wilcoxon			-1.1880 (0.23)			Wilcoxon			-1.3540 (0.18)
	Middle	Mean	2.3828	2.5561	-0.1733 (0.39)		Middle	Mean	2.3771	2.6895	-0.3124 (0.14)
		Wilcoxon			0.8615 (0.39)			Wilcoxon			-1.5814 (0.11)
RSEVW	High	Mean	2.7757	2.8616	-0.0858 (0.73)	RSEVW	High	Mean	2.7761	3.0606	-0.2845 (0.25)
		Wilcoxon			0.2630 (0.79)			Wilcoxon			-1.1266 (0.26)
	Low - High	Mean	-0.7515 (0.00)	-0.4736 (0.24)			Low - High	Mean	-0.7433 (0.00)	-0.9224 (0.00)	
		Wilcoxon	-4.9412 (0.00)	-2.0917 (0.04)				Wilcoxon	-4.9123 (0.00)	-3.0769 (0.00)	

			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
EXVW	Low	Mean	6.2459	3.3283	2.9176 (0.63)	EXVW	Low	Mean	6.5128	4.0020	2.5108 (0.68)
		Wilcoxon			-1.3693 (0.17)			Wilcoxon			-0.8166 (0.41)
	Middle	Mean	3.6075	8.1960	-4.5885 (0.38)		Middle	Mean	3.5364	22.9135	-19.3771 (0.00)
		Wilcoxon			-1.0066 (0.31)			Wilcoxon			-2.4497 (0.01)
	High	Mean	4.7336	24.5200	-19.7863 (0.00)		High	Mean	4.6139	23.7316	-19.1178 (0.00)
		Wilcoxon			-2.4757 (0.01)			Wilcoxon			-2.3050 (0.02)
	Low - High	Mean	1.5123 (0.69)	-21.192 (0.06)			Low - High	Mean	1.8989 (0.61)	-19.730 (0.07)	
		Wilcoxon	0.1491 (0.88)	-1.4133 (0.16)				Wilcoxon	0.2550 (0.80)	-1.5385 (0.12)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
NEWFIRM 5YR	Low	Mean	3.4036	0.5651	2.8385 (0.75)	NEWFIRM 5YR	Low	Mean	2.7128	-8.1816	10.8944 (0.21)
		Wilcoxon			0.9703 (0.33)			Wilcoxon			1.2300 (0.22)
	Middle	Mean	3.9067	-10.6685	14.5753 (0.18)		Middle	Mean	2.9401	-29.1185	32.0586 (0.00)
		Wilcoxon			1.3875 (0.17)			Wilcoxon			2.3050 (0.02)
	High	Mean	2.9789	2.3400	0.6390 (0.95)		High	Mean	4.4745	-10.4928	14.9673 (0.12)
		Wilcoxon			0.7527 (0.45)			Wilcoxon			1.5814 (0.11)
	Low - High	Mean	0.4247 (0.95)	-1.7749 (0.91)			Low - High	Mean	-1.7617 (0.79)	2.3112 (0.83)	
		Wilcoxon	0.0625 (0.95)	0.3204 (0.75)				Wilcoxon	-0.1780 (0.86)	0.4103 (0.68)	

