THREE ESSAYS ON

FINANCIAL ANALYSTS

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ABSTRACT OF THE DISSERTATION

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Financial analysts, as information intermediaries in capital markets, collect information, interact with management and process information to provide their clients useful advice. This dissertation focuses on analysts' forecasting activities to shed light on the analyst-management interaction and analysts' information processing activities. The first essay examines whether firm characteristics, in particular growth properties, motivate managers to take action to meet or exceed analysts' revenue forecasts. I find that growth firms are more likely to achieve zero or positive revenue surprises than non-growth firms. Further, revenue manipulation appears to be a preferred tool for growth firms to avoid unfavorable revenue surprises than revenue expectation management. This differential appears to be due to the incremental effectiveness of revenue manipulation for growth firms. The second essay, using analysts' earnings forecasts, examines whether estimates of post-earnings-announcement returns derived from the historical firm-specific relation between unexpected earnings and drift returns help predict future post-earnings-announcement returns. I find that firms with historically high post-earnings announcement returns continue to experience high post-earnings announcement returns following future earnings surprises. The final essay investigates whether individual analysts who possess superior forecasting performance benefit from private information

obtained from their access to selective disclosure or from their innate information processing skills. The frequency of extreme earnings forecasts is used to proxy for analysts' reliance on private information. The empirical analysis reveals that private information contributing to analysts' superior performance primarily stems from analysts' privileged access to corporate management rather than from their inherent information processing skills.

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Dedication

To Hannah, Sarah, and my parents.

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Chapter 1 Revenue Surprises: Growth versus Value Firms

1.1 Introduction

In this study, I seek to examine whether certain firm characteristics, particularly growth properties, are associated with stronger incentives in order to avoid negative revenue surprises. To the extent that market participants place heavier weight on the revenue signals of growth firms relative to non-growth firms, growth firms are more likely to emphasize revenue surprises than non-growth firms. Additionally, this paper focuses on the effectiveness of two possible tools for growth firms to achieve favorable revenue surprises: 1) revenue manipulation, and 2) revenue expectation management. Since costs associated with both mechanisms can be different depending on the firms' growth properties, I examine which is a more or less effective mechanism allowing growth firms to accomplish zero or positive revenue surprises relative to non-growth firms. Finally, given the different effectiveness of two mechanisms for growth firms, I also test whether growth firms are more (less) likely to use the effective (ineffective) mechanism to meet or beat the market expectations for revenues than are non-growth firms.

Prior literature provides numerous evidence that the market awards significantly higher equity premiums (penalties) to firms meeting or beating (missing) both analysts' earnings and revenues forecasts (Jegadeesh and Kim. 2006, Rees and Sivaramakrishnan. 2007, Chandra and Ro. 2008). More importantly, Ertimur et al. (2003) find that market participants react negatively to growth firms missing market expectations for revenues even if those firms successfully meet or beat earnings expectations. Furthermore, Kama (2009) reports that the impact of revenue surprises on stock returns is higher in R&D

intensive firms. These findings suggest that the costs associated with missing revenue expectations for growth firms are much greater than those for non-growth firms. These high costs might provide stronger incentives for growth firms to closely observe the revenue signals. As a result, these increased incentives may lead managers of growth firms to take additional actions such as manipulating reported revenues upward and managing revenue expectations downward to generate favorable revenue surprises. For instance, using the univariate analysis, Stubben (2006) presents that growth firms use more upward revenue manipulation to meet or beat analysts' revenue forecasts than do non-growth firms. Therefore, in this paper, I explore the intensified incentives for growth firms to accomplish the market expectations for revenues, the effectiveness of two tools which are available for manager to achieve their objectives, and the use of those mechanisms to meet or beat the expected revenues conditional on the firms' growth properties.

This paper uses the logistic regression model to investigate the relation between firm growth and incentives in order to avoid negative revenue surprises. I hypothesize that growth is positively associated with the likelihood of achieving zero or positive revenue surprises because the importance of revenue information in valuation is higher for growth firms. Using a book-to-market ratio as a growth proxy, this study finds that growth firms are more likely to meet or beat analysts' revenue expectations than are non-growth firms.

Since the costs and benefits derived from the use of two mechanisms may vary by growth properties, I test the effectiveness of two possible tools used by growth firms' managers to achieve zero or positive revenue surprises. In order to do this, I conduct the analysis to examine both the impacts of an interaction term between growth proxy and proxy for revenue manipulation and the impacts of an interaction term between growth proxy and proxy for revenue expectation management on the likelihood of meeting or beating analysts' revenue forecasts. I estimate the discretionary revenue, as the revenue manipulation proxy, using the Stubben (2010) model. In addition, I compute the unexpected revenue forecasts, as the revenue expectation management proxy, using a measure of the unexpected earnings model which is developed by Matsumoto (2002). The results suggest that for growth firms (non-growth firms), revenue manipulation increases (decreases) the likelihood of meeting or exceeding revenue expectations while expectation management decreases (increases) the likelihood of it. I find that revenue manipulation (revenue expectation management) is a more (less) effective tool for growth firms to accomplish favorable revenue news than for non-growth firm. In other words, for growth firms, revenue manipulation increases the probability of achieving the expected revenues. These results imply that for growth firms increasing their reported revenues is more cost effective to meet or exceed the market expectations for revenues relative to decreasing the expectations than it is for value firms.

Moreover, this study tests the existent relationship between growth properties and the probability of the: 1) upward revenue manipulation, and 2) downward revenue expectation management among firms meeting or exceeding analysts' revenue forecasts. I find that growth firms are more likely to manage their revenues upward to achieve analysts' revenue expectations than are value firms. In addition, growth firms are less likely to manage their revenue expectations downward to meet or beat analysts' revenue forecasts than non-growth firms. Taken together, these results imply that firms could use different mechanisms to avoid negative revenue surprises depending on their growth properties.

This study contributes to the literature in highlighting the importance of revenue information under certain firm characteristics. Prior research provides evidence that managers have strong incentives to focus on revenue signals because market participants may consider the revenue-related information as more important and value-relevant under various circumstances, such as a specific industry (internet business industry) (Bowen et al. 2002), firms having negative earnings (Hayn. 1995, Callen et al. 2008), firms having high volatility of earnings (Ertimur and Stubben. 2005), and firms having high growth properties (Ertimur et al. 2003, Kama. 2009). This paper adds to this research by providing additional evidence that firms' growth properties increase the desire to meet or exceed analysts' revenue expectations.

Moreover, this research also contributes to the research that examines some mechanisms used to successfully reach the desired revenue targets. Although some prior studies have investigated revenue manipulation to achieve zero or small positive revenue surprises (Stubben. 2006), there is no prior research on whether firms use the expectation management for revenues as a tool to achieve the expected revenues. By exploring revenue expectation management, this paper analyzes an additional tool available to managers for avoiding unfavorable revenue surprises. Further, by showing that the effectiveness of mechanisms can be differ by growth properties, this paper provides implications for future research that certain firm characteristics might affect the effectiveness in the use of both tools.

The remainder of this paper is organized as follows. Section 1.2 discusses the related literature. Then, in section 1.3, hypotheses development is outlined. The next section describes the data selection. Section 1.5 describes the testable research designs. Section 1.6 contains descriptive statistics and empirical results. Finally, section 1.7 provides the concluding remarks.

1.2 Related Literature

1.2.1 Effect of Meeting or Beating Analysts' Forecasts

Recent research shows that an increasingly high proportion of public companies are meeting or beating financial analysts' forecasts (Matsumoto. 2002, Brown. 2001b, Burgstahler and Eames. 2006). These findings suggest that firms are paying close attention to achieving analysts' forecasts. Research also has examined the impact of firms meeting or exceeding analysts' forecasts in order to identify firms' incentives to focus on analysts' forecasts as an important threshold.

Financial analysts forecast various aspects of corporate performance including earnings, revenues, and gross margins. However, a major part of the literature investigates the effects of meeting or beating analysts' earnings forecasts. A major reason for studies focusing heavily on analysts' earnings forecasts could be that market participants (investors, employees, auditors, analysts, and regulators) generally consider earnings to be one of the most significant indicators of corporate performance. Bartov et al. (2002) tested whether firms that achieve earnings expectations have higher returns over the fiscal quarter than firms that fail to meet them. By using analysts' earnings forecasts as a proxy for market expectations of earnings, they discovered the existence of higher market equity premiums for firms which meet or beat analysts' earnings forecasts rather than firms which fail to meet them. Additionally, Kasznik and McNichols (2002) showed that the market rewards firms that meet expected earnings. They found significantly greater abnormal annual returns for firms meeting expectations as evidence of market rewards. Lopez and Rees (2002) extended the above studies by testing whether firms' historical continuity in meeting or beating earnings expectations could affect the market equity premium for unexpected earnings. They documented evidence that the market gives more rewards to firms which consistently beat expected earnings.

In addition, several papers have examined the impact of meeting or beating analysts' revenue forecasts. Plummer and Mest (2001) provide evidence that the number of firms meeting or exceeding analysts' revenue forecasts is significantly higher than the expected number of firms. This is consistent with firms expending effort to achieve analysts' revenue forecasts as well as earnings forecasts. Additionally, Rees and Sivaramakrishnan (2007) focused on the impacts of revenues and earnings surprises on equity returns, a concept which has already been broadly investigated. By using analysts' revenues and earnings forecasts as proxies of market expectations of revenues and earnings, they found that the market assigns higher (lower) premium (penalties) to firms that meet or beat (miss) earnings forecasts only when the revenue forecast is also met (not met). Furthermore, Ertimur et al. (2003) investigated whether the market reacts differently to revenue and expense surprises. They reported evidence that market participants respond more strongly and positively to firms that meet/exceed analysts' revenue forecasts than expense forecasts. Kama (2009) extended Ertimur et al. (2003) work by investigating some circumstances where the revenue signal has the incremental explanatory power over the earnings signal in determining stock returns. He documented that the impact of revenue surprises on stock returns is higher in R&D intensive firms. Moreover, Hayn (1995) and Callen et al. (2008) have investigated whether revenue surprises are more important in valuation than earnings surprises under certain circumstances, particularly when firms have negative earnings. They provide evidence that investors tend to value loss firms on the basis of the level and growth in revenues instead of earnings.

1.2.2 Mechanisms for Achieving or Exceeding Analysts' Forecasts

After researchers have documented the high propensity and the incentive (favorable premiums) of meeting or exceeding analysts' forecasts, numerous studies have examined how managers accomplish analysts' forecast. Papers on this topic are heavily concentrated on two mechanisms: 1) the manipulation of reported accounting numbers to meet or beat analysts' forecasts, and 2) the management of the market expectations.

Several researchers provide evidence that firms tend to manipulate earnings to achieve zero or small positive surprises. Based on a comparison of discretionary accruals reported by firms with negative and positive earnings surprises, Payne and Robb (2000) tested whether managers manipulate earnings with the purpose of meeting or exceeding analysts' earnings forecasts. They show that managers have greater incentive to manipulate income in order to achieve earnings expectations when pre-managed earnings (measured as current period earnings before the discretionary accruals) are below the consensus earnings forecast. Moreover, Dechow et al. (2000) examined various earnings management techniques, such as discretionary accruals and the use of special items to investigate the existence of earnings manipulations to meet or exceed the consensus earnings forecasts. They found that firms meeting or beating analysts' earnings forecasts achieved their goals through earnings management because those firms reported higher discretionary accruals compared to firms that missed analysts' earnings forecasts. Additionally, as evidence of earnings manipulation, Burgstahler and Eames (2006) reported that firms that have zero or small positive earnings surprises also have more discretionary accruals than firms with small negative earnings surprises in the distribution of earnings surprises.

In addition, several studies tested whether firms meet or beat analysts' forecasts by influencing analysts. Bartov et al. (2002) examined whether firms manage analysts' earnings forecasts. They illustrated that optimistic analysts' forecasts at the beginning of the fiscal period gradually become pessimistic as the earnings announcement draws nearer. Additionally, as evidence of the management of market expectations, they documented that the proportion of negative forecasts errors (Actual earnings – First available earnings forecasts after prior earnings announcement) that end with zero or positive earnings shocks is greater than the proportion of positive forecasts errors that end with negative earnings shocks. Richardson et al. (2004) documented that managers who have incentives to sell stocks after earnings announcements are more likely to manage analysts' earnings forecasts downward to beatable targets. Moreover, Koh et al. (2008) investigated managers heightened tendency to meet or beat analysts' earnings forecasts after a period of scandal. They found that firms utilize earnings guidance to a greater extent in order to meet analysts' earnings expectations in the post-scandal period. Also, Athanasakou et al. (2009) focused on how UK firms are able to meet or exceed analysts' earnings forecasts. As an evidence of expectation management, they reported that the likelihood of achieving the favorable levels of earnings increases with downward-guided forecasts.

Finally, Matsumoto (2002) investigated whether firms use earnings management or expectation management (forecast management) to avoid missing earnings expectations. She concluded that firms effectively utilize both mechanisms to achieve the targeted levels of earnings, analysts' earnings forecasts.

1.3 Hypothesis Development

1.3.1 The Likelihood of Meeting or Beating Analysts' Revenue Forecasts Depending on Firm's Growth Property

Prior literature provides numerous evidence that the market awards significantly higher equity premiums (penalties) to firms meeting or beating (missing) both analysts' earnings and revenues forecasts (Rees and Sivaramakrishnan. 2007, Chandra and Ro. 2008, Jegadeesh and Livnat. 2006). This implies that market participants consider current successful performance, positive earnings surprises, to be more persistent in the future when it is accompanied with positive revenue surprises. More importantly, Ertimur et al. (2003) examined whether the market reacts differently to earnings and revenue surprises which are conditional on firms' growth perspectives. They provide evidence that market participants react negatively to growth firms missing market expectations for revenues even if those firms successfully met or beat earnings expectations. Besides, although they report that negative returns for growth firms meeting or beating the expected revenue and missing the earnings targets, those negative reactions are not statistically significant. In contrast, they do not find any significant market punishments to non-growth (called value) firms missing revenue targets as long as these firms meet or exceed the market expectations for earnings. These findings suggest that for growth firms, the market places higher weight on whether firms meet or beat revenue expectations than earnings expectations. Accordingly, market participants are more disappointed when growth firms fail to effectively meet or beat the expected revenue targets despite positive earnings surprises. Kama (2009) further extends Ertimur et al. (2003) research by investigating some circumstances where the revenue signal has the incremental explanatory power over the earnings signal in determining stock returns. He documents that the impact of revenue surprises on stock returns is higher in R&D intensive firms. This finding also suggests that under certain firm characteristics, particularly growth properties, make revenue information more important than other information. In addition, Dechow et al. (2000) documented that managers' meet or exceed market expectations in order to avoid negative market reactions associated with the failure of making favorable surprise news. This strong incentive which is the avoidance of unfavorable market response could lead growth firms' managers to more closely pay attention to achieving revenue targets. Consequently, I hypothesize that growth firms meet or exceed analysts' revenue forecasts more than non-growth firms. Therefore, the first hypothesis is as follow:

H1: Growth firms are more likely to meet or beat analysts' revenue forecasts than non-growth (value) firms.

1.3.2 Revenue Manipulation versus Revenue Expectation Management

Managers possess two tools that they can use to avoid negative revenue surprises. They can attempt to manipulate financial results or manage market expectations by influencing analysts' forecasts. To meet or beat analysts' revenue forecasts, managers may manipulate reported revenues by using discretionary portions in revenues. Dechow and Schrand (2004) indicated that over 70% of the 294 SEC Accounting and Auditing Enforcement Releases that they examined involve overstated revenues. This evidence suggests that revenue manipulation is very common. Furthermore, Bowen et al. (2002) show that certain industries (e.g. internet), have strong incentives to manipulate revenues since investors consider information related to revenue signals as more important and value relevant. Stubben (2006) and Zhang (2006) found that growth firms are more likely to use discretion in revenues to manipulate revenues. Hence, the studies documented above suggest a potential tool, revenue manipulation using discretionary revenues, to meet or beat market expectations for revenues.

Another tool available for managers to meet or exceed analysts' forecasts is to manage the overall market expectations. Several researchers have documented that firms avoid overly optimistic market expectations for earnings by guiding analysts' earnings forecasts downward (Bartov et al. 2002, Richardson et al. 2004, Athanasakou et al. 2009). In the same vein, managers can also achieve other market expectations, particularly expected revenues, by influencing analysts in order to drive revenue forecasts downward prior to the announcement.

Because of the market penalties associated with a failure to meet or exceed analysts' expectations (Rees and Sivaramakrishnan. 2007, Kasznik and McNichols. 2002), firms which have some potential to miss the market expectations may actively utilize either both tools or one of them to avoid negative surprises. Though both mechanisms can be available for managers to achieve their goals, a major consideration for them is the costs and benefits of each approach. If firms efficiently exercise revenue manipulation through discretionary revenues to avoid negative revenue surprises, they could enjoy higher equity premiums as rewards. However, this activity can be costly because the active use of discretionary revenue to achieve analyst' revenue forecasts can elevate suspicion by auditors and/or the board of directors. And once a firm's revenue manipulation is detected, the market severely punishes the firm. For example, Wu (2002) reported that larger stock return declines are associated with revenue restatements. Furthermore, the reversal of discretionary revenue in subsequent periods may prevent firms from the continuous use of revenue management to raise revenue above analysts' expectations in future periods. Expectation management is also costly. The management of analysts' revenue forecasts entails the revision of current expectations downward if initial revenue forecasts are excessively optimistic. These downward revision activities could result in unfavorable market reactions at the forecast revision date. Continually revising revenue forecasts downward to sustain beatable revenue forecast levels could also result in a period of falling share prices. Therefore, to be beneficial for managers who potentially need to use either mechanism, the cost of adverse market responses associated with downward revenue forecast revisions or the detection of revenue manipulation should not exceed the cost of missing the market expectations for revenues.

Accordingly, managers' selection of the use between two tools could be different depending on the cost-benefit associated with the use of them to achieve the expected revenue targets. In other words, the effectiveness and profitability of those methods to meet or exceed analysts' revenue forecasts might be one of critical determinants in managers' choice. The effectiveness of both mechanisms would differ by certain firms' characteristics, specifically the firm's growth property. I hypothesize that revenue manipulation is a more effective tool than expectation management, especially for growth firms to achieve positive revenue surprises. There are several reasons for this conjecture. First, the reversal of discretionary revenue accruals generated from upward revenue management is likely to be less concerning for growth firms. Growth firms are likely to sustain higher levels of revenue growth necessary to cover the accrual reversals which were used to achieve positive revenue surprises in previous periods. Hence, growth firms' ability of continually generating higher revenues could make the revenue manipulation a more effective method to achieve positive revenue surprises relative to expectation management. Second, the costs of managing revenue forecasts downward are likely to exceed the costs of missing the expected revenues for growth firms but not for non-growth firms (value firms). Negative market reactions accompanied with downward forecast revisions are likely to be stronger for growth firms than for value firms because, as documented in prior literature, market participants are more sensitive to the growth firms' news related to revenues than they are to the value firms' news. Hence, expectation management would not be more effective for growth firms to meet or beat the market expectations for revenues, compared to the revenue manipulation. Consequently, revenue manipulation is more likely to increase the probability for growth firms to achieve zero or positive revenue surprises. Therefore, the second hypotheses are as follow:

H2a: The marginal effect of revenue manipulation on the probability of meeting or exceeding analysts' revenue forecasts is greater for growth firms than it is for non-growth firms.

H2b: The marginal effect of revenue expectation management on the probability of meeting or exceeding analysts' revenue forecasts is smaller for growth firms than it is for non-growth firms.

1.3.3 The Revenue Manipulation of Growth Firms to Meet or Beat Analysts' Revenue Forecasts

As posited in the second hypothesis, revenue manipulation may be a more effective tool for growth firms to avoid negative revenue surprises than expectation management. Therefore, growth firms are likely to have greater incentives to manipulate their reported revenues upward to achieve positive revenue shocks than value firms as long as the revenue manipulation is a more effective method for growth firms than expectation management. On the contrary, growth firms may have reduced incentives to manage the market expectations for revenues than non-growth firms because meeting or exceeding analysts' revenue forecasts through expectation management is a less preferable mechanism for growth firms but not for value firms. In a similar vein, Matsumoto (2002) finds that growth firms are more likely to increase reported earnings to meet or exceed analysts' earnings forecasts whereas growth firms are less likely to manage earnings expectations downward to achieve their goals. Thus, I conjecture that relative to value firms, managers of growth firms are more inclined to use positive discretionary revenues to avoid negative revenue surprises. Also, I posit that growth firms are less likely to achieve positive revenue surprises by using downward expectation management than value firms. That is, growth firms will have a higher likelihood of engaging in upward-revenue manipulation activities to meet or beat analysts' revenue than value firms while growth firms will have a lower probability of managing revenue expectations downward to avoid negative revenue surprises. Therefore, combining both conjectures, my two additional hypotheses are as follow:

H3a: Growth firms are more likely to manipulate their reported revenues upward to meet or beat analysts' revenue forecasts than non-growth firms.

H3b: Growth firms are less likely to manage revenue expectations downwards to meet or beat analysts' revenue forecasts than non-growth firms.

1.4 Sample Selection

I use the consensus of analysts' annual revenue forecasts obtained from I/B/E/S as the proxy for the market's expectation for revenue (Rees and Sivaramakrishnan. 2007, Ertimur et al. 2003, Bartov et al. 2002). I begin to collect data by obtaining annual analysts' revenue forecasts from the Institutional Brokers Estimate System (I/B/E/S). I/B/E/S began to provide revenue forecasts in a machine-readable form from 1996. Therefore, limited observations are available between 1996 and 1998. Thus, I limit the sample to the years between 1999 and 2010. Also, following Bartov et al. (2000), I require that each firm has at least three revenue forecasts to ensure that there is an initial forecast, a forecast revision, and final forecast during the fiscal period. Additionally, I make sure that the first available revenue forecast is disclosed after the prior revenue announcement date and that the last available forecast is released before the current announcement date. I use annual revenue announcement date as the fourth quarter earnings announcement date collected from COMPUSTAT. For comparability, I estimate revenue surprises by comparing revenue forecasts and actual revenue from I/B/E/S. Annual accounting data to calculate discretionary revenues and others were compiled from the COMPUSTAT database. Furthermore, consistent with Matsumoto (2002), I exclude financial institutions, utilities industries, and regulated industries (SIC codes between 5999 and 7000, between 4799 and 5000, and 3999 and 4500) because these firms are likely to have different incentives for managing earnings or revenue from other firms. Panel A in Table 1.1 presents the summary of the sample selection procedure and the number of observations generating from each data requirement step. Also, Panel 2 in Table 1.1 shows the industry composition of final sample based on Fama and French (1997) industry classification.

1.5 Research Design

1.5.1 Definition of Meeting or Beating the Market Expectations for Revenues

Following the methodology of Rees and Sivaramakrishnan (2007), I define firms meeting or exceeding revenue market expectations (MBR) at the point when the firms' actual reported revenues at the announcement date met or exceeded latest consensus (median) of analysts' revenue forecasts. That is, I identify MBR firms when their revenue surprises, or the difference between their actual revenues and the consensus of forecasted revenues reported in I/B/E/S database, are equal to or greater than zero (Reported revenue ≥ Latest median revenue forecasts). Conversely, a firm with negative revenue surprises implies that the firm misses the market expectations for revenue.

Table 1.2 reports the annual distribution of the frequency of MBR observations over the sample period. It shows that MBR firms account for approximately 60% of total firm-year observations. Because analysts' forecasts which may fail to anticipate the global economic crisis could result in a large increase of negative revenue surprises, I also conduct the same analysis of sample after excluding 2008 observations. This approach provides more interesting results. The percentage of firm-year observations with a zero or positive revenue surprises has gradually increased over sample period (Spearman rank correlation = 0.65, p=0.03) excluding year 2008. Figure 1.1 plots the changes of MBR percentage over time period. The first plot in Figure 1.1 used total sample observations does not confirmatively show the clear tendency of MBR movement by year. However, the second plot in Figure 1.1 based on firm-year observations without year 2008 indicates an increasing trend of MBR percentage over the sample period.

1.5.2 Proxy for Growth Firms and Value Firms

I use the book-to-market ratio to identify growth versus value firms. In the analysis, firms that have high book-to-market ratios are identified as low growth firms while firms that have low book-to-market ratios are represented as high growth firms. When including this growth proxy in the logistic regression model, I winsorize the proxy variable (B/M) at the 1th percentile and 99th percentile of the variable values to mitigate the effect of outliers. Also, since I observe that some observations have zero or negative book-to-market ratio, I deal with those observations as missing values.

1.5.3 Empirical Analysis Model for H1

To test the first hypothesis, this paper examines both the relation between the probabilities of meeting or beating analysts' revenue forecasts and the growth proxy by using a multivariate model with control variables as suggested in prior research as potential confounding factors on meeting or exceeding the market expectations. I perform the following logistic regression analysis to estimate the probability that a firm successfully achieves analysts' revenue forecasts at the announcement date.

$$\begin{aligned}\textbf{Prob (MBR=1|X)} = \textbf{F} (&\alpha_0 + \alpha_1\textbf{GROWTH}_i + \alpha_2\textbf{LOSS\_Prop}_i + \alpha_3\textbf{VOL\_EARNINGS}_i \\ &+ \alpha_4\textbf{LTG\_RISK}_i + \alpha_5\textbf{POS}\Delta\textbf{REV}_i + \alpha_6\textbf{INDPROD}_i + \alpha_7\textbf{SIZE}_i \\ &+ \alpha_8|\textbf{FE}_i| + \alpha_9\,\textbf{E\_Sur}_i + \varepsilon_i) \qquad \textbf{(1)}\end{aligned}$$

where:

$$\mathbf{F(\alpha'X)} = \frac{e^{\alpha' X}}{1 + e^{\alpha' X}}$$

I code the value of 1 for the dependent variable, MBR, if the firm reported revenue greater than or equal to analysts' revenue forecasts; otherwise, 0. The GROWTH, variable is included in the above model in discrete or continuous forms. First, after dividing the final full sample into three groups (high, medium, low) by growth rate, I choose two groups, high growth rate firms and medium or low growth rate firms, to use them in logistic regression analysis as an independent variable. The GROWTH variable equals one if a firm is included in the medium or low growth rate groups and zero if it is included in the high growth rate group. In addition to the use of a discrete variable (1 or 0) for the GROWTH variable, I test the relation between the dependent variable and the GROWTH variable in continuous form. I predict that the coefficient α_1 on GROWTH is statistically and significantly negative, which implies that the probability of firms meeting or beating the analysts' revenue forecasts increases as book-to-market ratios decrease. That is, high growth firms are more likely to have positive revenue surprises than are low growth firms.

Furthermore, consistent with previous studies (Matsumoto. 2002, Athanasakou et al. 2009), I also include several variables to control for possible effects on the probability of achieving positive revenue surprises. Some research has indicated that revenues are more value relevant when the earnings information of firms is not very meaningful, specifically in loss situations and high volatility of earnings. That is market participants are likely to assign more value to revenue surprises than they to earnings surprises when firms report losses (Callen et al. 2008, Zhang. 2006). Thus, loss firms may be more highly focused on meeting or beating revenue targets relative to profit firms. To control for this effect, I contain the LOSS_Prop variable in the model. This variable is measured as percentage of prior-year reported losses (Income before extraordinary items < 0) in prior years. Therefore, consistent with prior research, I expect the coefficient on LOSS_Prop to be positive.

Additionally, if firms have a higher risk of shareholder litigation coupled with negative market reactions for missing market expectations, managers may also have a stronger desire to achieve the expected targets. Consistent with Matsumoto (2002), I include a variable of LTG_RISK in the model in order to control for the effect of this variable on the probability of meeting or beating the analysts' expectations. By using the industry dummy variable I classify firms in the high risk industries of biotechnology (SIC 2833~2836), computers (SIC 3570~3577 and 7370~7374), electronics (SIC 3600~3674), and retailing (SIC 5200~5961). I predict that the coefficient α_3 on LTG_RISK is positive.

To control for unexpected macroeconomic shocks to revenue surprises, the model also includes two other variables, POSΔREV and INDPROD. The inclusion of the first variable is intended to control for the effect of the firm's performance for the period of the revenue surprises since positive revenue shocks are more likely to lead to positive forecast errors than are negative revenue shocks (Athanasakou et al. 2009). POSΔREV is a dummy variable coded with the value of 1 if the firm's annual change of revenue is positive, 0 otherwise. The second variable is included to control for the impact of the general macroeconomic condition on revenue forecast errors. The average annual growth in industrial production is used because the prior literature has documented a positive association between forecast errors and industrial production growth. The coefficients of both variables are expected to be positive. Prior studies show that the bias in analyst forecasts could differ according to firm size. Therefore, I include a SIZE variable in the model to control for this effect. Following Matsumoto (2002), the log of the market value of equity is used as a proxy for firm size. The coefficient of this variable is predicted to be positive. Further, similar to Matsumoto (2002), the uncertainty in the forecasting environment is controlled by including an additional variable (|FE|), the absolute value of the earliest revenue forecast errors scaled by prior-year-end market value of equity. I predict the sign of this variable to be negative because the difficulty of managers achieving successful revenue targets increases as uncertainty increases. Finally, I include earnings surprises deflated by the price per share at the end of the preceding year (E_Sur) to control for earnings effects. Earnings surprises are measured as difference between the actual earnings per share and the consensus (median) of analysts' earnings forecasts.

1.5.4 Revenue Management vs. Expectation Management

Managers have two available tools to effectively meet or beat the market expectations for revenues: one is the ability to manipulate reported revenues upward and the other is managing analysts' revenue forecasts downward. To investigate which method is more likely to be actively utilized by managers to avoid negative revenue surprises, I examine the empirical relation between targeted revenues and proxies for revenue manipulation or expectation management.

1.5.4.1 Proxy for Revenue Management

Stubben (2010) developed a model to measure discretionary revenues as a proxy for revenue management. This study uses this model to detect revenue manipulation as this model focuses on identifying the discretionary portion of revenues.

$$\mathbf{\Delta AR_{it} / TA_{it-1} = \beta_0[1 / TA_{it-1}] + \beta_1[\Delta R1\_3_{it} / TA_{it-1}] + \beta_2[\Delta R4_{it} / TA_{it-1}] + \varepsilon_{it}} \quad \mathbf{(2)}$$

where:

ΔAR = Annual Change of Account Receivables at the end of fiscal year

$\Delta R1\_3$ = Annual Change in Revenues of the first three quarters (1Q, 2Q, and 3Q) relative to those of the prior year's first three quarters

$\Delta R4$ = Change in Revenue of the fourth quarter relative to that of the prior year's fourth quarter

TA = Average Total Assets at t-1

The model parameters ($\beta_0, \beta_1, \beta_2$) are estimated for each year and industry (Fama and French 48) using Ordinary Least Squares (OLS). I then compute nondiscretionary revenue based on the parameters estimated in model 2:

$$\mathbf{NonDR_{it} / Asset_{it-1} = \beta_0'[1/TA_{it-1}] + \beta_1'[\Delta R1\_3_{it}/TA_{it-1}] + \beta_2'[\Delta R4_{it}/TA_{it-1}]} \quad \mathbf{(3)}$$

where:

NonDR = Nondiscretionary revenues in the event year t

β_0' β_1' β_2' = Coefficients of $\beta_0, \beta_1, \beta_2$ acquired from the model (2) regression.

Finally, I compute discretionary revenue as the difference between the change in account receivables (ΔAR) and nondiscretionary revenues (NonDR). I consider that firms manipulated their reported revenue upward if the value of discretionary revenues is positive.

$$\mathbf{DR_{it} = \Delta AR_{it} - NonDR_{it}} \tag{4}$$

where:

DR_{it} = Discretionary revenues for firm *i* in year t

1.5.4.2 Proxy for Expectation Management

In the analysis, I apply a methodology suggested by prior research to estimate whether firms manage analysts' earnings forecasts (Matsumoto. 2002). By applying Matsumoto (2002) unexpected earnings forecasts model into the estimation of unexpected revenues forecasts, I compute a proxy of expectation management for revenues. Her expected forecast model contributes to being able to estimate the analysts' forecast revisions as genuine reactions to available sources for firms in the market during forecasting periods. That is, this model allows me to compute the expected analysts' forecasts during periods in the absence of the firms' expectation management. By comparing the last consensus of actual analysts' forecasts with the expected forecasts from the model, I can estimate analysts' downward forecast revisions which are likely to have been caused by the firms' forecast management. I apply her model after adjusting it to revenues. The first two equations, (5) and (6), are estimated to distinguish the expected portion of forecasts from the original analysts' revenue forecasts. I utilize all available information for financial analysts to employ in their revenue forecasts. The equation (5) is constructed under the assumption that actual revenue changes deflated by lagged market value of equity ($\Delta REV_{i,t}$ / $MV_{i,t-1}$) can be explained by the previous year's revenue changes by lagged market value of equity ($\Delta RVE_{i,t-1}$ / $MV_{i,t-2}$) and cumulative excess returns during the current year ($CRET_{it}$). The variable, CRET, is included to capture extra value-relevant information for analysts in forecasting periods. I use Ordinary Least Square regression method (OLS) by years and Fama-French 48 industry classification codes to estimate each coefficient in equation (5). Before running the OLS, I winsorize the top and bottom 1 percentile of all variables to alleviate the impact of extreme values on parameter estimation.

$$\mathbf{\Delta REV_{i,t} / MV_{i,t-1} = \lambda_{0,t} + \lambda_{1,t} (\Delta REV_{i,t-1} / MV_{i,t-2}) + \lambda_{2,t} (CRET_{it}) + \sigma_{it}} \quad \textbf{(5)}$$

where:

ΔREV = Annual Change of Revenue for firm *i* in year t

MV = Market Value of Equity for firm *i* at the end of year

CRET = Cumulative monthly excess (market-adjusted) returns from the month following the year t-1 revenue announcement to the month of the year t revenue announcement

After obtaining all parameter estimates of the prior year from the equation (5), I use them to determine the expected change of revenues ($E(\Delta REV_{i,t})$) in the equation (6). This process ensures that all information used in the estimation of the expected revenue forecasts is only data available to analysts when establishing revenue forecasts.

$$\mathbf{E(\Delta REV_{i,t}) = [\lambda'_{0,t} + \lambda'_{1,t} (\Delta REV_{i,t-1} / MV_{i,t-2}) + \lambda'_{2,t} (CRET_{it})]} \text{ X } \mathbf{MV_{i,t-1}} \quad \textbf{(6)}$$

Then, I add the estimated expected revenues, $E(\Delta REV_{i,t})$ to the actual revenues of prior year in order to calculate the expected portion of revenue forecasts for the current year ($E(F_{i,t})$).

$$\mathbf{E(F_{i,t}) = REV_{i,t-1} + E(\Delta REV_{i,t})} \quad \textbf{(7)}$$

Finally, the unexpected analysts' revenue forecast is calculated as the difference between the latest consensus of revenue forecasts and the expected revenue forecasts.

$$\mathbf{UE(F_{i,t}) = REV\_AF_{i,Last} - E(F_{i,t})} \quad \textbf{(8)}$$

By comparing the sign of unexpected revenue forecasts estimated from the model, I determine whether firms manage market expectations for revenues downward or upward. I consider firms to have managed expectations downward if the value of unexpected revenue forecasts is negative and upward if it is positive.

1.5.5 Empirical Analysis Model for H2

In order to test the second hypothesis, which is the effectiveness of revenue manipulation and expectation management for growth firms, this paper augments the Matsumoto (2002) model with interaction terms. The model (Equation (9)) allows me to test the relation between the probability of meeting or exceeding analysts' revenue forecasts and proxies for the revenue manipulation or for the expectation management conditional on firm's growth proxy. I use the logit regression model with all variables of interest except control variables as categorical terms (0 or 1). Similar to the earlier empirical model, I put in the value of 1 for firms having zero or positive revenue surprises, otherwise 0. Also, if firms have a positive discretionary revenue, a variable indicating revenue manipulation proxy (POSDR) has the value of 1 and otherwise 0. Furthermore, I code as 1 for the variable DOWN, if the firms manage analysts' expectations for revenue downward in order to meet or beat expectations, and zero otherwise. GROWTH equals one if the firm is in the lowest growth rate group (Highest or Medium B/M ratio) and zero if the firm is in the highest growth rate (Lowest B/M ratio). In similar vein with analysis of equation 1, I also test the model including continuous terms of GROWTH. Additionally, consistent with (Matsumoto. 2002), I include four control variables in the model. The coefficient of the interaction term (GROWTH*POSDR) provides a test of H2a. A significantly negative coefficient would indicate that the effectiveness of upward revenue manipulation is significantly greater for growth companies. Meanwhile, as a test of H2b, the coefficient of the interaction term ($GROWTH_i$*DOWN) is expected to be significantly positive because downward revenue expectation management is likely to make it challenging for growth firms to meet or exceed revenue expectations.

$$\mathbf{Prob(MBR=1|X) = F(\alpha_0 + \alpha_1 POSDR_i + \alpha_2 DOWN_i + \alpha_3 GROWTH_i}$$
$$\mathbf{+ \alpha_4 GROWTH_i{*}POSDR_i + \alpha_5 GROWTH_i{*}DOWN_i + \alpha_6 POS\Delta REV_i}$$
$$\mathbf{+ \alpha_7 INDPROD_i + \alpha_8 SIZE_i + \alpha_9 |FE_i| + \alpha_{10} E\_Sur_i + \varepsilon_i) \quad (9)}$$

1.5.6 Empirical Analysis Model for H3

By using the logistic regression analysis, I investigate whether growth firms are more likely to engage in upward-revenue manipulation or downward-forecast management to achieve favorable revenue surprises than non-growth firms (value firms). To test H3a, the first model is comprised of POSDR as the dependent variable and GROWTH as the main independent variable. In similar veins, I construct the second model containing DOWN as the dependent variable and GROWTH to test H3b. Then, I examine the association between GROWTH and the likelihood of POSDR (DOWN) with a subsample only including that firms have zero or positive revenue surprises. As the previous analysis in this paper, I test the model using GROWTH in both categorical variables and continuous term. Furthermore, I add the same control variables used in both model (Equation (1)) to account for additional impacts caused by other factors on discretionary revenues. The sign of the coefficient on GROWTH in both equations determines whether growth firms meeting or beating the market expectations for revenues use more (less) revenue manipulation (revenue expectation management) relative to value firms meeting or beating the expected revenue. Consistent with H3a, I expect that the coefficient of

GROWTH variable will be negatively associated with the dependent variable (POSDA). Also, to support H3b, I predict that the sign of the coefficient on GROWTH is positive and significant.

$$\mathbf{Prob(POSDR = 1|X) = F(\alpha_0 + \alpha_1 GROWTH_i + \alpha_2 LOSS\_Prop_i + \alpha_3 VOL\_EARNINGS_i + \alpha_4 LTG\_RISK_i + \alpha_5 POS\Delta REV_i + \alpha_6 INDPROD_i + \alpha_7 SIZE_i + \alpha_8 |FE_i| + \alpha_8 E\_Sup_i + \varepsilon_i)} \quad \mathbf{(10)}$$

$$\mathbf{Prob\ (DOWN = 1|X) = F(\alpha_0 + \alpha_1 GROWTH_i + \alpha_2 LOSS\_Prop_i + \alpha_3 VOL\_EARNINGS_i + \alpha_4 LTG\_RISK_i + \alpha_5 POS\Delta REV_i + \alpha_6 INDPROD_i + \alpha_7 SIZE_i + \alpha_8 |FE_i| + \alpha_8 E\_Sur_i + \varepsilon_i)} \quad \mathbf{(11)}$$

1.6 Empirical Analysis Results

1.6.1 Analysis Model for H1

1.6.1.1 Descriptive Statistics

Panel A of Table 1.3 reports descriptive statistic of the final sample. As mentioned before, I winsorize all continuous variables at both 1 percentile and 99 percentile of the variable distribution. The mean of the dependent variable (MBR) indicates that approximately 57% of firm-year observations are classified as meeting or beating the analysts' revenue forecasts. A growth proxy, the book to market ratio, has a mean (median) of 0.57 (0.44). On average (median), sample firms report losses 34% (25%) of the time in the sample period. The mean of the earnings volatility variable and forecasts errors variables are 1.64 and 0.16 whereas the medians are 0.52 and 0.05, which suggest that the distribution of both variables is slightly right skewed. Also, approximately 33% of firm-years in the final sample are from firms in high litigation risk industries. Moreover, 72% of observations in the entire panel have positive revenue changes relative to prior year (POSΔREV). Finally, the average (median) size of the sample firms is 6.38 (6.31).

Panel B presents the results of the t-test of differences in the means between two groups (MBR=1 and 0). Consistent with the prediction, firms meeting or exceeding the analysts' revenue expectations (MBR=1) have lower book to market ratios than those of firms missing the expected revenue (MBR=0). The mean for MBR=1 firms is 0.52 as compared to 0.65 for MBR=0 firms, and the difference between the two groups (0.12) is significantly different from zero. In contrast to my prediction, the average frequency of losses over the sample period is significantly lower for the MBR=1 group than for the MBR=0 group. In addition, between these two groups there are no significant mean differences in the volatility of earnings and the proportion of high-litigation-industry group. However, other variables (POSΔREV, INDPROD, SIZE, and lFEl) have significant differences in the means between MBR=1 and MBR=0.