Panel B: Sorted on EXCOV2											
	Mean EXCOV2					Median EXCOV2					
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
NUMEST	Low	N	40	19		NUMEST	Low	N	41	17	
		Mean	10.6455	6.1709	4.4747 (0.00)			Mean	10.5318	6.6336	3.8982 (0.00)
		Wilcoxon			3.9021 (0.00)			Wilcoxon			3.2377 (0.00)
	Middle	N	40	19			Middle	N	41	17	
		Mean	8.4098	5.7586	2.6512 (0.00)			Mean	8.2450	7.1481	1.0969 (0.23)
		Wilcoxon			3.0425 (0.00)			Wilcoxon			2.1440 (0.03)
	High	N	40	19			High	N	41	17	
		Mean	7.3290	4.8279	2.5011 (0.00)			Mean	7.1829	4.9850	2.1979 (0.00)
		Wilcoxon			3.3342 (0.00)			Wilcoxon			3.1351 (0.00)
	Low - High	Mean	3.3165 (0.00)	1.3429 (0.22)			Low - High	Mean	3.3488 (0.00)	1.6486 (0.17)	
		Wilcoxon	6.7887 (0.00)	0.9978 (0.32)				Wilcoxon	6.9185 (0.00)	1.2435 (0.21)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
LMVE	Low	Mean	14.1222	13.1505	0.9717 (0.00)	LMVE	Low	Mean	14.0493	13.3172	0.7320 (0.03)
		Wilcoxon			2.9443 (0.00)			Wilcoxon			2.5111 (0.01)
	Middle	Mean	13.1538	12.6909	0.4629 (0.02)		Middle	Mean	13.1098	12.7339	0.3759 (0.08)
		Wilcoxon			2.1819 (0.03)			Wilcoxon			1.5545 (0.12)
	High	Mean	12.3647	11.8633	0.5014 (0.01)		High	Mean	12.3348	11.8713	0.4635 (0.01)
		Wilcoxon			2.3603 (0.02)			Wilcoxon			2.0840 (0.04)
	Low - High	Mean	1.7575 (0.00)	1.2873 (0.00)			Low - High	Mean	1.7144 (0.00)	1.4459 (0.00)	
		Wilcoxon	7.2794 (0.00)	3.2406 (0.00)				Wilcoxon	7.1595 (0.00)	3.5477 (0.00)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
LSHR	Low	Mean	11.2636	10.4815	0.7820 (0.00)	LSHR	Low	Mean	11.1849	10.6001	0.5848 (0.05)
		Wilcoxon			3.2688 (0.00)			Wilcoxon			2.8528 (0.00)
	Middle	Mean	10.5612	10.2254	0.3358 (0.01)		Middle	Mean	10.5581	10.3307	0.2274 (0.05)
		Wilcoxon			2.1819 (0.03)			Wilcoxon			1.7766 (0.08)
	High	Mean	10.0042	9.6561	0.3481 (0.00)		High	Mean	10.0065	9.6564	0.3502 (0.01)
		Wilcoxon			2.0683 (0.04)			Wilcoxon			2.1353 (0.03)
	Low - High	Mean	1.2594 (0.00)	0.8254 (0.03)			Low - High	Mean	1.1784 (0.00)	0.9438 (0.02)	
		Wilcoxon	7.2121 (0.00)	2.9779 (0.00)				Wilcoxon	7.0668 (0.00)	3.3755 (0.00)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
BETAVW	Low	Mean	0.9672	1.1483	-0.1812 (0.04)	BETAVW	Low	Mean	0.9748	1.0282	-0.0535 (0.43)
		Wilcoxon			-1.5330 (0.13)			Wilcoxon			-0.5808 (0.56)
	Middle	Mean	0.9621	0.8929	0.0692 (0.32)		Middle	Mean	0.9431	0.9997	-0.0566 (0.41)
		Wilcoxon			0.8679 (0.39)			Wilcoxon			-0.7175 (0.47)
	High	Mean	0.9601	0.9343	0.0258 (0.66)		High	Mean	0.9534	0.8399	0.1135 (0.08)
		Wilcoxon			-0.1379 (0.89)			Wilcoxon			1.1104 (0.27)
	Low - High	Mean	0.0071 (0.85)	0.2140 (0.11)			Low - High	Mean	0.0214 (0.55)	0.1883 (0.11)	
		Wilcoxon	0.5918 (0.55)	1.3722 (0.17)				Wilcoxon	0.7234 (0.47)	1.6533 (0.10)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
RSEVW	Low	Mean	1.9768	2.4172	-0.4404 (0.05)	RSEVW	Low	Mean	2.0008	2.0793	-0.0784 (0.60)
		Wilcoxon			-1.5330 (0.13)			Wilcoxon			-0.7345 (0.46)
	Middle	Mean	2.3242	2.4521	-0.1279 (0.49)		Middle	Mean	2.3087	2.5480	-0.2392 (0.19)
		Wilcoxon			-0.7706 (0.44)			Wilcoxon			-12641 (0.21)
	High	Mean	2.7395	2.9814	-0.2419 (0.25)		High	Mean	2.6956	2.9609	-0.2653 (0.22)
		Wilcoxon			-1.2410 (0.21)			Wilcoxon			-1.4862 (0.14)
	Low - High	Mean	-0.7626 (0.00)	-0.5642 (0.08)			Low - High	Mean	-0.6948 (0.00)	-0.8817 (0.00)	
		Wilcoxon	-5.1817 (0.00)	-2.7735 (0.00)				Wilcoxon	-4.9801 (0.00)	-3.4788 (0.00)	