Table 1.4 reports the Pearson (Spearman) correlation matrix of all variables. Of particular interest is the correlation between the dependent variable and growth proxy (Book-to-Market) variable. As expected, the MBR is significantly and negatively correlated with the book-to-market ratio. While correlations between the MBR and the POSΔREV or INDPROD are significantly positive, correlations between the MBR and the LOSS_Prop or lFEl are significantly negative. However, VOL_Earnings and LTG_Risk variables are not significantly correlated with the dependent variables. Overall, correlations between the dependent variables and the independent variables are generally low in magnitude (< 0.2).

1.6.1.2 Contingency Table of MBR by Growth Proxy

A contingency table in Table 1.5 presents the frequency of firms meeting or beating (missing) the analysts' revenue forecasts depending on the growth proxy. The number of firms achieving zero or positive revenue surprises monotonically increases from 4796 to 5901, thereby moving from a low growth group to a high growth group. These numbers account for 17% and 21% of the total percentage of firms meeting or exceeding the expected forecasts (57%), respectively. These results indicate the significant differences in MBR among high growth group and low growth group ($\chi^2 = 282.53$, $p < 0.001$). In addition, Figure 1.2 provides a graphical view of the different percentage of the MBR group conditional on three growth groups. It shows that the frequency of MBR for a high growth group is greater than for a low growth group.

1.6.1.3 Results from Logistic Regression

By using logistic regression model (EQ 1), analysis results of testing H1 are reported in Table 1.6. I present the estimation results by not only using book-to-market ratio in a continuous form (labeled model (1)), but also by using the categorical variable of growth based on a book-to-market ratio (High Growth Group vs. Medium or Low Growth Group) (labeled model (2)). Both results are statistically similar.

As conjectured in H1, the coefficients on Book_to_Market and Rank_BtM are both negative and significant, a factor suggesting that high growth firms are more likely to meet or beat the analysts' revenue forecasts than are low growth firms. Also, consistent to prior research that firms having lower value-relevance of earnings are more inclined to focus on revenue signals, the coefficient on VOL_Earnings is significantly positive with both models. However, inconsistent with my prediction, LOSS_Prop is significantly and negatively associated with the likelihood of MBR. One possible explanation of this result could be that firms which frequently report losses do not have the strength in economic power necessary to satisfy the analysts' revenue expectations because their losses are not strategic losses but are permanent losses resulting from actual low performance of the firm. Also, the LTG_Risk variable does not have the expected positive and significant coefficient. One possible explanation is that shareholders in high litigation risk industries may consider the earnings signal to be the only critical factor in their decision making processes, rather than revenue signals or other information.

Columns 4 and 6 in Table 1.6 show the marginal effect of each variable included in the Models (1) and (2). I compute the marginal effects by using a semi-elasticity basis. In other words, the marginal effects in the logistic regression results represent the change of probability in terms of one unit change of the independent variable. Accordingly, the fact that the marginal effect of the Book_to_Market is - 7.9 means that for a single standard error increase in book-to-market ratio, the probability of meeting or exceeding the revenue expectations declines by approximately 8%. In the Model (2), a similar analysis suggests that moving from a high growth group (Rank_BtM=0) to a low growth group (Rank_BtM=1) decreases the probability of meeting or beating analysts' revenue forecasts by approximately 5%. Although other variables also have impacts on the MBR, it appears that the marginal effect of the growth proxy measured by the book-to-market ratio on the MBR is larger than other variables, except POSΔREV.

1.6.2 Analysis Model for H2

1.6.2.1 Estimate of an Revenue Expectation Management Proxy

Panel A in Table 1.7 shows the descriptive statistics on the parameter estimates using Equation (5) for all available firm-year observations. Consistent with results obtained from Matsumoto's model which is based on EPS, the parameter estimates for λ_1 and λ_2 computed from the revenue-based model are positive and significant on average. Moreover, the model is reasonably well constructed because the adjusted R square for the regression is roughly 0.30 and is slightly higher relative to the EPS-based model (0.24).

Panel B presents descriptive statistics for unexpected revenue forecasts. The mean of the unexpected revenue is approximately 165, suggesting that the overall analysts' revenue forecasts for firms in the sample are higher than the expected revenue forecasts calculated by the model. The results imply that revenue expectation management is not widely used by the market. However, Panel C in Table 1.7 provides more interesting results. Panel C displays the mean differences of unexpected revenue forecasts depending on firms' growth. The results show that the average of unexpected revenue forecasts monotonically declines from 360 to 4.7 when shifting from a high growth group to a low growth group, which suggests that consistent with my conjecture, expectation management for revenues is more widespread as the firm growth decreases while this tool is not extensively used as firm growth increases.

1.6.2.2 The Association between the MBR and Two Mechanisms

The contingency table in Table 1.8 provides an illustration of the relationship between meeting or beating the analysts' revenue forecasts (MBR) and two available mechanisms based on the overall firm-year observations. The first 2 by 2 table in Panel A shows the association between the MBR and the upward-revenue manipulation (POSDR). The results from this contingency table illustrate that 54% of firm-years in which firms achieve positive revenue surprises (MBR=1) manipulate their reported revenues upward (POSDR=1), relative to 49% of firm-years in which firms have negative revenue surprises (MBR=0). This finding demonstrates the significant positive relation between the MBR and revenue manipulation proxy (χ^2 = 282.53, p <0.001). Similarly, the second 2 by 2 table presents the relationship between the MBR and the downward-expectation management for revenues (DOWN). The outcomes show that 32% of firms meeting or exceeding analysts' revenue forecasts manage their revenue expectations downward, as compared to 25% of firms missing analysts' revenue expectations. The Chi-square test indicates that the difference between these two groups is statistically significant. Overall, the results from the two contingency tables in Panel A suggest that both revenue manipulation and revenue expectation management are effective mechanisms with which managers meet or exceed market expectations.

I also conduct a similar contingency analysis based on the differing levels of growth (high, medium, low). Panel B in Table 1.8 demonstrates that the association between the MBR and the PODR is conditional upon a firm's growth. The tables confirm that among firms using positive discretionary revenues (POSDR=1), the differences between the percentage of firms achieving zero or positive revenue surprises (MBR=1) and the percentage of firms having negative revenue surprises (MBR=0) are gradually increasing as they move from the low growth group to the high growth group (from 2.34% to 4.98%). These initial findings suggest that revenue manipulation is a more effective tool for high growth firms in order to meet or beat the analysts' revenue expectations relative to low growth firms. Furthermore, Panel C in Table 1.8 reports the association between of MBR and DOWN as being conditional on a firm's growth. In contrast to revenue manipulation, these results indicate that among firms using downward expectation management (DOWN=1), differences between the percentage of firms achieving expected revenues (MBR=1) and percentage of firms missing the expectations for revenues (MBR=0) are monotonically decreasing when shifting from the low growth group to the high growth group (from 13.99 to 1.68). These outcomes reveal that revenue expectation management is a less effective tool for high growth firms to employ in order to accomplish zero or positive revenue surprises than it is for low growth firms.

1.6.2.3 Results from Logistic Regression for H2a and H2b

Table 1.9 reports the results from the logistic regression analysis (EQ 9) which tests the effectiveness of the two mechanisms to meet or beat the analysts' revenue forecasts conditional on the firm growth. In order to establish consistency over the analysis, I show the test results by using growth proxy in a continuous form as well as in a discrete form.

In these two models, the coefficient on Book_to_Market and Rank_BtM are both negative and significant, which is consistent with the previous findings from the test of H1. Also, as expected, the coefficients on both indicators of the positive discretionary revenues (POSDR) and the downward-expectation management for revenue (DOWN) are positively associated with the probability of achieving zero or positive revenue surprises within these two models. These significant positive signs indicate that both mechanisms are effective means to avoid negative revenue surprises; for example, in model 1, revenue manipulation and revenue expectation management increase the probability of meeting or beating the expectations for revenue approximately by 10% and by 21%, respectively. More importantly, the coefficient on the interaction term of BtM*POSDR is significantly negative in the first model though Rank_BtM*POSDR is negative but is not significant.

The negative signs on these interaction variables reveal that revenue manipulation increases the probability of meeting or exceeding the expected revenue forecasts as firm growth increases. Specifically, in model 1, the marginal effect of BtM*POSDR is - 0.065, which indicates that the revenue manipulation contributes to roughly a 7% decrease in the probability of having positive revenue surprises when the book-to-market ratio increase by one unit. Thus, consistent with H2a, revenue manipulation is a more effective mechanism to accomplish favorable revenue surprises for growth firms than for value (non-growth) firms. On the other hand, the interaction of growth proxy and downward expectation management, BtM*DOWN (Rank_BtM*DOWN), is positively associated with the likelihood of achieving zero or positive revenue surprises in both models. The marginal effect of this variable implies that the revenue expectation management reduces the likelihood of meeting or exceeding the analysts' revenue expectations approximately by 16% as a one unit decrease in the book-to-market ratio. Hence, this result confirms that the expectation management for revenues is a less effective tool for growth firms to avoid negative revenue surprises than it is for value firms, which supports H2b.

1.6.3 Analysis Model for H3

1.6.3.1 Results from Logistic Regression for H3a

Table 1.10 presents the results of the logistic regression which examines the relation between growth proxy and the likelihood of using positive discretionary revenues (PODR) under the subsample which only include firm-years with zero or positive revenue surprises. Consistent with Stubben (2006), I find that the main variable of interest, Book_to_Market (Rank_BtM), is significantly negatively related to PODR, which indicates that higher growth firms are more likely to manage reported revenues by using positive discretionary revenues to meet or beat the analysts' revenue forecasts relative to lower growth firms. Therefore, this finding provides evidence to support H3a. Also, the marginal effect of Book_to_Market (Rank_BtM) is stronger when compared to other variables. This result suggests that the firm growth property has an economic and significant impact on the upward-revenue manipulation practices in achieving favorable revenue surprises. In addition, the coefficient on VOL_Earnings is associated with the probability of positive discretionary revenues. Firms having a higher volatility of earnings are more likely to use revenue-increasing practices to accomplish positive revenue signals. Contrary to the expected sign, the coefficient on LTG_Risk is significantly negative. One possible explanation is that firms in high-litigation-industries are more reluctant to increase the reported revenues than are firms in low-litigation-industries because the consequences associated with the detection of those activities might be perceived as much more grievous to them. INDPROD have positive and significant coefficients, suggesting that firms similarly have a higher propensity for manipulating revenues upward when their overall industrial productions increase. Further, the coefficient on lFEl is significantly negative. This finding implies that firms are less likely to increase their reported revenues in order to meet or beat the revenue expectations within a more uncertain environment.

1.6.3.2 Results from Logistic Regression for H3b

To test H3b, I examine the association between growth proxies (Book_to_Market and Rank_BtM) and the probability of downward-revenue expectation management for the subgroup comprised of only firms which meet or beat analysts' revenue forecasts.

The estimation results reported in Table 1.11 show that the coefficients on Book_to_Market and Rank_BtM are significantly positive, suggesting that consistent with H3b, growth firms are less likely to manage analysts' revenue expectations downward than are non-growth firms. Interestingly, the coefficients of most other variables are opposite to those coefficients acquired from the test of H3a. The frequency of the reported losses over the sample period (LOSS_Prop) is marginally associated with the likelihood of managing the revenue expectations downward in the Model 2. These results indicate that firms which frequently report negative earnings have a tendency of using downward expectation management for revenues with the intent of achieving positive revenue surprises. Additionally, the coefficients on POSΔREV and INDPROD are both negative and significant, contrary to the results from the H3a test. These findings imply that firms are less likely to manage expectations for revenues when they have positive revenue changes compared to a prior year and when the average industrial production is high. Moreover, the significant positive sign on the lFEl suggests that firms are more likely to use the revenue expectation management with the intent to meet or beat the revenue targets when the uncertainty related to any firm's conditions is high.

1.7 Conclusion

This paper investigates whether a firm's growth property is associated with the likelihood of meeting or beating the analysts' revenue forecasts. I expect that growth firms more closely pay attention to achieving zero or positive revenue surprises than do value firms, in part because revenue information of growth firms is more important and relevant for the market to make appropriate valuation decisions. Consistent with this conjecture, my findings provide evidence that high growth firms are more likely to meet or exceed analysts' revenue expectations than are low growth firms.

In addition, this study examines the effectiveness of two possible mechanisms (revenue manipulation and revenue expectation management), both of which can be used to avoid negative revenue surprises that are conditional on a firm's growth property. I postulate that the effectiveness of these tools might differ by their growth property, although they are both effective mechanisms to generate favorable revenue information. As a supportive evidence for my inference, results confirm that both mechanisms increase the likelihood of achieving zero or positive revenue surprises. More importantly, I find that upward-revenue manipulation is a more effective tool for growth firms to meet or exceed analysts' revenue forecasts relative to value firms, while downward-revenue expectation management is a less effective mechanism for growth firms than for value firms.

Furthermore, this paper tests whether the firm's growth property is associated with the likelihood of both engaging in the revenue-increasing practices and employing downward-revenue expectation activities, which are conditional on meeting or exceeding the analysts' revenue expectations. The results show that growth firms have a higher propensity for using positive discretionary revenues with the purpose to accomplish the expected revenues than do value firms. However, I also find that firms with a high growth property are less likely to manage analysts' revenue forecasts downward in order to avoid negative revenue surprises. Taken together, my findings suggest that depending on the firm's growth property, managers select a more effective mechanism to meet or beat the analysts' revenue forecasts.

1.8 Tables for Chapter 1

Table 1.1

Sample Selection and Industry Composition

Panel A: Sample Selection Procedure

Sample Selection	Observations
Total Revenue Analysts' Forecasts from I/B/E/S for period 1999 - 2010*	44,411
Less:	
Insufficient data in I/B/E/S**	(1,505)
Firms in financial institutions, utilities, and regulated industries (SIC codes between 5999 and 7000, between 4799 and 5000, and 3999 and 4500)	(11,193)
Firms without Fama-French industry classification code	(2,193)
Total Sample Observations	29,520

*The sample includes the first consensus of revenue forecasts after prior earnings announcement and the last consensus revenue forecasts before current earnings announcement. Also, this sample requires that each firm has at least three revenue forecasts.

** I delete firm-year observations if actual revenues are not available in I/B/E/S.

Panel B: Industry Composition Based on Fama and French (1997) Industry Classification

Code	Industry Name	Obs.	Code	Industry Name	Obs.
1	Agriculture	85	22	Electrical Equipment	543
2	Food Products	538	23	Automobiles and Trucks	471
3	Candy & Soda	91	24	Aircraft	183
4	Beer & Liquor	131	25	Shipbuilding, Railroad Equipment	17
5	Tobacco Products	5	26	Defense	50
6	Recreation	204	27	Precious Metals	125
7	Entertainment	490	28	Non-Metallic and Industrial Metal Mining	167
8	Printing and Publishing	260	29	Coal	78
9	Consumer Goods	472	30	Petroleum and Natural Gas	1617
10	Apparel	461	33	Personal Services	475
11	Healthcare	635	34	Business Services	5100
12	Medical Equipment	1282	35	Computers	1611
13	Pharmaceutical Products	2588	36	Electronic Equipment	2672
14	Chemicals	669	37	Measuring and Control Equipment	817
15	Rubber and Plastic Products	228	38	Business Supplies	404
16	Textiles	84	39	Shipping Containers	120
17	Construction Materials	512	40	Transportation	501
18	Construction	434	41	Wholesale	980
19	Steel Works Etc	474	42	Retail	2002
20	Fabricated Products	32	43	Restaurants, Hotels, Motels	657
21	Machinery	1139	48	Other	116

Table 1.2

Frequency of Meeting or Beating Analyst Revenue Forecasts (MBR=1) and Missing Analyst Revenue Forecasts (MBR=0) by Year

		MBR=1	MBR=0	
Year	**Entire Sample**	**N**	**N**	**Freq(%)**
1999	2110	1086	1024	51.47%
2000	2360	1115	1245	47.25%
2001	2403	1099	1304	45.73%
2002	2422	1412	1010	58.30%
2003	2452	1660	792	67.70%
2004	2580	1646	934	63.80%
2005	2659	1545	1114	58.10%
2006	2703	1544	1159	57.12%
2007	2708	1586	1122	58.57%
2008	2557	1078	1479	42.16%
2009	2477	1584	893	63.95%
2010	2089	1376	713	65.87%
All Years	29520	16731	12789	56.68%

Spearman Rank Corr	**0.3986**	**Excluding 2008**	**Spearman Rank Corr**	**0.64545**
p-value	**0.1993**		**p-value**	**0.0320**

Table 1.3

Descriptive Statistics

Panel A: Descriptive Statistics for Dependent Variable and Proxies for Growth, and Control Variables

Variable	N	Mean	Std Dev	Median	1Q	3Q
Dependent Variable:						
MBR	29520	0.567	0.496	1.000	0.000	1.000
Proxies for Growth:						
Book_to_Market	28545	0.574	0.495	0.444	0.264	0.716
Control Variables:						
LOSS_Prop	29520	0.336	0.337	0.250	0.000	0.571
VOL_Earnings	27706	1.636	3.855	0.522	0.243	1.290
LTG_RISK	29520	0.334	0.472	0.000	0.000	1.000
POSΔREV	29520	0.718	0.450	1.000	0.000	1.000
INDPROD	29520	0.376	4.154	2.088	-3.136	2.990
SIZE	28220	6.378	1.796	6.306	5.135	7.522
lFEl	28224	0.160	0.327	0.051	0.017	0.143

* MBR is categorical variable equal to 1 if a firm has a zero or positive revenue surprise. Revenue surprises are computed as difference between their actual revenues reported and the consensus of forecasted revenues reported in I/B/E/S database (Reported revenue ≥ Latest median revenue forecasts).

Panel B: t-test of Mean Difference between MBR=1 and MBR=0

Variables	MBR		Diff(G1-G2)	t Value	Pr > |t|
	0	1			
Book_to_Market	0.6446	0.5216	0.123	20.96	<.0001
LOSS_Prop	0.3798	0.302	0.0778	19.55	<.0001
VOL_Earnings	1.6595	1.6178	0.0416	0.89	0.3732
LTG_RISK	0.3389	0.3302	0.00872	1.57	0.1158
POSΔREV	0.6409	0.7765	-0.1356	-25.46	<.0001
INDPROD	1.2431	0.4080	-0.126	-2.6	0.0093
SIZE	6.0479	6.6327	-0.5848	-27.27	<.0001
lFEl	0.1873	0.1406	0.0466	11.44	<.0001

Table 1.4

Pearson (above the diagonal) and Spearman (below the diagonal) Correlation Coefficients

Prob > |r| under H0: Rho=0

	MBR	Book_to_Market	LOSS_Prop	VOL_Earnings	LTG_RISK	POS_RC	INDPROD	SIZE	lFEl
MBR	1	-0.123	-0.115	-0.005	-0.009	0.149	0.015	0.161	-0.067
		<.0001	<.0001	0.373	0.116	<.0001	0.010	<.0001	<.0001
Book_to_Market	-0.107	1	0.120	0.074	-0.094	-0.214	-0.101	-0.420	0.252
	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
LOSS_Prop	-0.107	0.106	1	0.094	0.228	-0.168	0.017	-0.484	0.058
	<.0001	<.0001		<.0001	<.0001	<.0001	0.004	<.0001	<.0001
VOL_Earnings	-0.002	0.156	0.373	1	-0.015	-0.051	0.003	-0.091	0.077
	0.711	<.0001	<.0001		0.015	<.0001	0.628	<.0001	<.0001
LTG_RISK	-0.009	-0.151	0.200	0.002	1	0.007	0.010	-0.070	-0.084
	0.116	<.0001	<.0001	0.744		0.200	0.080	<.0001	<.0001
POS_RC	0.149	-0.211	-0.178	-0.102	0.007	1	0.269	0.180	-0.191
	<.0001	<.0001	<.0001	<.0001	0.200		<.0001	<.0001	<.0001
INDPROD	0.022	-0.113	0.005	0.023	0.002	0.223	1	0.026	-0.089
	0.000	<.0001	0.397	0.000	0.763	<.0001		<.0001	<.0001
SIZE	0.161	-0.383	-0.495	-0.214	-0.084	0.180	0.037	1	-0.191
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001
lFEl	-0.070	0.333	0.084	0.172	-0.153	-0.274	-0.046	-0.245	1
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	

Table 1.5

Frequency of MBR by Growth Proxies

Frequency Percent MBR	Rank_BM 2 (High)	 1 (Mid)	 0 (Low)	 Total
1	5901 20.67	5610 19.65	4796 16.8	16307 57.13
0	3614 12.66	3905 13.68	4719 16.53	12238 42.87
Total	9515 33.33	9515 33.33	9515 33.33	28545 100
		Chi-Square 281.5382	***p*-value** <.0001	

Table 1.6

Logit Analysis of the Probability of MBR and Growth Proxy (Book-to-Market Ratio)

Model: Prob (MBR=1|X) = F (α_0 + α_1GROWTH$_i$ + α_2LOSS_Prop$_i$ + α_3VOL_EARNINGS$_i$ + α_4LTG_RISK$_i$ + α_5POSΔREV$_i$ + α_6INDPROD$_i$ + α_7SIZE$_i$ + α_8|FE$_i$| + α_9E_Sur$_i$ + ε_i)

		Model (1)		**Model (2)**	
VARIABLES	**Exp. Sign**	**Coefficient (z-stat)**	**Marginal Effects**	**Coefficient (z-stat)**	**Marginal Effects**
Constant	?	-0.628*** (-3.45)		-0.737*** (-4.76)	
Proxies for Growth:					
Book_to_Market	-	-0.183** (-2.49)	-0.079		
Rank_BtM	-			-0.107** (-2.07)	-0.046
Control Variables:					
LOSS_Prop	+	-0.124** (-2.26)	-0.053	-0.121** (-2.15)	-0.052
VOL_Earnings	+	0.010*** (3.41)	0.004	0.010*** (3.40)	0.004
LTG_Risk	+	0.001 (0.02)	0.000	0.004 (0.08)	0.002
POSΔREV	+	0.574*** (5.32)	0.246	0.586*** (5.59)	0.251
INDPROD	+	-0.016 (-0.62)	-0.007	-0.015 (-0.58)	-0.006
SIZE	+	0.104*** (4.44)	0.045	0.115*** (5.63)	0.049
lFEl	-	-0.046 (-0.50)	-0.020	-0.075 (-0.89)	-0.032
E_Sur	+	1.674*** (9.65)	0.718	1.748*** (10.78)	0.750
Log Likelihood		-16800.83		-16811.34	
Wald Chi-square		1278.72		1257.70	
p-value		< 0.001		< 0.001	
Pseudo R-squared		0.037		0.036	
Total Observations		25,535		25,535	

Dependent variable (MBR) is equal to 1 if a firm has a zero or positive revenue surprise and otherwise 0. Reported z-statistics are based on firm and year clustered standard errors. Notations ***, **, and * indicate significance at 1, 5, 10 percent significance levels, respectively.

Table 1.7

Descriptive Statistics of Revenue Expectation Management Proxy Based on Matsumoto's Unexpected Earnings Forecast Model

Panel A: Regression Estimates from the Model of Expected Change in Revenues (n = 20,216)

***Model*: $\Delta REV_{i,t} / MV_{i,t-1} = \lambda_{0,t} + \lambda_{1,t} (\Delta REV_{i,t-1} / MV_{i,t-2}) + \lambda_{2,t} (CRET_{it}) + \sigma_{it}$**

Variable	Mean	Std Dev	t Value	Median	Lower Quartile	Upper Quartile
λ_0	0.052	0.373	2.8	0.044	-0.018	0.108
λ_1	0.272	1.019	5.3	0.153	-0.043	0.449
λ_2	0.158	0.848	3.7	0.099	-0.022	0.223
Adjusted R^2	0.287	0.258	22.15	0.206	0.090	0.432

Panel B: Descriptive Statistics on Unexpected Forecast Proxy

***Model*: $UE(F_{i,t}) = REV\_AF_{i,Last} - \{ REV_{i,t-1} + [\lambda'_{0,t} + \lambda'_{1,t} (\Delta REV_{i,t-1} / MV_{i,t-2}) + \lambda'_{2,t} (CRET_{it})] \text{ X } MV_{i,t-1} \}$**

Variable	Mean	Std Dev	t Value	Median	Lower Quartile	Upper Quartile
Unexp_Forecast	164.61	2791.48	8.38	22.711638	-5.476	145.929

Panel C: Descriptive Statistics on Unexpected Forecast Proxy by Growth Proxy (Book-to-Market Ratio)

Variable	B-to-M	Mean	Std Dev	t Value	Median	Lower Quartile	Upper Quartile
Unexp_Forecast	High	359.94	2904.98	9.88	45.36	2.71	273.03
Unexp_Forecast	Medium	146.86	3018.41	4.05	34.17	-1.48	167.98
Unexp_Forecast	Low	4.65	2462.77	0.15	6.74	-19.41	57.78

Table 1.8

Association between the Probability of MBR and (1) Revenue Manipulation or (2) Revenue Expectations Management

Panel A: Contingency Tables Organizing Firm-year Observations Based on: Indicators of Meeting or Beating Analysts' Revenue Forecasts and (1) Indicators of Positive Discretionary Revenues (POSDR) and (2) of Unexpected Revenue Forecasts (DOWN)

	Frequency	**POSDR**		
	Percent	1	0	Total
MBR	1	8193	7009	15202
		53.89%	46.11%	56.53%
	0	5774	5915	11689
		49.4%	50.6%	43.47%
	Total	13967	12924	26891
		51.94%	48.06%	100%

$\chi^2 = 282.53$ $p < 0.001$

	Frequency	**DOWN**		
	Percent	1	0	Total
MBR	1	3767	8075	11842
		31.81%	68.19%	58.58%
	0	2129	6245	8374
		25.42%	74.58%	41.42%
	Total	5896	14320	20216
		29.17%	70.83%	100%

$\chi^2 = 282.53$ $p < 0.001$

Table 1.8 (Continued)

Panel B: Contingency Tables Organizing Firm-year Observations Based on: Indicators of Meeting or Beating Analysts' Revenue Forecasts and (1) Indicators of Positive Discretionary Revenues (POSDR) and (2) of Unexpected Revenue Forecasts (DOWN) conditional on Growth Proxy (Book-to-Market Ratio)

(1) MBR and POSDR by the Level of Growth

High Growth

Frequency / Percent		PODR 1	PODR 0	Total
MBR	1	3170	2197	5367
		59.06%	40.94%	62.02%
	0	1777	1509	3286
		54.08%	45.92%	37.98%
	Total	4947	3706	8653
		57.17	42.83	100

$\chi^2 = 20.70$ p <0.001

Medium Growth

Frequency / Percent		PODR 1	PODR 0	Total
MBR	1	2747	2366	5113
		53.73%	46.27%	58.66%
	0	1790	1813	3603%
		49.68%	50.32%	41.34%
	Total	4537	4179	8716
		52.05	47.95	100

$\chi^2 = 13.86$ p <0.0002

Low Growth

Frequency / Percent		PODR 1	PODR 0	Total
MBR	1	2083	2257	4340
		48%	52%	50.2%
	0	1966	2340	4306
		45.66%	54.34%	49.8%
	Total	4049	4597	8646
		46.83	53.17	100

$\chi^2 = 4.75$ p <0.029

(2) MBR and DOWN by the Level of Growth

High Growth

Frequency / Percent		DOWN 1	DOWN 0	Total
MBR	1	885	3150	4035
		21.93%	78.07%	63.48%
	0	470	1851	2321
		20.25%	79.75%	36.52%
	Total	1355	5001	6356
		21.32%	78.68%	100

$\chi^2 = 2.49$ p <0.11

Medium Growth

Frequency / Percent		DOWN 1	DOWN 0	Total
MBR	1	1216	2977	4193
		29%	71%	60.46%
	0	600	2142	2742
		21.88%	78.12%	39.54%
	Total	1816	5119	6935
		26.19%	73.81%	100%

$\chi^2 = 43.47$ p <0.001

Low Growth

Frequency / Percent		DOWN 1	DOWN 0	Total
MBR	1	1522	1788	3310
		45.98%	54.02%	52.63%
	0	953	2026	2979
		31.99%	68.01%	47.37%
	Total	2475	3814	6289
		39.35	60.65	100%

$\chi^2 = 128.6$ p <0.001

Table 1.9

Logit Analysis of the Effectiveness of Mechanisms to MBR depending on Growth Proxy (Book-to-Market Ratio)

Model: Prob(MBR=1|X) = F(α_0 + α_1POSDR$_i$+α_2 DOWN$_i$+α_3GROWTH$_i$+α_4GROWTH*POSDR$_i$ +α_5GROWTH$_i$*DOWN$_i$+α_6POSΔREV$_i$+α_7INDPROD$_i$+α_8SIZE$_i$+α_9|FE$_i$|+α_{10}E_Sur$_i$+ε_i)

		Model (1)		Model (2)	
VARIABLES	**Exp. Sign**	**Coefficient**	**MEs**	**Coefficient**	**MEs**
Constant		-0.802***		-0.993***	
		(-4.13)		(-6.18)	
Proxies for Growth:					
Book_to_Market	-	-0.350***	-0.144		
		(-4.22)			
Rank_BtM	-			-0.173**	-0.071
				(-2.22)	
Proxies for Mechanisms:					
POSDR	+	0.231***	0.095	0.197***	0.081
		(4.13)		(3.72)	
DOWN	+	0.509***	0.209	0.457***	0.187
		(4.99)		(3.92)	
Interaction b/w Growth Proxy and Mechanisms:					
BtM * POSDR	-	-0.158***	-0.065		
		(-2.80)			
BtM * DOWN	+	0.377***	0.155		
		(3.44)			
Rank_BtM * POSDR	-			-0.069	-0.028
				(-0.94)	
Rank_BtM * DOWN	+			0.375***	0.154
				(3.56)	
Control Variables:					
POSΔREV	+	0.672***	0.276	0.692***	0.284
		(7.98)		(8.60)	
INDPROD	+	0.017	0.007	0.019	0.008
		(0.69)		(0.73)	
SIZE	+	0.094***	0.039	0.111***	0.046
		(3.11)		(4.24)	
lFEl	-	-0.046	-0.019	-0.085	-0.035
		(-0.53)		(-1.02)	
E_Sur	+	1.465***	0.601	1.550***	0.636
		(6.86)		(7.91)	
Log Likelihood		-11914.86		-11933.24	
Wald Chi-square		916.93		907.97	
p-value		< 0.001		< 0.001	
Pseudo R-squared		0.0432		0.0417	
Total Observations		18,398		18,398	

Dependent variable (MBR) is equal to 1 if a firm has a zero or positive revenue surprise and otherwise 0. Reported z-statistics are based on firm and year clustered standard errors. Notations ***, **, and * indicate significance at 1, 5, 10 percent significance levels, respectively.

Table 1.10

Logit Analysis of the Association between Growth Proxy and the Probability of Revenue Manipulation Conditional on MBR

Model: Prob (POSDR = 1|X) = F (α_0 + α_1GROWTH$_i$ + α_2LOSS_Prop$_i$ + α_3VOL_EARNINGS$_i$ + α_4LTG_RISK$_i$ + α_5POSΔREV$_i$ + α_6INDPROD$_i$ + α_7SIZE$_i$ + α_8|FE$_i$| + α_9E_Sur$_i$ + ε_i)

		Model (1)		Model (2)	
VARIABLES	**Exp. Sign**	**Coefficient (z-stat)**	**Marginal Effects**	**Coefficient (z-stat)**	**Marginal Effects**
Constant		0.3331***		0.2635*	
		(3.14)		(1.93)	
Proxies for Growth:					
Book_to_Market	-	-0.3566***	-0.1655		
		(-6.52)			
Rank_BtM	-			-0.2858***	-0.1327
				(-5.80)	
Control Variables:					
LOSS_Prop	+	0.0873	0.0405	0.0668	0.0310
		(1.10)		(0.81)	
VOL_Earnings	+	0.0172***	0.0080	0.0179***	0.0083
		(3.75)		(3.99)	
LTG_Risk	+	-0.1328**	-0.0616	-0.1384**	-0.0643
		(-2.08)		(-2.25)	
POSΔREV	+	0.0986	0.0457	0.1125	0.0522
		(0.97)		(1.11)	
INDPROD	+	0.0432***	0.0200	0.0432***	0.0200
		(3.27)		(3.14)	
SIZE	+	-0.0127	-0.0059	-0.0023	-0.0011
		(-1.10)		(-0.17)	
lFEl	-	-0.1799***	-0.0835	-0.2096***	-0.0973
		(-3.02)		(-3.67)	
E_Sur		-0.1486	-0.0690	0.0206	0.0096
		(-0.90)		(0.14)	
Log Likelihood		-9278.4945		-9279.8982	
Wald Chi-square		243.93		245.88	
p-value		< 0.001		< 0.001	
Pseudo R-squared		0.014		0.014	
Total Observations		13,626		13,626	

Dependent variable (POSDR) is equal to 1 if a firm has a positive discretionary revenue and otherwise 0. Reported z-statistics are based on firm and year clustered standard errors. Notations ***, **, and * indicate significance at 1, 5, 10 percent significance levels, respectively.

Table 1.11

Logit Analysis of the Association between Growth Proxy and the Probability of Revenue Expectation Management Conditional on MBR

Model: Prob (DOWN = 1|X) = F ($\alpha_0 + \alpha_1$GROWTH$_i$ + α_2LOSS_Prop$_i$ + α_3VOL_EARNINGS$_i$ + α_4LTG_RISK$_i$ + α_5POSΔREV$_i$ + α_6INDPROD$_i$ + α_7SIZE$_i$ + α_8|FE$_i$| + α_9E_Sur$_i$ + ε_i)

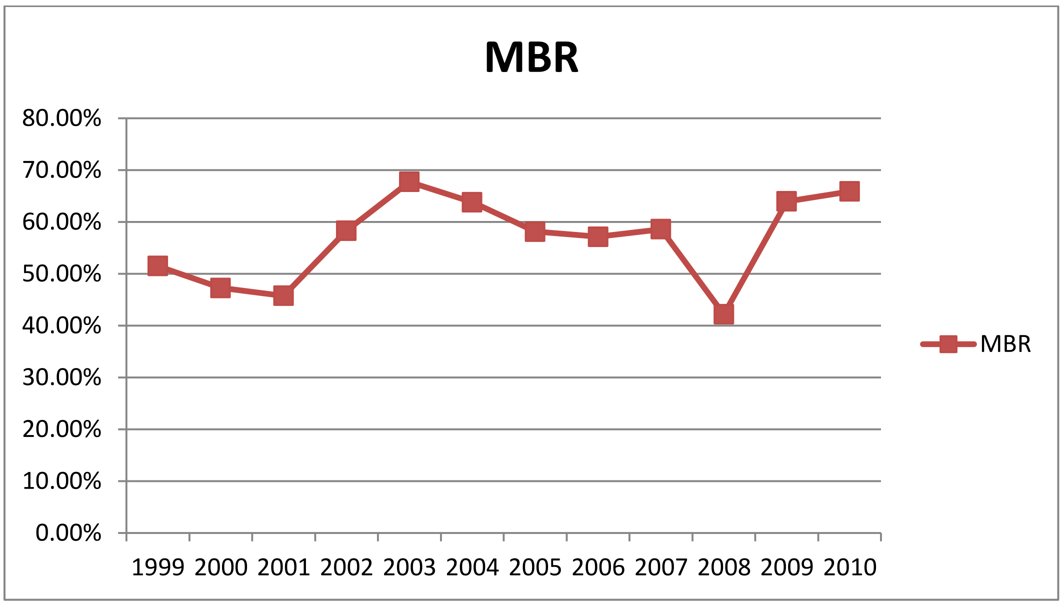
VARIABLES	Exp. Sign	Model (1) Coefficient (z-stat)	Model (1) Marginal Effects	Model (2) Coefficient (z-stat)	Model (2) Marginal Effects
Constant		-0.298		-0.026	
		(-0.85)		(-0.08)	
Proxies for Growth:					
Book_to_Market	+	0.633**	0.4343		
		(2.32)			
Rank_BtM	+			0.418**	0.2866
				(2.41)	
Control Variables:					
LOSS_Prop	+	0.468	0.3214	0.480*	0.3296
		(1.56)		(1.65)	
VOL_Earnings	+	0.010	0.0070	0.009	0.0063
		(1.17)		(1.11)	
LTG_Risk	+	-0.017	-0.0118	-0.030	-0.0204
		(-0.10)		(-0.18)	
POSΔREV	+	-1.322***	-0.9076	-1.350***	-0.9264
		(-9.14)		(-9.35)	
INDPROD	+	-0.220***	-0.1507	-0.222***	-0.1526
		(-6.93)		(-7.00)	
SIZE	+	-0.024	-0.0162	-0.054	-0.0369
		(-0.70)		(-1.51)	
lFEl	-	0.576***	0.3953	0.621***	0.4265
		(2.77)		(3.23)	
E_Sur		-0.248	-0.1699	-0.561	-0.3854
		(-0.54)		(-1.35)	
Log Likelihood		-5296.63		-5316.54	
Wald Chi-square		2424.34		2408.81	
p-value		< 0.001		< 0.001	
Pseudo R-squared		0.26		0.26	
Total Observations		11,512		11,512	

Dependent variable (DOWN) is equal to 1 if a firm has a negative unexpected revenue forecast and otherwise 0. Reported z-statistics are based on firm and year clustered standard errors. Notations ***, **, and * indicate significance at 1, 5, 10 percent significance levels, respectively.

1.9 Figures for Chapter 1

Figure 1.1

Percentage of Meeting or Beating Analyst Revenue Forecasts by Year



Percentage of Meeting or Beating Analyst Revenue Forecasts by Year

(Excluding 2008 Observations)

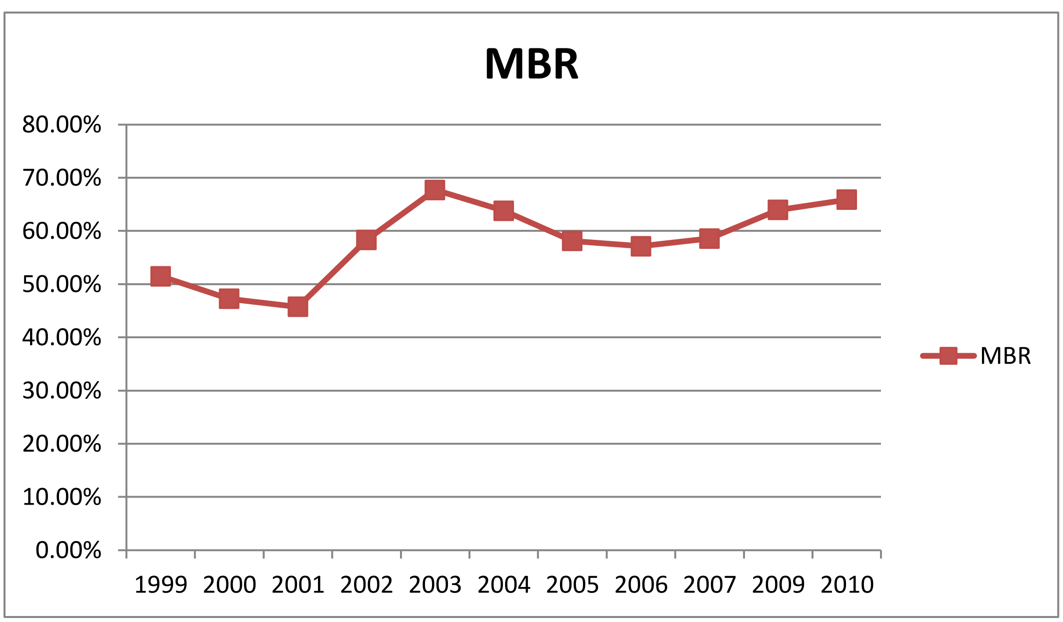
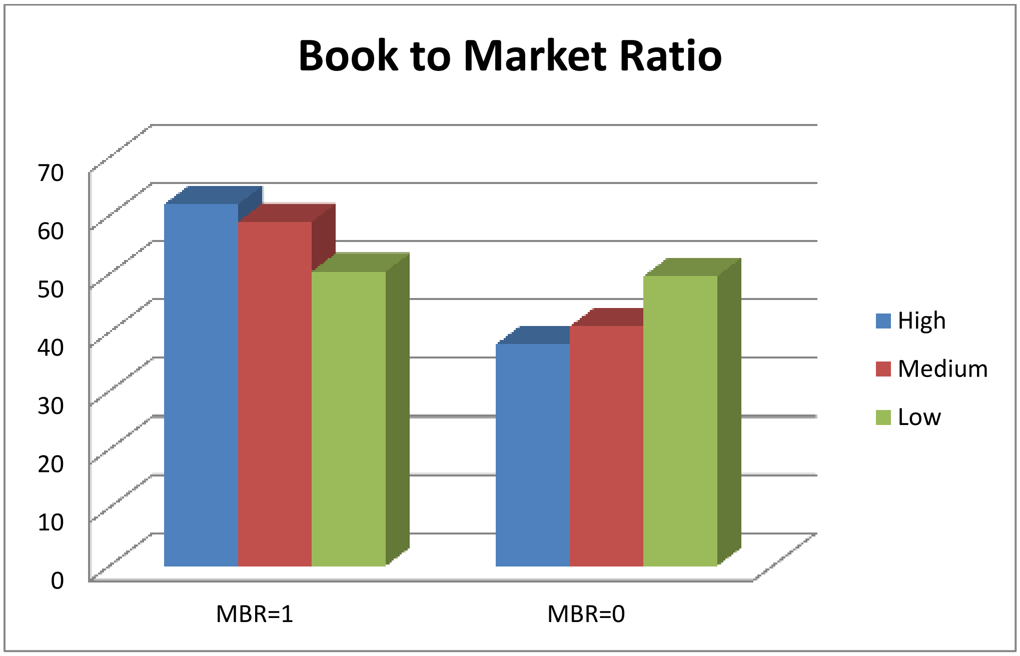


Figure 1.2

Percentage of Meeting or Beating Analysts' Revenue Forecasts by Growth Proxies



Chapter 2 The Persistence of Firm-Specific Post-Earnings Announcement Returns

2.1 Introduction

The post-earnings-announcement drift which refers to the positive relation between unexpected earnings and subsequent abnormal returns is widely documented in the accounting and finance literature. Trading strategies that exploit this relation have been found to be profitable (Ball and Brown. 1968, Foster et al. 1984, Bernard and Thomas. 1989, Bernard and Seyhun. 1997, Livnat and Mendenhall. 2006). However, the existence of a significant association between public information and future abnormal returns is in stark contrast with the efficient market hypothesis. Efficient market theory posits that when there is mispricing, arbitrageurs will quickly act to take positions thereby eliminating temporary deviations from intrinsic values. A more puzzling issue is why the post-earnings announcement drift continues to persist. Bayesian theory predicts that market participants who observe a positive relation between past returns and unexpected earnings revise their information and subsequently facilitate future market pricing that fully incorporates earnings information into prices.