			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
EXVW	Low	Mean	3.4110	22.7157	-19.3047 (0.02)	EXVW	Low	Mean	3.1266	19.6065	-16.4800 (0.01)
		Wilcoxon			-2.1657 (0.03)			Wilcoxon			-2.4086 (0.02)
	Middle	Mean	5.2095	16.1792	-10.9697 (0.03)		Middle	Mean	5.4371	19.8960	-14.4589 (0.01)
		Wilcoxon			-1.6790 (0.09)			Wilcoxon			-1.8107 (0.07)
	High	Mean	3.9267	18.8535	-14.9268 (0.03)		High	Mean	3.5972	14.8174	-11.2202 (0.08)
		Wilcoxon			-2.3767 (0.02)			Wilcoxon			-1.7936 (0.07)
	Low - High	Mean	-0.5157 (0.83)	3.8622 (0.79)			Low - High	Mean	-0.4707 (0.84)	4.7891 (0.69)	
		Wilcoxon	-0.0433 (0.97)	-0.1460 (0.88)				Wilcoxon	0.1484 (0.88)	0.3100 (0.76)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
NEWFIRM 5YR	Low	Mean	4.6911	6.0473	-1.3563 (0.88)	NEWFIRM 5YR	Low	Mean	5.2756	1.9798	3.2958 (0.75)
		Wilcoxon			0.6408 (0.52)			Wilcoxon			1.0420 (0.30)
	Middle	Mean	3.1094	-3.9977	7.1071 (0.37)		Middle	Mean	3.1930	-12.9181	16.1111 (0.02)
		Wilcoxon			1.3059 (0.19)			Wilcoxon			2.0840 (0.04)
	High	Mean	2.5035	-12.2765	14.7800 (0.09)		High	Mean	4.5436	-10.9410	15.4846 (0.09)
		Wilcoxon			1.3708 (0.17)			Wilcoxon			1.3666 (0.17)
	Low - High	Mean	2.1875 (0.72)	18.3238 (0.16)			Low - High	Mean	0.7320 (0.91)	12.9207 (0.35)	
		Wilcoxon	0.3512 (0.73)	0.8613 (0.39)				Wilcoxon	-0.0835 (0.94)	0.3790 (0.70)	

Panel C: Sorted on EXCOV3 or EXCOV4											
	Mean EXCOV3					Mean EXCOV4					
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
		N	40	16				N	40	17	
	Low	Mean	4.5290	3.2739	1.2550 (0.00)		Low	Mean	4.7804	3.3524	1.4280 (0.00)
		Wilcoxon			3.5116 (0.00)			Wilcoxon			3.5704 (0.00)
		N	40	16				N	40	17	
	Middle	Mean	7.6884	6.2361	1.4524 (0.12)		Middle	Mean	7.7976	4.8212	2.9764 (0.00)
NUMEST		Wilcoxon			2.5310 (0.01)	NUMEST		Wilcoxon			3.6555 (0.00)
		N	40	16				N	40	17	
	High	Mean	11.6820	7.4691	4.2129 (0.00)		High	Mean	11.4765	7.9696	3.5069 (0.00)
		Wilcoxon			3.5820 (0.00)			Wilcoxon			3.1835 (0.00)
	Low - High	Mean	-7.1531 (0.00)	-4.1952 (0.00)			Low - High	Mean	-6.6961 (0.00)	-4.6172 (0.00)	
		Wilcoxon	-7.6932 (0.00)	-2.9552 (0.00)				Wilcoxon	-7.6932 (0.00)	-3.5117 (0.00)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
	Low	Mean	13.3608	12.8479	0.5129 (0.02)		Low	Mean	13.3685	12.6127	0.7558 (0.00)
		Wilcoxon			2.3306 (0.02)			Wilcoxon			2.7298 (0.01)
	Middle	Mean	13.1212	12.8553	0.2659 (0.24)		Middle	Mean	13.1207	12.6269	0.4938 (0.04)
LMVE		Wilcoxon			1.7502 (0.08)	LMVE		Wilcoxon			2.1891 (0.03)
	High	Mean	12.9476	12.2854	0.6623 (0.00)		High	Mean	12.9478	12.4904	0.4574 (0.03)
		Wilcoxon			2.9291 (0.00)			Wilcoxon			1.9972 (0.05)
	Low - High	Mean	0.4132 (0.01)	0.5625 (0.05)			Low - High	Mean	0.4207 (0.01)	0.1223 (0.69)	
		Wilcoxon	2.8050 (0.00)	2.2425 (0.02)				Wilcoxon	2.8338 (0.00)	0.2755 (0.78)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
	Low	Mean	10.6302	10.1651	0.4650 (0.00)		Low	Mean	10.7206	10.3898	0.3308 (0.05)
		Wilcoxon			2.0948 (0.04)			Wilcoxon			1.3344 (0.18)
	Middle	Mean	10.5446	10.4467	0.0979 (0.51)		Middle	Mean	10.5711	10.1593	0.4119 (0.01)
LSHR		Wilcoxon			0.9341 (0.35)	LSHR		Wilcoxon			2.3461 (0.02)
	High	Mean	10.4841	9.9618	0.5223 (0.00)		High	Mean	10.4101	10.0878	0.3223 (0.02)
		Wilcoxon			3.0017 (0.00)			Wilcoxon			1.9972 (0.05)
	Low - High	Mean	0.1461 (0.06)	0.2033 (0.43)			Low - High	Mean	0.3105 (0.00)	0.3020 (0.28)	
		Wilcoxon	2.2084 (0.03)	0.9611 (0.34)				Wilcoxon	3.5555 (0.00)	1.2744 (0.20)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
	Low	Mean	0.9233	0.8792	0.0441 (0.64)		Low	Mean	1.0181	0.9298	0.0883 (0.31)
		Wilcoxon			0.1360 (0.89)			Wilcoxon			0.1134 (0.91)
	Middle	Mean	0.9372	0.8419	0.0953 (0.23)		Middle	Mean	0.9553	0.9297	0.0256 (0.60)
BETAVW		Wilcoxon			0.7890 (0.43)	BETAVW		Wilcoxon			0.4099 (0.68)
	High	Mean	1.0279	0.9602	0.0677 (0.28)		High	Mean	0.9510	0.9417	0.0093 (0.86)
		Wilcoxon			0.5894 (0.56)			Wilcoxon			0.3401 (0.73)
	Low - High	Mean	-0.1046 (0.02)	-0.0811 (0.58)			Low - High	Mean	0.0671 (0.10)	-0.0119 (0.93)	
		Wilcoxon	-2.4970 (0.01)	-0.8480 (0.40)				Wilcoxon	1.6310 (0.10)	0.8611 (0.39)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
	Low	Mean	2.2107	2.2393	-0.0286 (0.87)		Low	Mean	2.3307	2.8629	-0.5321 (0.01)
		Wilcoxon			-0.4262 (0.67)			Wilcoxon			-1.9275 (0.05)
	Middle	Mean	2.3933	2.6132	-0.2199 (0.30)		Middle	Mean	2.4145	2.5813	-0.1668 (0.38)
RSEVW		Wilcoxon			-1.1517 (0.25)	RSEVW		Wilcoxon			-0.9506 (0.34)
	High	Mean	2.5945	2.8240	-0.2295 (0.25)		High	Mean	2.5009	2.8682	-0.3673 (0.07)
		Wilcoxon			-1.2061 (0.23)			Wilcoxon			-1.6658 (0.10)
	Low - High	Mean	-0.3838 (0.01)	-0.5847 (0.01)			Low - High	Mean	-0.1702 (0.22)	-0.0053 (0.99)	
		Wilcoxon	-2.8819 (0.00)	-2.0917 (0.04)				Wilcoxon	-1.6214 (0.10)	-0.2755 (0.78)	