This study focuses on whether market participants revise their information processing in light of the relation that they observed in the past between unexpected earnings and post-earnings announcement returns. I estimate the firm-specific relation between unexpected earnings and post-earnings-announcement returns separately for each firm-quarter using historical unexpected earnings and return data. This estimation measures the extent to which share prices drifted per unit of unexpected earnings in the past. As market participants learn from past firm-specific experience, the relation between unexpected earnings and future returns is expected to weaken in the future. Market participants are expected to use the information available from the historical relation and facilitate a more efficient processing of earnings whereby a smaller degree of post-earnings announcement drift is evident.

I estimate the historical firm-specific relation between unexpected earnings and post-earnings announcement returns for a large sample of U.S. public companies. The first-stage estimation is repeated for each firm-quarter based on data available as of the corresponding earnings announcement date. Since the relation is estimated using only data that was available prior to the earnings announcement, it provides information that was available to market participants prior to new quarter's earnings announcement. Once investors receive the new earnings information they are expected to incorporate the current quarter's earnings information as well as the tendency of the firm's share prices to drift in the direction of the earnings surprise. To the extent that this process fails to take place, a positive and statistically significant association between return predictions generated using past experience may be evident.

I find that return estimates derived from the historical earnings and drift relation are positively associated with future post-earnings-announcement returns. This positive relation is robust after controlling for current quarter unexpected earnings surprises, accounting-based anomalies, and other confounding factors documented in the extant literature. My findings suggest that share prices do not reflect the historical firm-specific relation between unexpected earnings and returns.

This paper intends to shed light on the issue of whether investors use past firm-specific experience and facilitate an environment in which there is less mispricing. My analysis does not aim to explain why the post-earnings announcement drift exists in the historical data. Instead this research focuses on whether investors learn from past firm-specific experience. In this respect, this paper differs from the prior literature and intends to contribute to an overlooked area which is *why* we continue to observe the post-earnings-announcement drift anomaly. This study has direct implications for financial analysts, investors and portfolio managers implementing earnings-based trading strategies. The results suggest that the returns to the post-earnings announcement trading strategy can be significantly improved if the firm-specific relation between past unexpected earnings and returns is taken into account.

2.2 Literature Review and Hypotheses Development

Since Ball and Brown (1968) first presented their evidence in support of a systematic association between earnings surprises and stock price movements over the subsequent period, the post-earnings announcement drift anomaly became one of the most extensively investigated subjects in the accounting and finance literatures. Bernard and Thomas (1989) refer to the relation between unexpected earnings and following quarter's returns as the "post-earnings-announcement drift" (hereafter, PEAD). [1] The primary factor which caused the PEAD to become an enigma is the predictability of abnormal returns using public information. This empirical finding poses a challenge to the efficient

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[1] The post-earnings announcement drift refers to the positive relation between unexpected earnings and subsequent quarter's returns. That is, after earnings announcement firms with higher (lower) than expected earnings generate significantly positive (negative) abnormal returns during subsequent earnings announcement period.

market hypothesis. Accordingly, earlier research shows that the PEAD-based trading strategies generate approximately 3 to 4 percent abnormal returns in the 60-day period following earnings announcements (Bernard and Thomas. 1989).[2] However, an even more puzzling feature of the post-earnings announcement drift anomaly is that despite 30 years of rigorous research and increased awareness, future returns continue to be predictable based on past earnings announcements (Kothari. 2001).

After documenting the existence of PEAD (Ball and Brown. 1968, Foster et al. 1984), numerous studies sought to explain its existence. Some researchers argue that high post-earnings-announcement period returns are compensation for bearing risks of firms with extreme earnings surprises. While several prior studies (Foster et al. 1984, Bernard and Thomas. 1989) conduct analyses to test the risk-based explanation for the PEAD, most studies fail to fully explain the predictability of returns using a risk-based explanation. Conversely, many prior studies provide evidence that the occurrence of the PEAD is due to market participants' failure to fully incorporate information contained in the current earnings announcement. Rendleman et al. (1987) as well as Freeman and Tse. (1989) offer support for the notion that the PEAD is a result of market participants' misperceptions of the time-series properties of earnings. Further, Bernard and Thomas (1990) show that the predictable relationship between current and subsequent period earnings is not fully impounded into stock prices. Their findings indicate that investors react to the component of current earnings that could have been predicted based on previous quarter's earnings. They find that the PEAD is observed because investors fail

[2] The post-earnings announcement drift trading strategy consist of taking long positions in firms that are in the top earnings surprise decile and long positions in firms that are in the bottom earnings surprise decile.

to fully account for the serial correlation in quarterly earnings surprise and that this inefficiency in information processing leads to the systematic mis-measurement of future expected earnings. Similarly, Ball and Bartov (1996) demonstrate that market participants partially incorporate past earnings changes to establish the earnings expectations for the current quarter.

Additionally, Bernard et al. (1997) compare the underreaction and the risk-based explanations and show that the PEAD is more appropriately explained as an artifact of mispricing than as a misestimation of risk. Further, Doyle et al. (2006) and Livnat and Mendenhall (2006) each use earnings surprises based on analysts' earnings forecasts and document confirming evidence of the existence of the PEAD. Finally, Brandt et al. (2008) show that the PEAD is evident when sorting stocks by stock price reaction around earnings announcements as a proxy for the earnings surprise. By using ex post returns as an alternative measure of the earnings surprise they provide support for the work of Bernard and Thomas (1989) and Bernard and Thomas (1990). In summary, the predominant consensus is that the PEAD represents investors' under-reactions to the information contained in earnings announcements.

A number of studies focusing on the PEAD anomaly find that its strength varies based on firm characteristics. Foster et al. (1984) in addition to Bernard and Thomas (1989) document that the magnitude of the PEAD is negatively associated with firm size. Bartov et al. (2000) suggest that firms with less institutional following have stronger post-earnings-announcement drifts, since institutional investors are sophisticated market participants less likely to underreact to earnings information. Similarly, Brown and Han (2000) find that the PEAD is smaller for firms with richer information environments (such as large firms, with high institutional ownership, and firms followed by numerous analysts). In addition, Narayanamoorthy (2006) provides evidence that firms that report losses or earning decreases experience a smaller PEAD because market participants are not able to appropriately understand the different level of persistence for those firms. Soffer and Lys (1999) demonstrate that the degree of PEAD can be affected by the dissemination of predictable information. Also, Zhang (2008) finds that responsive financial analysts can alleviate the PEAD because they have the ability to reduce mispricing by providing more timely information. Furthermore, by using their measure of market efficiency, Chung and Hrazdil (2011) find that firms with superior informational environments experience significantly lower post-earnings-announcement abnormal returns. In sum, prior research suggests that firm-specific characteristics influence the magnitude of the PEAD.

This study's objective is to investigate whether market participants incorporate historical firm-specific data to facilitate a future environment where there is less mispricing. The growing body of literature indicates the existence of the PEAD and its persistence over several decades. Research on the post-earnings announcement drift has undoubtedly contributed to an increased awareness of the tendency of returns to drift in the direction of the earnings surprise. In this paper, I take a different approach and rely on the historical relation between unexpected earnings and post-earnings announcement returns at a firm-level to estimate the PEAD for the current quarter. With this approach this research attempts to quantify the tendency of firms' share prices to drift in the direction of the earnings surprise. To the extent that market participants account for variations in the strength of the relation between past unexpected earnings and post-earnings announcement returns I expect the return estimates to provide no predictive value. Conversely, if investors fail to incorporate the tendency of firms' share prices to drift in the direction of the earnings surprise I expect the post-earnings announcement return estimates based on the historical unexpected earnings and returns relation to possess incremental predictive power of future returns. It is unclear whether market participants incorporate the information reflected in the past relation between earnings surprises and returns. I therefore test the following non-directional hypothesis.

H1: The historical firm-specific relation between unexpected earnings and post-earnings-announcement returns is not useful in estimating future returns.

2.3 Methodology

2.3.1 Estimation of Unexpected Earnings and Post-Earnings-Announcement Returns

Consistent with the prior literature (Livnat and Mendenhall. 2006, Abarbanell and Bernard. 1992), this paper measures the unexpected earnings as the difference between actual earnings and consensus earnings forecasts deflated by stock price. The estimate of the unexpected earnings ($UE_{i,t}$) is as follow:

$$\boldsymbol{UE_{i,t} = (Actual\_Earnings_{i,t} - AF\_Earnings_{i,t}) / Price_{i,t-1}}$$

where $Actual\_Earnings_{i,t}$ is Earnings Per Share (EPS) before extraordinary items announced on the earnings announcement date for firm i in quarter t obtained from the I/B/E/S database, $AF\_Earnings_{i,t}$ is the median of analysts' most recent earnings forecasts reported in I/B/E/S during the 90-day period prior to the earnings announcement, and $Price_{i,t-1}$ is share price for firm *i* at the beginning of the fiscal quarter.

Following Livnat and Mendenhall (2006), I measure post-earnings announcement returns as the cumulative size and book-to-market adjusted daily returns over the period from two days after the earnings announcement to one day after the subsequent quarterly earnings announcement date. To estimate daily abnormal returns, I use daily returns on the portfolio of firms with similar size (based on the market value of equity) and book-to-market (B/M) ratio as benchmark returns. I acquire the benchmark returns and breakpoints for each size and book-to-market decile from Professor Kenneth French's online data library.[3] Therefore, the daily abnormal return for firm *i* is measured as the raw daily return for firm *i* obtained from CRSP minus the daily benchmark returns. The post-earnings announcement drift is computed as follows:

$$\boldsymbol{PEAD_{i,t}} = \sum_{EA1+2}^{EA2+1}(\boldsymbol{Return_{i,t}}) - \sum_{EA1+2}^{EA2+1}(\boldsymbol{Return_{bench,t}})$$

where $PEAD_{it}$ is the cumulative size and book-to-market adjusted return over the event window (from two days after current earnings announcement to one day after the following earnings announcement), $Return_{i,t}$ is the raw daily return for firm *i* on day *t*, and $Return_{bench,t}$ is the daily benchmark return on the Fama-French portfolio in which firm *i* is included.

2.3.2 Estimation of the Historical Firm-Specific Earnings-Drift Relation

Given the existing empirical research documenting the significant relation between unexpected earnings and post-earnings announcement returns, I develop a model to

[3] Available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

predict the PEAD. I predict current post-earnings announcement returns for each firm-quarter based on the historical firm-specific relation between unexpected earnings and post-earnings announcement returns. In the first stage, I estimate Equation (1) separately for each firm using unexpected earnings and return data for prior quarters. In this estimation, I require that each firm have at least eight quarters of historical data.

$$\boldsymbol{PEAD_{i,t} = \alpha + \eta_1 UE_{i,t} + \varepsilon_{it},} \tag{1}$$

where $UE_{i,t}$ is the unexpected earnings for firm *i* in quarter *t* and $PEAD_{i,t}$ is the post-earnings announcement return for firm *i* in quarter *t*.

I then use estimates of the parameters, α and $\eta_{1,}$ from Equation (1) to compute expected post-earnings announcement returns (*EDRIFT*) based on the historical earnings-returns relation. Estimated parameters (ά and $ή_1$) indicate the firm-specific association between past unexpected earnings and post-announcement period returns. In other words, these parameters measure the firm-specific tendency of share prices to drift in the direction of unexpected earnings.

$$\boldsymbol{EDRIFT_{i,t+1} = ά + ή_1\, UE_{i,t+1}} \tag{2}$$

where ά and $ή_1$ are the firm-specific parameter estimates from Equation (1), $UE_{i,t+1}$ is the unexpected earnings for firm *i* at the current earnings announcement, and $EDRIFT_{i,t+1}$ is the expected PEAD for firm *i* over the event window.

2.3.3 Empirical Analysis Model

This study estimates the empirical model below which controls for various confounding factors documented in the literature. This model allows me to test whether the estimates of the expected post-earnings announcement drift (*EDRIFT*) possesses predictive value of future post-earnings-announcement returns incremental to previously documented predictors of future returns.

$$\mathbf{PEAD_{i,t} = \alpha + \beta_1 DEDRIFT_{i,t} + \beta_2 DUE_{i,t} + \beta_3 DEARNINGS_{i,t} + \beta_4 DB/M_{i,t}}$$
$$\mathbf{+ \beta_5 DACCRUAL_{i,t} + \beta_6 (DUE{\times}LOGMV)_{i,t} + \beta_7 (DUE{\times}MERGE)_{i,t}}$$
$$\mathbf{+ \beta_8 (DUE{\times}SPECIAL)_{i,t} + \beta_9 (DUE{\times}Q4)_{i,t} + \beta_{10} (DUE{\times}BNEWS)_{i,t}}$$
$$\mathbf{+ \beta_{11} (DUE{\times}COV)_{i,t} \quad + \beta_{12} (DUE{\times}\ IO)_{i,t} + \nu_{i,t}} \qquad \mathbf{(3)}$$

where

DEDRIFT : The decile of the predicted post-earnings-announcement drift derived from the historical firm-specific relation between unexpected earnings and abnormal returns.

Detailed descriptions of other independent variables are provided in Table 2.1. Following several previous studies (Livnat and Mendenhall. 2006, Bernard and Thomas. 1990), I conduct the analysis using the decile of the unexpected earnings (*DUE*) and the expected post-earnings announcement drift (*DEDRIFT)* to mitigate the influence of outliers on the results and to accommodate the non-linear nature of the relation between unexpected earnings and future returns. To form decile rankings, each fiscal quarter I independently classify firms into deciles based on unexpected earnings (from smallest unexpected earnings as decile 1, to largest unexpected earnings as decile 10) and predicted post-earnings announcement drift (from lowest expected drift as decile 1 to highest expected drift as decile 10). Then, prior to including the decile variables in the regression model, I subtract one from each decile variable, divide it by nine and deduct 0.5. As a result of this numerical operation, each decile variable ranges between -0.5 and +0.5 and the coefficients of decile variables provide an estimate of the return differential between firms that are in the bottom and top deciles.

Given the predictability of abnormal returns based on earnings information (Bernard and Thomas. 1989, Bernard and Thomas. 1990), I expect the coefficient of unexpected earnings decile (*DUE*) to be positive and statistically significant. Consistent with my hypothesis I do not make any predictions on the sign of the coefficient of the *DEDRIFT* variable. If market participants incorporate information conveyed in past occurrences of unexpected earnings and post-earnings announcement returns I should observe no association between predicted and actual post-earnings-announcement returns. To the extent that investors fail to readjust their information processing based on past firm-specific experiences I predict the relation between expected and actual post-earnings-announcement drift to be positive.

As documented in Balakrishnan et al. (2010), I also include two additional variables in order to control for the accrual and book-to-market anomalies. Sloan (1996) concludes that the accrual component of earnings is negatively related to future returns due to investors' failure to incorporate information conveyed in accruals. Thus, the empirical model includes the decile of the total accruals (*DACCRUAL)* to account for the impact of accruals on the post-earnings announcement returns. In addition, Fama and French (1992) and Lakonishok et al. (1994) document the book-to-market ratio anomaly which is also referred to as the value-glamour anomaly. They find that future returns of value stock (firms with high B/M ratio) outperform those of glamour stock (firms with low B/M ratio) despite lower perceived growth potential of value stocks than glamour stocks. To account for the predictability of returns based on book-to-market ratios, I also include the decile of the book-to-market ratio (*DB/M)* in the regression model.

Further, consistent with prior literature, I include several variables to control for confounding factors that may affect the relation between unexpected earnings and PEAD. First, consistent with Foster et al. (1984) and Bernard and Thomas (1989), my model contains the natural log of the market value of equity (*LOGMV*) to control for the effect of firm size. Also, as suggested in Balakrishnan et al. (2010), I include *MERGE* and *SPECIAL* in order to account for the impact of uncertainty caused by merger, acquisition and restructuring activities. Third, I control for the fourth-quarter effect by including the interaction of the fourth-quarter dummy variable and unexpected earnings (*DUEXQ4)*. Das et al. (2009) and Livnat (2003) find that the fourth quarter which likely contains larger transitory items than other quarters can affect the relation between unexpected earnings and returns over the following quarter. In addition, the regression model consists of the dummy variable, *BNEWS*, to account for the differential predictive power of negative earnings surprises compared with positive earnings surprises. Firms that report negative earnings surprises are likely to have earnings that are less persistent which may make it more challenging for investors to incorporate the implications of the current earnings on future earnings (Hong et al. 2000). Finally, to the extent that financial analysts and institutional investors facilitate a richer information environment, the post-earnings announcement returns are expected to be lower when there is greater analyst coverage and/or a larger portion of outstanding stocks held by institutions.

2.4 Sample Selection

The initial sample, based on the CRSP/Compustat merged file for the period between the first quarter of 1989 and the fourth quarter of 2009, consists of 480,750 firm-quarters with non-missing earnings announcement dates and the necessary accounting data. After collecting analysts' earnings forecasts from I/B/E/S, I merge it with the initial CRSP/Compustat dataset. I require at least eight quarters of prior unexpected earnings data to estimate the predicted PEAD. This requirement along with the I/B/E/S restriction reduces the total firm-quarter observations to 124,468. Finally, the sample is merged with the CDA/Spectrum database to obtain institutional ownership data and with CRSP to obtain security returns. Due to missing observations in CDA/Spectrum and CRSP, the final sample is reduced to 113,690 firm-quarter observations. Panel A in Table 2.2 shows the industry composition of the final sample based on Fama and French (1997) industry classification (using 48 industry codes). Firms with undefined Fama-French industry codes are classified as 'Other'. Also, Panel B presents the yearly distribution of firm-quarter observations over the sample period. Consistent with the increase in the number of public companies and of financial analysts' coverage of firms, this panel shows an increasing trend of firm-quarter observations over time.