			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
	Low	Mean	9.8556	-11.8868	21.7423 (0.02)		Low	Mean	10.4892	-10.8476	21.3368 (0.01)
		Wilcoxon			-0.0998 (0.92)			Wilcoxon			-2.2414 (0.03)
	Middle	Mean	9.7416	-9.6582	19.3999 (0.02)		Middle	Mean	9.8364	8.1860	1.6504 (0.89)
EXVW		Wilcoxon			-3.7007 (0.00)	EXVW		Wilcoxon			-2.5031 (0.01)
	High	Mean	8.6457	-5.4156	14.0614 (0.10)		High	Mean	8.1715	-4.0243	12.1958 (0.14)
		Wilcoxon			-2.2399 (0.03)			Wilcoxon			-2.6252 (0.01)
	Low - High	Mean	1.2099 (0.84)	-6.4711 (0.60)			Low - High	Mean	2.3176 (0.69)	-6.8233 (0.56)	
		Wilcoxon	6.3076 (0.00)	0.5465 (0.58)				Wilcoxon	0.7265 (0.47)	0.2067 (0.84)	
			Post-Good	Post-Bad	Diff (Gd - Bd)				Post-Good	Post-Bad	Diff (Gd - Bd)
	Low	Mean	14.5357	-10.0764	24.6121 (0.00)		Low	Mean	14.9530	-10.2414	25.1945 (0.00)
		Wilcoxon			1.9316 (0.05)			Wilcoxon			2.0670 (0.04)
	Middle	Mean	13.0176	-12.3598	25.3774 (0.00)		Middle	Mean	13.4010	-12.0671	25.4681 (0.00)
NEWFIRM		Wilcoxon			1.9316 (0.05)	NEWFIRM		Wilcoxon			1.0204 (0.31)
5YR	High	Mean	11.8008	-14.9827	26.7836 (0.00)	5YR	High	Mean	11.1740	-15.1761	26.3501 (0.00)
		Wilcoxon			1.8046 (0.07)			Wilcoxon			1.5437 (0.12)
	Low - High	Mean	2.7349 (0.00)	4.9063 (0.00)			Low - High	Mean	3.7790 (0.00)	4.9346 (0.00)	
		Wilcoxon	0.1876 (0.85)	0.1885 (0.85)				Wilcoxon	0.2646 (0.79)	-0.1722 (0.86)	

Chapter 4: Conclusion

Financial analysts have long been considered as professional market participants who bring price-relevant information to the market, prompts price discovery and market efficiency. However, the conventional wisdom is being challenged as evidence show that the analysts may not be able to bring new information to the market through the forecasts or recommendations they provide (Kim and Song, 2014; Loh and Stulz, 2010; Altinilic and Hansen, 2009; and Atinkilic, Balashov, and Hansen, 2013). In addition, recent development in experimental literature in learning in financial markets casts doubt on the ability of financial analysts to remain rational after observe consecutive negative outcomes, hence the usefulness of their forecasts and the role of financial analysts in financial markets (Kuhnen, 2015). My dissertation attempts to contribute to the debate regarding the role of financial analysts by focusing on two topics: the usefulness of earnings forecasts issued by financial forecast, and how financial analysts behave change depends on the ongoing economy conditions.

In Chapter 2, I examine how the quality of private information and the quality of public information contained in analyst revised one-year-ahead earnings forecasts issued right after a quarterly earnings announcement affect the post-earnings announcement drift (PEAD). I find that high precision of private information contained in revised forecasts reduces the level of PEAD, and the reduction if partially offset by the precision of public information contained in the revised one-year-ahead earnings forecasts. In addition, I find the effect of precision of private information on PEAD decreases after Reg FD, which was issued in the year 2000 and required that analysts could not contact the firm insiders to obtain private information and trade on it.

The primary purpose of my second essay is to empirically test the implication of Kuhnen (2015) by examining whether the effect of determinants on financial analysts' following decisions

change after they observed consecutive negative outcome during the economic downturn. I also examine how analysts incorporate pessimism bias into their expectation of a firm's future performance and adjust their forecast accordingly. I find that analysts become less sensitive to firm size, shares outstanding, and stock volatility when making the following decisions after observing bad outcomes, and the impact of asymmetric learning continues to exist one year later. In addition, I find that analysts fail to fully recognize the impact of the recession on the firm's performance on time in their forecasts. Moreover, I find that analysts suffer from pessimistic bias and deliver less optimistic forecasts after observing bad outcomes last year.

Overall, my dissertation adds to the debate about the role of financial analysts. Revised earnings forecasts issued by financial analysts deliver high-quality private information, which could help reduce information uncertainty and help investors estimate the true distribution of firm value. The results indicate that financial analysts do bring price-relevance information to the market. However, the usefulness of earning forecast could change depends on the on-going economic conditions, as the asymmetric learning in bad times could introduce pessimistic bias on analyst's perspective on a firm, hence the usefulness of the information contained in the forecasts. The results in my dissertation suggest that it may be beneficial to the financial market if financial analysts are given high-quality information to an extent. It would be fruitful to examine to what extent financial analysts should obtain insider information. In addition, the result in my dissertation calls for further research on how we could incorporate the pessimistic bias into the expectation forming process on a firm's future performance and get a better valuation of the firm.

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Appendix

Appendix A Variable Definitions

Variables	Descriptions
D	Revised forecast dispersion for each firm quarter. The variable calculated as the variance of 1-year ahead forecasts made within 30 trading days just after a quarterly earnings announcement.
Disp	Forecast dispersion (D) scaled by the adjusted closing stock price on the 45^{th} trading day before the quarterly earnings announcement.
SE	Squared error in the mean forecast. The variable is calculated as the square of the difference in EPS between an actual annual announcement and mean 1-year ahead forecasts issued just after a quarterly earnings announcement. This is a measure of forecast accuracy for the one-year-ahead forecast.
N	Number of financial analysts that make at least one forecast before and one forecast after the same quarterly earnings announcement.
Nr	Divide firms into ten deciles 0 (lowest) to 9 (highest) based on the number of financial analysts (N). Then scale decile number by 9, and the scaled decile numbers are *Nr*.
H	The precision of public information defined by Barron et al. (1998). Calculated as $h = \dfrac{SE - \frac{D}{N}}{\left[\left(1 - \frac{1}{N}\right) D + SE\right]^2}$.
S	The precision of private information defined by Barron et al. (1998). Calculated as $s = \dfrac{D}{\left[\left(1 - \frac{1}{N}\right) D + SE\right]^2}$.
Size	Firm size is in millions. Calculated as the product of shares outstanding and adjusted stock price at the day of quarterly announcement.

UE6 Quarterly earnings surprise. Calculated as the difference between the actual EPS and the mean 1-quarter ahead earnings forecasts issued within 45 days before the actual quarterly earnings accouchement, scaled by the adjusted closing stock price on the 45th day before the quarterly earnings announcement.

CARv [1, 60] trading days' cumulative abnormal returns (CAR). Daily abnormal return is calculated as the difference between stock returns and value-weighted index return.

CARe [1, 60] trading days' cumulative abnormal returns (CAR). Daily abnormal return is calculated as the difference between stock returns and equal weighted index return.

CARsp [1, 60] trading days' cumulative abnormal returns (CAR). Daily abnormal return is calculated as the difference between stock returns and S&P 500 index return.