2.5 Empirical Results

2.5.1 Descriptive Statistics

Table 2.3 presents descriptive statistic of the final sample, which consists of 113,690 firm-quarter observations. All variables are winsorized at the top and bottom one percentile to reduce the impact of extreme values. Table 2.3 reports that the mean post-earnings announcement drift is -0.008 whereas the median is -0.005. The average (median) expected post-earnings announcement drift (EDRIFT) and unexpected earnings

(UE) for the overall sample observations are -0.009 (-0.001) and -0.002 (0.00), respectively. Also, the mean (median) values of EARNINGS, B/M, and ACCRUALS are 0.007 (0.011), 0.552 (0.450), and -0.026 (-0.018), respectively. On average, 1.5% of firms in the sample undergo merger and acquisition (MERGE) during the fiscal quarter. Further, 25.4% of sample firms report negative special items (SPECIAL) during the sample period. The average market value of firms (MV) included in the sample is approximately $5.1 billion whereas the median is $826.23 million, which suggests that the sample is composed of relatively large and well-established companies. The mean of BNEWS indicates that only about 30.1% of total firm-quarter observations report negative earnings surprises, which is consistent with prior literature that presents the increasing tendency of meeting or beating the earnings expectations. The average number of analysts issuing earnings forecasts (COV) over the sample period is 7.97, suggesting that approximately 8 financial analysts issue earnings forecasts for each firm over the sample period. On average about 62.4% of firms' shares in the sample are held by institutional investors (IO).

Table 2.4 reports the Spearman correlation matrix of all variables. *DEDRIFT* is significantly and positively correlated with *DEARNINGS, DUE, LOGMV, MERGE, COV*, and *IO* while it is negatively correlated with *DB/M*, *SPECIAL*, and *BNEWS*. However, *DEDRIFT* does not have any relation with *DACCRUAL* or *Q4*. Overall, most correlations among the independent variables are low in magnitude. In order to ensure that correlations among independent variables do not represent multicolinearity problems, I also check variance inflation factors in the regression models.

2.5.2 Univariate Analysis

Table 2.5 reports the cumulative size and book-to-market adjusted abnormal returns from two days after current earnings announcement to one day after the subsequent earnings announcement for ten portfolios constructed by the composition of each decile of the unexpected earnings (*DUE*) and the expected post-earnings-announcement drift (*DEDRIFT*). The results show that a portfolio containing the lowest *DEDRIFT* decile and the highest *DUE* decile (Return = 1.0%) outperforms a portfolio containing the highest *DEDRIFT* decile and the lowest *DUE* decile (Return = 0.1%), which suggests that the impact of current unexpected earnings on PEAD dominates the impact of the historical relation between past unexpected earnings and post-earnings announcement drift. Additionally, all returns obtained from the hedge portfolio based on the PEAD-based trading strategy (returns from the highest *DUE* decile minus returns from the lowest *DUE* decile) are significantly positive for all *DEDRIFT* deciles and is consistent with prior studies (Bernard and Thomas. 1989, Bernard and Thomas. 1990) that document the positive relation between unexpected earnings and returns over the subsequent earnings announcement period. More importantly, the reported results indicate that the trading strategy based on the expected post-earnings-announcement drift (*DEDRIFT*) provides incremental returns beyond the conventional post-earnings-announcement trading strategy that invests solely based on the level of unexpected earnings. The hedge portfolios formed based on *DEDRIFT* deciles yield significantly positive returns (Returns from the highest *DEDRIFT* decile minus returns from the lowest *DEDRIFT* decile) for all *DUE* deciles. Further, the combination of two trading strategies is associated with returns that are superior to the performance based only on the post-earnings-announcement trading strategy. This finding implies that the returns to the post-earnings-announcement trading strategy can be improved by using the past firm-specific relation between unexpected earnings and post-earnings-announcement returns. In summary, the results from the univariate test provide evidence that the historical relation between earnings and drifts has predictive value beyond unexpected earnings.

2.5.3 Regression Analysis

Table 2.6 reports the ordinary least squares (OLS) estimation results of equation (3). Models 1 and 2 provide the estimation results of the base model where post-earnings-announcement returns are regressed only on *DEDRIFT* and *DUE*, respectively. The *DEDRIFT* variable, which is the predicted post-earnings announcement drift computed based on the past relation between unexpected earnings and return, is also estimated to be positive and statistically significant. The coefficient of the variable indicates that firms in the top *DEDRIFT* decile outperform firms in the bottom decile by 1.6 percent. The statistically significant coefficient on the *DEDRIFT* variable suggests that market participants fail to take into account the firm-specific relation between unexpected earnings and post-earnings announcement returns. This implies that investors, despite observing a tendency for firm's share prices to drift, fail to facilitate a market pricing in which earnings information is fully incorporated into share prices. The estimated coefficient on *DUE* in Model 2 is also statistically significant and positive. The *DUE* coefficient confirms the previously documented PEAD anomaly. The coefficient indicates that firms in the top *DUE* decile have abnormal returns that are 2.9 percent higher than the returns of those firms in the bottom *DUE* decile. Further, Model 3 presents the estimation results of the model with both the *DEDRIFT* and *DUE* variables. Although the magnitude of parameter estimates on *DEDRIFT* and *DUE* are slightly reduced, both are significantly positive. The positive coefficient estimate on the *DEDRIFT* variable suggests that by exploiting the historical firm-specific earnings-returns relation, the returns to a PEAD-based trading strategy can be improved by 1.4 percent.

In Model 4, I regress the returns on *DEDRIFT* while including *DUE*, *DEARNINGS*, *DB/M* and *DACCRUAL* to determine if the expected post-earnings-announcement drift predicts future post-earnings-announcement returns after controlling for other accounting-based anomalies such as the book-to-market anomaly and accruals anomaly. The parameter estimate on *DEDRIFT* in Model 4 is significantly positive, which indicates that firms in the top *DEDRIFT* portfolio outperform firms in the bottom portfolio by one-percent. This finding further demonstrates that the impact of *DEDRIFT* on the post-earnings-announcement returns is incremental to other previously well-documented anomalies.

In Model 5, I include control variables to test whether the incremental predictive power of the *DEDRIFT* variable is sensitive to other confounding factors that may affect the relation between unexpected earnings and post-earnings-announcement drift returns.[4] The coefficient on the *DEDRIFT* variable continues to be positive and statistically significant, indicating that the firm-specific relation between past earnings and returns is useful in predicting future returns. Further, signs of coefficients on control variables are consistent with prior findings. The interaction of the *MERGE* and *SPECIAL* variables with the *DUE* variable is found to be positive and negative, respectively. These findings

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[4] I also conduct the analysis with main effects as well as interaction terms. The results (not tabulated) remain consistent with the main analysis.

imply that the magnitude of the PEAD is larger for firms undergoing a merger or acquisition while it is smaller for firms containing negative special items. Moreover, significantly negative coefficients on the interactions of *Q4*, *BNEWS*, *COV*, and *IO* with *DUE* suggest that the PEAD is smaller for fourth quarter earnings, for firms that have negative earnings surprises, for firms with greater analyst coverage, and for firms with higher percentage of institutional ownership.

In sum, the regression analysis shows that the historical firm-specific relation between earnings and returns is useful in predicting future returns. Further tests provide evidence that the predictability of the expected drift is consistently robust after controlling for accounting-based anomalies and various confounding factors. Therefore, overall findings suggest that investors systematically fail to take into account the tendency of firms' share prices to drift after earnings announcements in the same direction of the earnings surprise. The results complement the prior literature that documents inefficient information processing by market participants.

2.5.4 Portfolio Analysis

In this section, I perform a trading strategy analysis to test whether a trading strategy that incorporates the firm-specific historical relation between unexpected earnings and post-earnings announcement returns outperforms the trading strategy based only on unexpected earnings.

To examine the profitability between two trading strategies, I construct two portfolios: one based only on unexpected earnings (DUE) deciles and the other based on unexpected earnings (DUE) and expected drift (DEDRIFT) deciles. Two days after the firm's earnings announcement date, each firm is assigned to one of ten portfolios according to its unexpected earnings and expected post-earnings-announcement drift, respectively. Each position is held until one day after the subsequent earnings announcement date. I then compare the hedge portfolio returns from each trading strategy to investigate whether using the historical earnings-returns relation improves the profitability of the post-earnings-announcement trading strategy. The first trading strategy consists of going long on shares of companies within the top unexpected earnings decile and going short on shares of companies within the bottom unexpected earnings decile. The second trading strategy goes long on shares of companies that are in the top unexpected earnings and expected PEAD deciles and short on shares of companies within the bottom unexpected earnings and expected post-earnings-announcement drift deciles.

Consistent with recent research (Jiang et al. 2012, Yu. 2012, Lam et al. 2010) I estimate abnormal returns for both hedge portfolios based on Jensen's alphas obtained from the capital asset pricing, three-factor and four factor models. The four-factor model which encompasses the CAPM and three-factor models is as follow:

$$\mathbf{R}_{p} = \boldsymbol{\alpha}_{p} + \boldsymbol{\beta}_{p}\,(\mathbf{MKTRF}_{t}) + \boldsymbol{\beta}_{p}\,(\mathbf{SMB}_{t}) + \boldsymbol{\beta}_{p}\,(\mathbf{HML}_{t}) + \boldsymbol{\beta}_{p}\,(\mathbf{UMD}_{t}) + \boldsymbol{\varepsilon}_{p} \qquad \mathbf{(4)}$$

where R_p is the excess portfolio return, $MKTRF_t$ is the daily excess return on the CRSP value-weighted NYSE/AMEX/Nasdaq index return. SMB_t, HML_t and UMD_t are the daily size, book-to-market and momentum factor returns, respectively.[5]

[5] I obtain MKTRF, SMB, HML, and UMD from Professor Kenneth French's online data library available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 2.7 presents the calendar-time portfolio regression results. The intercepts provide an estimate of the average abnormal monthly return that is associated with each trading strategy. Consistent with prior research, all intercepts in Panel A of Table 2.7 are significantly positive, suggesting that the conventional PEAD trading strategy is associated with monthly average abnormal returns of approximately by 1.3%-1.4%. In addition, Panel B presents the hedge portfolio returns for the combined trading strategy. Significant and positive intercepts in columns one through three indicate that the trading strategy that incorporates both unexpected earnings and the firm-specific historical relation between unexpected earnings and returns generates abnormal returns of 1.9%-2.1%. The results reported in Panel B suggest that the trading strategy that incorporates the historical firm-specific relation between earnings and returns provides superior returns. In Panel C, I estimate the abnormal returns associated with a trading strategy that goes long on the portfolio in Panel B and short on the portfolio in Panel A to test whether the returns are significantly different. Panel C indicates that the average abnormal return associated with the trading strategy in Panel B is significantly higher than the returns associated with the conventional post-earnings announcement trading strategy shown in Panel A. The portfolio analysis results suggest that using the past relation between unexpected earnings and returns enhances the returns to the post-earnings-announcement trading strategy 7.2 percent, annually.

2.6 Conclusion

The primary objective of this study is to examine whether the firm-specific relation between past unexpected earnings and post-earnings announcement returns provide information that is useful to predict future post-earnings announcement returns. Market participants who observe a propensity for firm's share price to drift in the direction of the earnings surprise are expected to facilitate a market pricing whereby stock prices reflect all available information. To the extent that investors fail to incorporate this observable information into security prices, I expect the predicted post-earnings announcement returns based on the historical unexpected earnings and returns relation to possess incremental predictive power of future post-earnings announcement returns.

I find that estimates of the predicted post-earnings announcement returns are positively associated with the following announcement period returns when controlling for the current unexpected earnings surprises, accounting-based anomalies, and other confounding factors documented in the literature. The results suggest that share prices do not reflect the historical firm-specific relation between unexpected earnings and post-announcement period returns. This is consistent with market participants failing to learn from the past observations and realigning their information processing.

2.7 Tables for Chapter 2

Table 2.1

Variable Definitions

DEDRIFT :	The decile of the predicted post-earnings-announcement drift derived from the historical firm-specific relation between unexpected earnings and abnormal returns.
DUE	The decile of the standardized unexpected earnings using analysts' expectations.
DEARNINGS	The decile of earnings before extraordinary items and discontinued operations deflated by total assets.
DB/M	The decile of book-to-market ratio computed as the fiscal year-end book value of equity scaled by the market value of equity.
DACCRUAL	The decile of total accruals scaled by average total assets.
LOGMV	The natural log of market value of the firm at the end of the previous fiscal quarter.
MERGE	Dummy variable that equals one for firm-quarters in which the firm had a merger or acquisition.
SPECIAL	Dummy variable that takes a value of one for firm-quarters in which negative special items were reported.
Q4	Dummy variable that takes a value of one for fourth fiscal quarters.
BNEWS	Dummy variable that equals one when the unexpected earnings is negative.
COV	The number of financial analysts who made earnings forecasts during the fiscal quarter.
IO	The percentage of shares held by institutional investors.

Table 2.2

Sample Composition

Panel A: Industry Composition Based on Fama and French (1997) Industry Classification

Industry Name	**Obs**	**Industry Name**	**Obs**
Agriculture	256	Defense	246
Food Products	2056	Precious Metals	273
Candy & Soda	224	Non-Metallic and Industrial Metal Mining	414
Beer & Liquor	467	Coal	119
Tobacco Products	120	Petroleum and Natural Gas	4901
Recreation	727	Utilities	2359
Entertainment	1524	Communication	2491
Printing and Publishing	1254	Personal Services	1347
Consumer Goods	2082	Business Services	5416
Apparel	1728	Computer Hardware	3522
Healthcare	1833	Computer Software	7915
Medical Equipment	3616	Electronic Equipment	7608
Pharmaceutical Products	6032	Measuring and Control Equipment	2687
Chemicals	2787	Business Supplies	2046
Rubber and Plastic Products	847	Shipping Containers	521
Textiles	746	Transportation	3076
Construction Materials	2062	Wholesale	4077
Construction	1580	Retail	8649
Steel Works Etc	2139	Restaurants, Hotels, Motels	2239
Fabricated Products	345	Banking	4126
Machinery	4467	Insurance	5048
Electrical Equipment	1716	Real Estate	168
Automobiles and Trucks	1785	Trading	1866
Aircraft	635	Other	1303
Shipbuilding, Railroad Equipment	245		

The final sample consists of 113,690 firm-quarter observations corresponding to the intersection of Compustat, CRSP, I/B/E/S and CDA/Spectrum databases for the period 1989Q1 – 20009Q4.

Panel B: Observations per Year

Year	Obs	Year	Obs
1989	89	2000	5459
1990	667	2001	5759
1991	2140	2002	6171
1992	3055	2003	6879
1993	3420	2004	7391
1994	4228	2005	7524
1995	4854	2006	8025
1996	5518	2007	8234
1997	5800	2008	8220
1998	5966	2009	8115
1999	6176		
Total	113690		

The final sample consists of 113,690 firm-quarter observations corresponding to the intersection of Compustat, CRSP, I/B/E/S and CDA/Spectrum databases for the period 1989Q1 – 20009Q4.

Table 2.3

Descriptive Statistics

	Mean	1^{st}Q	Median	3^{rd}Q	Std. Dev.
PEAD	-0.008	-0.114	-0.005	0.103	0.206
EDRIFT	-0.009	-0.042	-0.001	0.036	0.714
UE	-0.002	-0.001	0.000	0.002	0.060
EARNINGS	0.007	0.002	0.011	0.023	0.048
B/M	0.552	0.277	0.450	0.695	0.498
ACCRUALS	-0.026	-0.051	-0.018	0.005	0.085
MV	5131.711	273.873	826.228	2755.725	19898.323
LOGMV	6.831	5.613	6.717	7.921	1.723
MERGE	0.015	0.000	0.000	0.000	0.121
SPECIAL	0.254	0.000	0.000	1.000	0.435
Q4	0.238	0.000	0.000	0.000	0.426
BNEWS	0.301	0.000	0.000	1.000	0.459
COV	7.973	3.000	6.000	11.000	6.152
IO	0.624	0.463	0.644	0.799	0.229
N	113,690				

UE is the unexpected earnings based on analyst earnings expectations scaled by share prices at the beginning of the fiscal quarter. EDRIFT is the predicted post earnings announcement drift based on the firm-specific historical relation between unexpected earnings and abnormal returns. EARNINGS is earnings before extraordinary items and discontinued operations. B/M is the book-to-market ratio computed as the fiscal year-end book value of equity scaled by the market value of equity. ACCRUAL is the total accruals computed as the difference between the reported earnings and total cash flows. MV is the market value of the firm at the end of the previous fiscal quarter. LOGMV is the natural log of the market value of equity. MERGE is a dummy variable that takes a value of one for companies that underwent a merger during the past fiscal quarter. SPECIAL is a dummy variable that takes a value of one for companies that reported negative special items during the fiscal quarter. Q4 is a dummy variable that equals one for fourth fiscal quarters. BNEWS is a dummy variable that takes a value of one for firm-quarters where the unexpected earnings is negative. COV is the number of analysts who issued an earnings forecast during the fiscal quarter. IO is the percentage of institutional ownership.

Table 2.4

Correlation Table

		1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
1	*DEDRIFT*	1.00											
2	*DEARNINGS*	0.23**	1.00										
3	*DUE*	0.10**	0.17**	1.00									
4	*DB/M*	-0.36**	-0.39**	-0.01**	1.00								
5	*DACCRUAL*	-0.00	0.13**	0.01**	0.02**	1.00							
6	*LOGMV*	0.28**	0.27**	0.01*	-0.38**	0.03**	1.00						
7	*MERGE*	0.07**	0.05**	0.01*	-0.08**	0.01*	0.04**	1.00					
8	*SPECIAL*	-0.03**	-0.21**	-0.04**	0.03**	-0.10**	0.11**	-0.00	1.00				
9	*Q4*	-0.00	0.00	-0.00	-0.00	0.00	0.04**	-0.01**	0.11**	1.00			
10	*BNEWS*	-0.15**	-0.26**	-0.78**	0.14**	-0.03**	-0.15**	-0.03**	0.03**	0.01**	1.00		
11	*COV*	0.25**	0.15**	0.01	-0.24**	-0.07**	0.68**	0.01**	0.13**	0.07**	-0.12**	1.00	
12	*IO*	0.13**	0.16**	0.03**	-0.10**	0.01**	0.37**	-0.01**	0.15**	0.01**	-0.11**	0.34**	1.00

DUE is the decile of the standardized unexpected earnings using analysts' expectations minus one divided by 9. DEDRIFT is the decile of the predicted post-earnings-announcement drift derived from the historical firm-specific relation between unexpected earnings and abnormal returns minus one divided by 9. DEARNINGS is the decile of earnings before extraordinary items and discontinued operations deflated by total assets minus one divided by 9. DB/M is the decile of book-to-market ratio computed as the fiscal year-end book value of equity scaled by the market value of equity minus one divided by 9. DACCRUAL is the decile of total accruals scaled by average total assets minus one divided by 9. LOGMV is the natural log of market value of the firm at the end of the previous fiscal quarter. MERGE is a dummy variable that takes a value of one for companies that underwent a merger during the past fiscal quarter. SPECIAL is a dummy variable that takes a value of one for companies that reported negative special items during the fiscal quarter. Q4 is a dummy variable that equals one for fourth fiscal quarters. BNEWS is a dummy variable that takes a value of one for firm-quarters where the unexpected earnings. COV is the number of analysts who issued an earnings forecast during the fiscal quarter. IO is the percentage of institutional ownership. The symbols *, **, and *** indicate statistical significance at ten, five and one percent levels, respectively.

Table 2.5

Univariate Analysis

	DEDRIFT decile									
	1	2	3	4	5	6	7	8	9	10
DUE decile	Mean (se)	Mean (se)	Mean (se)	Mean (se)	Mean (se)	Mean (se)	Mean (se)	Mean (se)	Mean (se)	Mean (se)
1	-0.021	-0.022	-0.019	-0.031	-0.035	-0.021	-0.011	-0.010	-0.017	0.001
	(0.004)	(0.006)	(0.008)	(0.008)	(0.010)	(0.011)	(0.011)	(0.012)	(0.010)	(0.007)
2	-0.024	-0.033	-0.025	-0.018	-0.016	-0.019	-0.012	-0.011	-0.009	-0.008
	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.008)
3	-0.048	-0.043	-0.025	-0.017	-0.014	-0.014	-0.009	-0.016	-0.020	-0.017
	(0.010)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.010)
4	-0.022	-0.024	-0.019	-0.018	-0.013	-0.013	-0.011	-0.008	-0.008	-0.012
	(0.009)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.008)
5	-0.013	-0.031	-0.025	-0.006	-0.006	-0.011	-0.008	-0.007	-0.017	0.007
	(0.016)	(0.009)	(0.007)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.009)
6	-0.015	-0.021	-0.015	-0.010	-0.014	-0.003	-0.008	-0.011	0.002	0.005
	(0.016)	(0.008)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.007)
7	-0.009	-0.024	-0.013	-0.011	-0.010	-0.006	0.002	0.002	0.007	0.003
	(0.010)	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.006)	(0.007)
8	-0.011	-0.018	-0.017	-0.011	-0.011	0.001	0.004	-0.006	0.002	0.008
	(0.009)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)
9	0.002	-0.005	-0.013	0.005	-0.003	0.003	0.006	0.008	0.007	0.016
	(0.007)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
10	0.010	0.008	0.014	0.008	0.013	0.001	0.013	0.010	0.015	0.030
	(0.006)	(0.006)	(0.007)	(0.008)	(0.008)	(0.010)	(0.008)	(0.008)	(0.007)	(0.006)

This table reports size and book-to-market adjusted excessive returns of portfolios formed on the unexpected earnings and the predicted post-earnings announcement drift for the event window (from two days after current earnings announcement to one day after the following earnings announcement). Standard errors are in parenthesis. DUE is the decile of the standardized unexpected earnings using analysts' expectations minus one divided by 9. DEDRIFT is the decile of the predicted post-earnings-announcement drift derived from the historical firm-specific relation between unexpected earnings and abnormal returns minus one divided by 9.

Table 2.6

OLS Regression of Post-Earnings Announcement Returns

Model: $PEAD_{it} = \alpha + \beta_1 DEDRIFT_{i,t} + \beta_2 DUE_{i,t} + \beta_3 DEARNINGS_{i,t} + \beta_4 DB/M_{i,t} + \beta_5 DACCRUAL_{i,t} + \beta_6(DUE \times LOGMV)_{i,t} + \beta_7(DUE \times MERGE)_{i,t} + \beta_8(DUE \times SPECIAL)_{i,t} + \beta_9(DUE \times Q4)_{i,t} + \beta_{10}(DUE \times BNEWS)_{i,t} + \beta_{11}(DUE \times COV)_{i,t} + \beta_{12}(DUE \times IO)_{i,t} + \nu_{i,t}$

	Exp. signs	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	?	0.019	0.018	0.019	0.023	0.018
		(1.08)	(1.03)	(1.09)	(1.33)	(1.07)
DEDRIFT	?	0.016***		0.014***	0.010***	0.010***
		(7.20)		(6.06)	(3.95)	(4.03)
DUE	+		0.029***	0.027***	0.025***	0.097***
			(13.20)	(12.82)	(11.67)	(9.18)
DEARNINGS	+				0.018***	0.021***
					(7.19)	(8.12)
DB/M	+				-0.001	-0.003
					(-0.25)	(-1.11)
DACCRUAL	+				-0.043***	-0.043***
					(-19.70)	(-19.57)
DUEXLOGMV	-					-0.001
						(-0.56)
DUEXMERGE						0.036*
						(1.65)
DUEXSPECIAL						-0.019***
						(-3.89)
DUEXQ4						-0.023***
						(-4.62)
DUEXBNEWS						-0.038***
						(-6.02)
DUEXCOV						-0.001**
						(-2.17)
DUEXIO						-0.053***
						(-5.04)
Fixed Year Effects		Included	Included	Included	Included	Included
Fixed Industry Effects		Included	Included	Included	Included	Included
N		113,690	113,690	113,690	113,690	113,690
R^2		0.007	0.008	0.009	0.013	0.015
Adjusted R^2		0.006	0.008	0.008	0.012	0.014

DEDRIFT is the decile of the expected post-earnings announcement drift minus one divided by 9 and DUE, DEARNINGS, DB/M and DACCRUAL are the deciles of the unexpected earnings, earnings, book-to-market and accruals minus one divided by nine. LOGMV is the natural logarithm of the market value of the firm at the end of the previous fiscal quarter. The other variables are as defined previously. The standard errors clustered by firm are reported. The symbols *, **, and *** indicate statistical significance at ten, five and one percent levels, respectively. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 2.7

Calendar-Time Portfolio Regression Results

Panel A: Traditional post-earnings-announcement-drift trading strategy

	CAPM		Three-Factor Model		Four-Factor Model	
Intercept	0.014***	(5.91)	0.014***	(6.37)	0.013***	(5.61)
MKTRF	-0.085	(-1.39)	-0.079	(-1.31)	0.001	(0.01)
SMB			-0.204***	(-3.89)	-0.221***	(-3.75)
HML			-0.157	(-1.42)	-0.089	(-0.91)
UMD					0.205***	(4.08)
N	246		246		246	
R^2	0.014		0.062		0.160	
Adjusted R^2	0.009		0.051		0.146	

For each quarter I sort firms into two deciles one based on unexpected earnings and the other based on estimated post-earnings-announcement-returns. This table reports the results for the portfolio that goes long (short) on firms within the top (bottom) unexpected earnings decile. CAPM based abnormal returns are estimated using the intercept from the time-series regression of portfolio returns (rp-rf) on the market excess returns (rm-rf). Three-factor model based abnormal returns are estimated using the intercept from the regression of excess portfolio returns on excess market, size factor and book-to-market factor returns. Four-factor model based abnormal returns are estimated using the intercept from the regression of excess portfolio returns on excess market, size factor, book-to-market and momentum factor returns. t-statistics based on Newey and West (1987) corrected standard errors are reported in parentheses. ***, **, and * denote significance at the 1, 5 and 10 percent significance levels.

Panel B: Enhanced post-earnings-announcement drift trading strategy

	CAPM		Three-Factor Model		Four-Factor Model	
Intercept	0.019***	(4.96)	0.021***	(5.56)	0.019***	(5.03)
MKTRF	0.200*	(1.83)	0.102	(1.21)	0.192**	(1.97)
SMB			-0.071	(-0.95)	-0.091	(-1.22)
HML			-0.567***	(-5.54)	-0.491***	(-3.98)
UMD					0.230**	(2.40)
N	246		246		246	
R^2	0.026		0.127		0.169	
Adjusted R^2	0.022		0.116		0.155	

For each quarter I sort firms into two deciles one based on unexpected earnings and the other based on estimated post-earnings-announcement-returns. This table reports the results for the portfolio that goes long (short) of firms that in the top (bottom) decile based on both unexpected earnings and estimated future post-earnings-announcement-returns. Three-factor model based abnormal returns are estimated using the intercept from the regression of excess portfolio returns on excess market, size factor and book-to-market factor returns. Four-factor model based abnormal returns are estimated using the intercept from the regression of excess portfolio returns on excess market, size factor, book-to-market and momentum factor returns. t-statistics based on Newey and West (1987) corrected standard errors are reported in parentheses. ***, **, and * denote significance at the 1, 5 and 10 percent significance levels.

Panel C: The return differential between Panels A and B

	CAPM		Three-Factor Model		Four-Factor Model	
Intercept	0.005*	(1.70)	0.007**	(2.37)	0.006**	(2.27)
MKTRF	0.285***	(3.63)	0.181***	(2.63)	0.191***	(2.61)
SMB			0.133*	(1.81)	0.130*	(1.76)
HML			-0.410***	(-3.37)	-0.402***	(-3.04)
UMD					0.026	(0.39)
N	246		246		246	
R^2	0.077		0.187		0.188	
Adjusted R^2	0.073		0.177		0.174	

For each quarter I sort firms into two deciles one based on unexpected earnings and the other based on estimated post-earnings-announcement-returns. This table reports the results for a trading strategy that goes long on the portfolio reported in Panel B and short on the portfolio reported in Panel A. CAPM based abnormal returns are estimated using the intercept from the time-series regression of portfolio returns (rp-rf) on the market excess returns (rm-rf). Three-factor model based abnormal returns are estimated using the intercept from the regression of excess portfolio returns on excess market, size factor and book-to-market factor returns. Four-factor model based abnormal returns are estimated using the intercept from the regression of excess portfolio returns on excess market, size factor, book-to-market and momentum factor returns. t-statistics based on Newey and West (1987) corrected standard errors are reported in parentheses. ***, **, and * denote significance at the 1, 5 and 10 percent significance levels.

Chapter 3 The Source of Analyst's Forecasting Superiority: Evidence from the Frequency of Extreme Earnings Forecasts

3.1 Introduction

Financial analysts play an important role as information intermediaries in capital markets. They provide various types of service that help market participants to make better investment decisions. Prior studies also show that analysts bring valuable advices into markets (Stickel. 1995, Womack. 1996, Barber et al. 2001, Jegadeesh and Kim. 2006). Kim and Verrecchia (1994) suggest that informed investors, such as financial analysts, can generate superior assessments of firm performance by interpreting public information conditional on their own superior private information. Thus, the factor which makes the analysts' information more valuable is that they incorporate their private information, i.e. data which is not readily available or accessible to investors, into their forecasts or recommendations; this process then eventually enhances the market participants' understanding of firms by providing for a more accurate or profitable body of information.

Analyst's private information can be acquired from two sources: 1) their innate ability in information interpretation and fundamental analysis, and 2) their privileged access to selective disclosures by corporate management (Clement. 1999, Francis et al. 2002, Ivković and Jegadeesh. 2004). By focusing on the investors' different valuation in analysts' reports, some studies investigate the dominant source of value in analysts' research. For example, Ivković and Jegadeesh (2004) suggest that the value of analysts' forecasts mainly stems from their ability to acquire private information rather than from their skills at interpreting public information because stock-price reactions to revisions are stronger in the week before earnings announcement and those revisions are relatively more accurate than others previously issued. Even though prior research provides evidence on relative importance of the source of value brought by analyst to the market, it has not widely examined whether the individual analysts' superior performance is primarily due to the acquisition of private information from their inherent information analysis ability or from their ability to access the management' private information. The major objective of this study is to disentangle the impact of the analysts' inherent information analysis ability and their access to management on their performance, particularly on their accuracy of earnings forecasts.

In this paper, I examine the association between the analysts' forecasting accuracy and the analysts' reliance on their private information in order to determine whether analysts produce superior forecasts because they are more skillful at information interpretation and fundamental analysis or because they possess privileged access to selective management disclosure. To capture the analysts' reliance on private information, I develop own measurements based on prior literature. This study specifically focuses on the frequency of extreme earnings forecasts deviating from other forecasts issued on the same day over each forecasting period.[1] When there are any public disclosures – such as earnings announcement, management earnings guidance or presses related to firms' upcoming earnings, many analysts release or update their forecasts on the same day.

[1] I define the clustered analysts' earnings forecasts as forecast revisions which occur if at least three earnings forecasts are issued by different analysts within one day. I consider any clusters consisting of less than three analysts as non-clustered forecasts. I then classify the extreme earnings forecasts as more than one standard deviation away from average of each clustered-forecast. More detail explanation about the definition of extreme forecasts is provided in section 4.

Stickel (1989), Ivković and Jegadeesh (2004), Bagnoli et al. (2005), and Zhang (2008) provide evidence that the clustered form of analysts' earnings forecasts are significantly associated with corporate public disclosure events, such as earnings guidance. To the extent that public information is equally available to all analysts, the analysts' outputs (i.e. the forecasts or recommendations from the financial analysts) which are based on public information are more likely to be similar with each other. However, as a result of a different level of private information that is possessed by several analysts, these analysts may provide forecasts which deviate significantly from the forecasts of others. Consistent to this assumption, Kandel and Pearson (1995) suggest that when two analysts observe the same information, such as public disclosures, and have the same beliefs, then their forecast revisions should be pointed in a similar direction. It is only when two analysts have differing beliefs, possibly caused by dissimilar private information, that their revisions will be different and move apart. These findings imply that those analysts who are issuing extreme earnings forecasts relative to the forecasts of others within the clustered pattern of forecasts are more likely to incorporate their private information into their estimates. By focusing on the tendency for an analyst to produce extreme forecasts over the forecasting period, I believe that the developed measure is able to capture and present the analysts' reliance on private information. Therefore, this estimate indicates that those analysts having a higher (lower) frequency of extreme forecasts among the clustered forecasts rely to a greater (lesser) extent on private information to produce their forecasts.

To unravel the influence of the analysts' innate abilities and their privileged access to management on their forecasting performance, I partition the sample forecast revisions into two subsample periods: before and after the enactment of the Regulation Fair Disclosure (hereafter referred to as Reg FD). Reg FD prohibits managers from selective disclosing nonpublic information to preferred financial analysts before the public announcement of said information. Thus, Reg FD creates the natural research setting required to distinguish the effects of these two differing private information gathering channels on analysts' performance by comparing the association between the measure for analysts' reliance on private information and forecasting accuracy in the pre-FD setting to that in the post-FD setting. Given an assumption that Reg FD successfully eliminates or significantly reduces firm's selective disclosure activities (Eleswarapu et al. 2004, Janakiraman et al. 2007, Gintschel and Markov. 2004, Palmon and Yezegel. 2011), if analysts having a high frequency of extreme forecasts perform better than others having a lower frequency of extreme forecasts in the pre-FD period mainly due to private information obtained from their innate ability in information analysis, I would expect that these analysts would continue to perform well in the post-FD period. On the other hand, if a significant portion of the analysts' superiority in performance is heavily stemmed from private information acquired from selective management disclosures, then I expect that the analysts who more frequently rely on private information would no longer provide better (or less precise) estimates than those analysts who less frequently rely on private information in the post-FD. Therefore, this study tests whether the relation between forecast accuracy and the proxy for an analyst's reliance on private information in the pre-Reg FD period is changed in the post-Reg FD period. I find that analysts who more frequently issue extreme earnings forecasts relative to those of others eventually produce more accurate earnings forecasts in the pre-Reg FD period, whereas those analysts produce less accurate earnings forecasts in the post-Reg FD period. These findings indicate that the analysts' superior performance ratings are dominantly attributed to their receipt of selective disclosures from management rather than to their innate abilities in information processing.

In addition, this study explores whether the effect of the reliance on private information on forecasting accuracy differs with the analysts' forecast dispersions in a firm both before and after Reg FD. Barry and Jennings (1992) suggest that forecast dispersion can be attributed to differences in the private information possessed by analysts. Further, Abarbanell et al. (1995) and Barron and Stuerke (1998) present that forecast dispersion is positively associated with the quality of private information acquired by financial analysts. These studies suggest that more private information is incorporated into analysts' earnings forecasts when there is higher forecast dispersion. Their findings imply that any restrictions on analysts' private information acquisition more severely influence analysts who cover firms with higher forecast dispersion than those who follow firms with lower forecast dispersion. In this study, I compare the impact of their reliance on private information on their performance which is conditional to the level of earnings forecast dispersion in pre- and post-Reg FD periods. This comparison can contribute to seeing a more pronounced distinction between the impact of private information acquisitions through their access to management and from their own analyzing skills. I conjecture that if certain analysts' outperformance is due to their possession of private information obtained from corporate selective disclosures, the loss of their superiority in forecasting would be manifested after Reg FD when the level of dispersion is high. Empirical results are consistent with my expectations, in that during pre-Reg FD those analysts who frequently issue extreme earnings forecasts supply more accurate earnings estimates for both groups having a high level of earnings forecast dispersion and having a low level of dispersion. In contrast, the results show that in the post-Reg FD period those analysts provide significantly less accurate earnings forecasts in both levels of forecast dispersion. Also, analysts with high frequency of extreme forecasts produce less accurate estimates with regard to a high forecast dispersion group as compared to a low forecast dispersion group in the post-Reg FD period. Further, consistent with my prediction, I document that negative effect of the frequency of extreme earnings forecasts on accuracy in the post-Reg FD period more pronounced among firms in the high forecast dispersion group. Hence, the findings based on the further analysis also suggest that the superior performance of such analysts in relation to their peers mainly stems from their privileged access to management, and not from their inherent forecasting skills.

This study makes several contributions to both the accounting and finance literature. First, I develop a new way (the frequency of extreme forecast) to measure the analysts' reliance on private information. Second, through use of the developed measure, this paper sheds light on research by attempting to differentiate the source of analysts' private information between the privileged access to management and their innate abilities in information processing. Although several papers focus on separating the analysts' reliance on private and public information (Barron et al. 1998, Barron et al. 2002b), few studies directly examine the impact of private information on the analysts' performance with regards to the source of the private information (Ivković and Jegadeesh. 2004). Additionally, this research provides further evidence related to the effectiveness of

Reg FD. There are numerous studies investigating whether analysts' privileged access to management has declined after the adoption of Reg FD. (Mohanram and Sunder. 2006) Current study contributes to this literature by documenting that analysts who frequently rely on private information do not perform better than their peers after the implementation of Reg FD due to the restrictions placed on access to managements' private information, consistent with a decline in the selective disclosure practices by management.

In sum, the overall results documented in this study suggest that private information – which defines the analysts' services as value-added activities within capital markets – primarily stems from analysts' privileged access to corporate management, and not from their inherent personal abilities. Therefore, the findings provide little clue as to whether, with the implementation of Reg FD, which forbids the selective disclosures of management to favor analysts, the role of financial analysts in the capital market might be changed from that of the information intermediary to an information provider (Bhushan. 1989). The results documented in this study show that in the pre-Reg FD period, analysts seemed to play a role as information intermediaries by receiving information from firms and disseminating improved information to the market after incorporating such with their own private information. Conversely, in the post-Reg FD period, without the private information acquired from selective disclosure practices, financial analysts seem to no longer be able to provide useful information that may be incorporated with their own private information, suggesting that they play a another role which is that of transmitting the disclosed firm's information which is publically available into the market.

However, it should be noted that I am cautious to conclude that the role of financial analysts in the capital market has truly altered after Reg FD due to some limitations in this study. Although a developed measure for the reliance on private information successfully captures private information obtained from privileged access to management, there is a possibility that this proxy does not fully detect that private information generated from the analysts' own information processing abilities, especially within the post-Reg FD period. Also, it could be possible that analysts who are providing extreme forecasts which deviate from other forecasts within a one day cluster do not rely on private information after the enactment of Reg FD.[2]

The remainder of this paper is organized as follows. Section 3.2 discusses the related literature and Section 3.3 is the hypotheses development. Section 3.4 describes the method of sample selection, and Section 3.5 then describes the testable research designs. Section 3.6 contains the descriptive statistics and empirical results of this research. Finally, Section 3.7 provides the concluding remarks for this paper.

3.2 Related Literature

3.2.1 Two Sources of Analysts' Private Information and Their Performance

Since Stickel (1992) and Sinha et al. (1997) provided evidence that the performance of financial analysts can differ dependent upon their forecasting abilities, numerous studies have been designed to examine the various factors which may influence the analysts' abilities to produce better estimates (Clement. 1999, Jacob et al. 1999, Brown. 2001a, Clement and Tse. 2005). The divergent levels of forecasting ability among analysts can

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[2] After Reg FD, analysts might provide extreme forecasts in order to increase their commission revenue streams by generating high trading volume.

be largely attributable to the analysts' differing abilities to generate private information, i.e. that information which is not readily available to the public. According to prior literature (Clement. 1999, Francis et al. 2002, Ivković and Jegadeesh. 2004), an analyst's private information can be acquired from two sources: 1) that analyst's innate ability to produce his or her own private information from information interpretation and fundamental analysis, and 2) the analyst's privileged access to selective disclosures made available by corporate management. Mikhail et al. (1997) expect that the performance of analysts increases over time because these analysts are then able to achieve a better understanding of the particular firms' reports as their experience with these firms develops. In other words, analysts improve their innate ability for information processing with some specific firms as they accumulate their personal work experience with these firms. They find that their forecast accuracy is positively related to firm-specific forecasting experience. In addition, Clement (1999) predicts and establishes that various characteristics – such as an analyst's experience, size of the brokerage house, and number of firms and industries that are being followed – are all significantly associated with the analysts' forecasting accuracy. His explanation of these documented relationships is that those analysts' characteristics reflect on their forecasting ability to produce information acquired either from their sophisticated analysis skills or from their superior access to private information. Also, Janakiraman et al. (2007) suggest that each analyst's forecasting performance differs, in part, as a result of the private information obtained from selective disclosures. Overall, prior studies document that the performance of analysts can be determined by their varied characteristics reflecting their ability to generate private information attained from their inherent information analysis or from their private access to management.

3.2.2 Analysts' Reliance on Public or Private Information

Some prior research indicates that the timing of analysts' forecast revisions can reflect their reliance on public or private information. Several studies indicate that many financial analysts provide their earnings forecasts along with those of others within a specific time period as a reaction to public information disclosures. Cotter et al. (2006) examine the responses of financial analysts in relation to public management forecasts, and they present that over 30% of the analysts issue forecast revisions within one day after management issues guidance. Also, Guttman (2010) demonstrates that at the equilibrium one of two patterns may be observed, either: 1) a pattern of clustered forecasts or 2) a separation occurring at the time of the forecasts. Through his use of theoretical models, Guttman exhibits that the clustered patterns of forecasts typically occur if there is an arrival of exogenous information, such as a company press release. Additionally, Bagnoli et al. (2005) provide empirical evidence suggesting that the clustered form of analysts' earnings forecasts significantly relate to corporate public disclosures. They observe that clustered forecast revisions are significantly associated with elements such as: corporate information events, earnings announcements, and management guidance. Their findings then imply that the analysts' earnings estimates tend to be clustered when there are public disclosures. Moreover, Zitzewitz (2002) argues that multiple-forecasts made on a single day are reasonably and highly correlated with public information, indicating that analysts are more likely to release their estimates at the same time as when the information becomes publically available. Overall, prior research suggests that the clustered pattern of analysts' earnings forecasts can indicate the arrival of public information.