CARszew [1, 60] trading days' cumulative abnormal returns (CAR). Daily abnormal return is calculated as the difference between stock returns and corresponding decile return of equally weighted Fama French portfolios formed on size.

CARszvw [1, 60] trading days' cumulative abnormal returns (CAR). Daily abnormal return is calculated as the difference between stock returns and corresponding decile return of value-weighted Fama French portfolios formed on size.

CARRv [1, 60] trading days' cumulative abnormal returns (CAR). Daily abnormal return is calculated as the difference between stock returns and expected stock return calculated from a market model where market index is value-weighted index return.

CARRe [1, 60] trading days' cumulative abnormal returns (CAR). Daily abnormal return is calculated as the difference between stock returns and expected stock return calculated from a market model where market index is equal weighted index return.

CARRsp [1, 60] trading days' cumulative abnormal returns (CAR). Daily abnormal return is calculated as the difference between stock returns and expected stock

return calculated from a market model where market index is S&P 500 index return.

CARRszew [1, 60] trading days' cumulative abnormal returns (CAR). Daily abnormal return is calculated as the difference between stock returns and expected stock return calculated from a market model where market index is corresponding decile return of equally weighted Fama French portfolios formed on size.

CARRszvw [1, 60] trading days' cumulative abnormal returns (CAR). Daily abnormal return is calculated as the difference between stock returns and expected stock return calculated from a market model where market index is corresponding decile return of value-weighted Fama French portfolios formed on size.

CompRet 6-month compound return. Calculated as compounding individual daily stock return from 6 months before a quarterly earnings announcement to the day before the announcement.

CompRetr Divide firms deciles 0 (lowest) to 9 (highest) based on the compound returns. Then scale the decile numbers by 9, and the scaled decile numbers are *CompRetr*.

%Vol For each trading day, the turnover ratio is measured as the number of shares traded that day scaled by shares outstanding on the same day. Calculate the ratio each day from 45 trading days before a quarterly earnings announcements to one day before earnings announcements and then calculate the mean trading volumes of those days. The ratio is in percent form.

Volr Divide firms into ten deciles 0 (lowest) to 9 (highest) based on the mean trading volumes (%Vol). Then scaled decile numbers by 9 and the scaled decile numbers are *Volr*.

Sign Sign of quarterly earnings surprise, 1 if the earnings surprise is positive and 0 otherwise.

EPr For each firm quarter, find mean annual earnings forecasts issued within 45 days before the coming actual quarterly earnings announcement, scaled the mean forecast by stock price 45 days before the announcement. Divide all those ratios into ten groups. Classify negative P/E ratios into group 0 and then divide positive P/E ratios into nine groups from 1(lowest) to 9(highest) based

on the size of the ratio. Then use a dummy variable to represent whether P/E ratio is extreme or in top 2 portfolios (8, 9) or bottom two portfolios (0, 1). The dummy variable, ***PEr***, equals 1 if the observation falls into portfolio 2 to 7 and 0 otherwise.

Vita

Lifei Xue completed his Bachelor of Economics at the East China University of Political Science and Law in 2009. He then received her Master of Science in Finance at University of Tulsa in 2013. In August 2014, he joined the Doctoral of Business Administration program at the University of Texas at El Paso, with a concentration in Finance. During the course of the Ph.D. program at UTEP, she worked as an assistant instructor and research assistant in the Department of Economics and Finance. His research interests includes areas of corporate finance, corporate governance, influence of financial analysts, usefulness of financial forecasts, executive compensation, and financial market learning. A number of his research paper have been presented at various international, national and regional conference in the finance discipline, including the conference of Financial Management Association European, Eastern Finance Association and Southwestern Finance Association. Lifei Xue has taught various courses in Economics and Finance in the undergraduate level at the University of Texas at El Paso. The courses he taught include Portfolio Analysis and the associated Lab, Financial Analysis of Firm and Valuation, Investment, Business Finance, Microeconomics, and Macroeconomics

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