To the extent that public information is made available equally to all market participants, analysts' outputs (forecasts or recommendations from financial analysts) which are based on public information become more likely to share a similarity with each other. However, a few studies suggest that, even given the same information, analysts provide different forecasts that are dependent on the types of information these analysts possess. Kandel and Pearson (1995) suggest that when two analysts observe the same information and have the same beliefs, their forecast revisions should follow along in the same direction and converge; it is only when two analysts have differing beliefs – possibly arising from differing private information – that their revisions will tend to be different and move apart. These conclusions imply that analysts who possess a greater amount of private information are more likely to issue earnings estimates which deviate from those of others, while analysts who have uncovered a smaller amount of private information typically follow or mimic others' estimates of earnings.

3.2.3 Regulation FD and the Reliance of Analysts on Private Information

As the enactment of Reg FD has prohibited corporate management from disclosing material information in order to favor information user groups (SEC 2000), numerous academic researchers extensively investigated the impact of Reg FD both on analysts' performance and on their information environment (Agrawal et al. 2006, Chiyachantana et al. 2004, Francis et al. 2006, Wang. 2007). One stream of research is focused on the reliance of financial analysts' on either private or public information after the passage of Reg FD. Mohanram and Sunder (2006) examine whether the operations of analysts are changing following the enactment of Reg FD. Their findings indicate that due to the restrictions placed on analysts' accessibility to managements' private information, analysts expend greater efforts to analyze the available information in order to discover idiosyncratic information in post-Reg FD period. Additionally, Kross and Suk (2012) are exploring whether analysts' reliance on public disclosure have changed after the enactment of Reg FD. Their findings indicate that the analysts' reactions to earnings announcements, management guidance, and conference calls become more rapid following the implementation of Reg FD. Zitzewitz (2002) also presents evidence indicating that Reg FD contributed to an increase in analysts' reliance on public information.

3.2.4 Analysts' Forecast Dispersion and the Reliance on Private Information

Prior literature points out that the differences existent in the private information possessed by financial analysts can cause forecast dispersion among these individuals. Numerous studies indicate that forecast dispersion is an increasing function of the amount of private information that analysts acquired. Barry and Jennings (1992) demonstrate that the diversity of analysts' opinions can be ascribed, in part, to the varied impact of the analysts' personal private information. These researchers show that the divergence of analysts' opinions becomes greater when the amount of private information increases. Moreover, Abarbanell et al. (1995) and Barron and Stuerke (1998) argue that forecast dispersion captures the uncertainty of the analysts' idiosyncratic information. They document that forecast dispersion increases as the differences in the quality of private information possessed by analysts similarly increase. Using their theoretical models, these researchers show that a high rate of forecast dispersion is indicative of a high level of the analysts' heterogeneity. Lang and Lundholm (1996) also investigate the relationship found between the corporate disclosure policy and analysts' forecast dispersion. In their analysis, these researchers argue that forecast dispersion can depend on either the differing levels of private information owned by analysts or the particular differences in the analysts' forecasting models which have been used to produce their estimates. Collectively, prior research suggests that analysts' forecast dispersion is positively associated with the level of private information possessed by analysts.

3.3 Hypotheses Development

Prior literature shows that the analysts' information advantage influences their forecasting performance (Clement. 1999, Clement and Tse. 2003, Clement and Tse. 2005, Mohanram and Sunder. 2006). These papers find that analysts who possess a higher quality of private information are more likely to issue more accurate forecasts than those who possess information of lesser quality. A number of studies suggests that there are two sources of private information for financial analysts: 1) the information obtained from an analyst's inherent ability in information processing, and 2) that information acquired from the analyst's privileged access to management (Clement. 1999, Francis et al. 2002, Ivković and Jegadeesh. 2004). This study focuses on which source of private information can make the analysts' forecasts superior relative to those of others. I use the frequency of extreme earnings forecasts, deviated from other estimates released on the same day (the clustered pattern of forecasts), as a proxy for an analyst's reliance on private information. I assume that Reg FD reduced or eliminated selective disclosure practices. Under this assumption, I compare the association between the proxy for the reliance on private information and the varied analysts' levels of forecasting accuracy before and after Reg FD. This comparison helps identify the dominant source of private information which contributes to the analyst's forecasting superiority. In a comparison under both pre- and post-Reg FD settings, if I observe that the analysts who frequently rely on private information continue to release more accurate earnings forecasts than do others in the post-Reg FD period, this implies that the superiority of analysts in forecasting ability dominantly stems from their innate ability in information processing. On the other hand, to the extent that analysts are enabled to perform better than their peers primarily as a result of their access to management's private information, I expect that those analysts who frequently release extreme earnings forecasts deliver more (less) accurate earnings forecasts than others in the pre- (post-) Reg FD period.

Several findings in prior literature provide some clues as to the fact that private information obtained from corporate selective disclosures is a dominant determinant in analysts' performance because of a higher level of information quality. Surveys conducted by professionals working in the securities industry present these individuals' concerns as they relate to the deterioration of the quality of information flow in the market since the enactment of Reg FD.[3] (Securities Industry Association 2001) In addition, according to a survey of analysts directed by the Association for Investment Management and Research (AIMR), a large number of analysts believes that Reg FD leads to a significant reduction in the quality of oral communications.[4] Also, Brown et al.'s survey of analysts (Brown et al. 2013) documents that analysts consider their private

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[3] According to Securities Industry Association (SIA), 72% of the survey participants respond that they believe the quality of information communication has declined after the implementation of Reg FD.

[4] The AIMR survey documents that over half of the survey participants reply that the quality of oral communication is worsened in post-Reg FD period.

phone calls with management to be extremely valuable. These survey results imply that the selective disclosures made by corporate management are a primary factor in the analysts' forecasting abilities. Additionally, Soltes (2014) suggests that analysts can benefit from private interaction with management in various perspectives including forecasting performance. Mohanram and Sunder (2006) suggest that when analysts performed better than others in pre-Reg FD period, this was at least partially due to informational advantages which said analysts had acquired from their firm's management. Hence, I postulate that the analysts' privileged access to management's private information plays a more dominant role in their forecasting processes employed to make their earnings forecasts superior relative to those of their peers. The first hypothesis is as follows:

H1: Analysts' reliance on private information will be positively (negatively) associated with the forecast accuracy in the pre- (post-) Reg FD period.

In addition, this study examines the impact of the analysts' reliance on private information on their performance conditional on analysts' forecast dispersion during the pre- and post-Reg FD periods.[5] Forecast dispersion can be attributed to differences in the private information possessed by analysts (Barry and Jennings. 1992). Further, several previous papers point out that forecast dispersion reflects the uncertainty arisen by different levels of private information which analysts possess (Abarbanell et al. 1995, Barron and Stuerke. 1998). They show that forecast dispersion is positively associated with the quality of private information acquired by financial analysts. Their findings

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[5] Following prior literature (Diether et al. 2002, Yeung. 2009), I quantify the analysts' forecast dispersion by the standard deviation of the latest consensus earnings per share forecasts for firm *i* in year *t* deflated by stock price.

suggest that in the presence of a high level of forecast dispersion, analysts' earnings estimates are more likely to be based on a higher quality of private information that is obtained from either privileged access to selective disclosures or analysts' innate analyzing abilities. Accordingly, if analysts have any difficulties in private information acquisition from either possible channel and eventually are not able to obtain high quality of private information, the deterioration in their superior forecasting ability is more pronounced when there is higher forecast dispersion. Accordingly, I compare the association between analysts' reliance on private information and their forecasting performance in the pre- and post-Reg FD periods conditional upon the level of analysts' forecast dispersion. Though this comparison, more distinctive classification of the primary source of these analysts' private information which contributes to their superior performance relative to that of others would be expected. Consistent with the first hypothesis, I expect that private information acquired through analysts' private communication with management is a primary source of their forecasting superiority as compared to that of their peers because of its high information quality. Thus, I posit that although analysts who exhibit a higher frequency of extreme forecasts issue more accurate earnings forecasts for both firms with low and high forecast dispersions during the pre-Reg FD period, the reductions in their forecasting superiority in post-Reg FD due to the restrictions on the access to management private information become more evident in the presence of high forecast dispersions. The second hypothesis is as follows:

H2: Analysts' reliance on private information will be more positively (negatively) related in magnitude with forecast accuracy in the pre- (post-) Reg FD for firms in a high level of forecast dispersion than for those in a low level of forecast dispersion.

3.4 Research Design

3.4.1 Variable Definitions

3.4.1.1 The Proxy for the Analysts' Reliance on Private Information

This study uses the frequency of extreme earnings forecasts relative to others included in the clustered forecasts as a proxy for the analysts' reliance on private information. First, I define the clustered earnings forecasts under the assumption that multiple earnings forecasts released by several analysts for a firm within a day indicate the dissemination of public information within the market, consistent with prior research (Bagnoli et al. 2005, Zitzewitz. 2002). I consider that earnings forecasts are clustered when there are at least three forecasts issued on one single day. To the extent that extreme forecasts which move apart from others are more likely to be based on analysts' private information acquired by their privileged access to management or by means of their own information processing skills (Kandel and Pearson. 1995), I then classify the extreme earnings forecasts as more than one standard deviation away from average of each clustered-forecast.[6]

After identifying extreme earnings forecasts, I count how many times each earnings forecast issued by the individual analyst *i* for firm *j* are considered as extreme forecasts over one year forecasting period, *t*. Finally, I scale the number of extreme earnings forecasts of analyst *i* for firm *j* in year *t* by the total number of forecasts issued by the analyst *i* for firm *j* during the same forecasting period (year *t*). Formally, this is measured as follows:

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[6] I also define the extreme forecasts as the forecasts included in both the top and bottom groups after dividing forecasts within each cluster into three groups based on the magnitude of forecasts. The results are qualitatively consistent.

$$\textbf{Frequency (Percentage) of Extreme Earnings Forecasts}_{i,j,t}\ \textbf{(Pert\_EXT}_{i,j,t}\textbf{)} = \frac{\textbf{Number of Forecasts Classified as Extreme Forecasts}_{i,j,t}}{\textbf{Total Number of Forecasts}_{i,j,t}}$$

This measure indicates how often an analyst issues forecasts that deviate from those of others when there is public information arrival. In other words, it reflects the tendency of an analyst's earnings forecasts to be based on private information in a manner obtained by selective disclosure from management or on his/her self-assessed ability in information processing.

I transform the variable of the frequency of extreme forecasts so that it ranges between 0 and 1. Specifically, I calculate the difference between the frequency of extreme forecasts for the individual analyst *i* and the minimum frequency of extreme forecasts for the analysts following firm *j* in year *t*, divided by the distance in the frequency of extreme forecasts for the analysts following firm *j* in year *t*. I use this scaled measure for the analysts' reliance on private information to control for both time- and firm-specific effects (Clement and Tse. 2005, Herrmann and Thomas. 2005, Keung. 2010).

3.4.1.2 Analysts' Forecast Accuracy and Other Characteristics

This paper focuses on the last earnings forecast of each individual analyst for a firm in order to estimate his/her absolute forecast error, absolute value of difference between the actual and forecasted earnings for analyst *i* following firm *j* in year *t*. Using the absolute forecast errors for individual analysts, I compute the forecast accuracy measure derived by scaling the transformation (Clement and Tse. 2005). In order to ensure that the forecast accuracy variable increases with the higher values of the measure, I scale the forecast accuracy measure to range between 0 (the least accurate forecast) and 1 (the most accurate forecast). Formally, this scaled accuracy measure for analyst *i* is estimated as follows:

$$\textbf{Forecast Accuracy}_{i,j,t} = \frac{\textbf{Max}(\textbf{AFE}_{j,t}) - \textbf{AFE}_{i,j,t}}{\textbf{Max}(\textbf{AFE}_{j,t}) - \textbf{Min}(\textbf{AFE}_{j,t})}$$

where Max($AFE_{j,t}$) and Min($AFE_{j,t}$) are the maximum and minimum absolute forecast errors for analysts following firm *j* in year *t*. $AFE_{i,j,t}$ is the absolute forecast error (absolute value of the difference between the actual and last forecasted earnings per share) for analyst *i* following firm *j* in year *t*. A higher value of accuracy measure indicates a more accurate forecast.

To remain consistent with prior research (Mikhail et al. 1997, Clement. 1999, Clement and Tse. 2005), various analysts-specific characteristics which have an influence on forecasting accuracy are also included as control variables. The model contains analysts experience (general and firm-specific), the size of the brokerage house, the number of companies and industries each analyst follows during the forecasting period, forecast frequency, forecast horizon, days elapsed since the last forecast, and prior earnings forecast accuracy.[7] In a similar manner used in the frequency of extreme forecasts, I scale each analyst's characteristic variable to lie between 0 and 1 by calculating the difference between the value of the characteristic for individual analyst *i* and the minimum value of the characteristic for the analysts following firm *j* in year *t*, divided by the distance between the value of the characteristic for the analysts following firm *j* in year *t*. The formal equation is as follows:

$$\textbf{Analyst's Characteristics}_{i,j,t} = \frac{\textbf{Raw\_Characteristics}_{i,j,t} - \textbf{Min}(\textbf{Characteristics}_{j,t})}{\textbf{Max}(\textbf{Characteristics}_{j,t}) - \textbf{Min}(\textbf{Characteristics}_{j,t})}$$

[7] For detail variable definitions, please see Table 3.1.

where Max(Characteristics$_{j,t}$) and Min(Characteristics$_{j,t}$) are the maximum and the minimum values of the characteristic of analysts following firm *j* in year *t*. Raw_Characteristics$_{i,j,t}$ is the raw value of characteristic for analyst *i* following firm *j* in year *t*.

3.4.2 Empirical Model Development

To examine the association between the frequency of extreme earnings forecasts and forecast accuracy, I model forecast accuracy as a function of the frequency of extreme forecasts and various analysts characteristics, such as the analysts' general and firm-specific experience, brokerage house size, the numbers of companies and industries each analyst follows, forecast frequency, prior earnings forecast accuracy, the forecast horizon, and the days elapsed since the last forecast (Clement. 1999, Jacob et al. 1999, Gleason and Lee. 2003). Also, the model contains an interaction term between the frequency of extreme forecasts and the post-Reg FD indicator variable, Reg FD, used to compare the impact of the frequency of extreme forecasts on forecast accuracy before and after Reg FD periods. The indicator variable, DRegFD, equals 1 if observations are included in the post-Reg FD period (between 2001 and 2011). The OLS regression model is as follows:

$$\begin{aligned}\mathbf{Accuracy_{i,j,t}} = {} & \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\mathbf{PertEXT_{i,j,t}} + \boldsymbol{\beta_2}\mathbf{DRegFD_t} + \boldsymbol{\beta_3}\mathbf{(PertEXT_{i,j,t} * DRegFD)} \\ & + \boldsymbol{\beta_4}\mathbf{GExp_{i,j,t}} + \boldsymbol{\beta_5}\mathbf{FExp_{i,j,t}} + \boldsymbol{\beta_6}\mathbf{Bsize_{i,j,t}} + \boldsymbol{\beta_7}\mathbf{NFirm_{i,j,t}} + \boldsymbol{\beta_8}\mathbf{NInd_{i,j,t}} \\ & + \boldsymbol{\beta_9}\mathbf{Frequency_{i,j,t}} + \boldsymbol{\beta_{10}}\mathbf{PriorAccuracy_{i,j,t}} + \boldsymbol{\beta_{11}}\mathbf{Horizon_{i,j,t}} \\ & + \boldsymbol{\beta_{12}}\mathbf{DaysElapsed_{i,j,t}} + \boldsymbol{\nu_{i,j,t}} \qquad \mathbf{(1)}\end{aligned}$$

where:

DRegFD : Dummy variable indicating the post-Reg FD period. DRegFD is equal to 1 (0) if firm-year observations are included in a range between 2001 and 2011 (1993 and 1999).

Detailed descriptions of other independent variables are provided in Table 3.1. The test variables are PertEXT and PertEXT*DRegFD. A coefficient on PertEXT indicates the impact of the frequency of extreme earnings forecasts on accuracy in the pre-Reg FD period while the interaction term represents the same effect in the post-Reg FD period. In line with H1, I expect a significantly positive coefficient on PertEXT and negative coefficient on the interaction term, PertEXT*DRegFD. In addition, if the primary source of private information which has contributed to the analysts' superior performance relative to peers stems from privileged access to management, I expect a significantly negative difference between the two coefficients. Also, consistent with prior literature, I predict that forecast accuracy is an increasing function of analyst experience (GExp and FExp), broker size (Bsize), forecast frequency (Frequency), and prior accuracy (PriorAccuracy), and a decreasing function of the numbers of companies (NFirm) and industries (NInd) which the analyst follows, forecast horizon (Horizon), and days elapsed since the last forecast (DaysElapsed).

Next, this study examines whether the relation between analysts' reliance on private information and forecast performance differs before and after Reg FD depending on the level of forecast dispersion. I first define earnings forecast dispersion as the standard deviation of the latest earnings per share forecasts for firm *i* in year *t* deflated by stock price. To test the different effects of the frequency of extreme forecasts on accuracy, I divide the final sample into three groups (High, Medium, and Low) based on the level of earnings forecast dispersion for firms in each year. Observations included in the

Medium group are excluded in this analysis. I add an interaction term between the frequency of extreme forecasts and the indicating variable, DDisp, in the model to test whether the impact of private information employed by analysts on their performance varies with the level of forecast dispersion. To investigate how Reg FD has an influence on the association between the frequency of extreme forecasts and accuracy conditional on the presence of forecast dispersion, I independently estimate regression coefficients using sample observations in the pre-Reg FD period and in the post-Reg FD period. Finally, using Model (1) I compare two combined coefficients (PertEXT and PertEXT*DRegFD) obtained from separate regressions with high and low dispersion groups to examine whether high dispersion group are more evidently affected by Reg FD. Model (2) also includes other independent variables reflecting the various analysts' characteristics, consistent with Model (1). The second OLS regression model is as follows:

$$\begin{aligned}\mathbf{Accuracy}_{i,j,t} = {} & \beta_0 + \beta_1\mathbf{PertEXT}_{i,j,t} + \beta_2\mathbf{DDisp}_{j,t} + \beta_3(\mathbf{PertEXT}_{i,j,t} * \mathbf{DDisp}_{j,t}) \\ & + \beta_4\mathbf{GExp}_{i,j,t} + \beta_5\mathbf{FExp}_{i,j,t} + \beta_6\mathbf{Bsize}_{i,j,t} + \beta_7\mathbf{NFirm}_{i,j,t} + \beta_8\mathbf{NInd}_{i,j,t} \\ & + \beta_9\mathbf{Frequency}_{i,j,t} + \beta_{10}\mathbf{PriorAccuracy}_{i,j,t} + \beta_{11}\mathbf{Horizon}_{i,j,t} \\ & + \beta_{12}\mathbf{DaysElapsed}_{i,j,t} + \nu_{i,j,t} \qquad \mathbf{(2)}\end{aligned}$$

where:

DDisp : Dummy variable indicating the level of analysts' forecasts dispersion for firm j in year t. The forecast dispersion is computed as the standard deviation of the latest earnings per share forecasts for firm *i* in year *t* deflated by stock price. DDisp is equal to 1 (0) if firms are included in a group having the highest (lowest) dispersion.

My variables of interest are PertEXT and PertEXT*DDisp estimated from two regressions using observations in the pre- and in the post-Reg FD periods. Regardless the sources of private information, analysts who rely more on their own private (better) information are expected to better perform relative to their peers who rely less (Brown et al. 2013). To the extent that forecast dispersion is positively related to the level of private information which analysts possess (Abarbanell et al. 1995, Barron and Stuerke. 1998), I anticipate that the impact of the reliance on private information on forecast accuracy is more pronounced in the presence of high levels of forecast dispersion. In addition, although the level of private information is low for low dispersion group, this information would contribute to providing better estimates by analysts. Thus, I predict that both coefficients on PertEXT and PertEXT*DDisp in pre-Reg FD period are significantly positive. On the other hand, consistent with the first hypothesis due to the restrictions placed on the access of the higher quality information after the passage of Reg FD, analysts with a greater frequency of extreme earnings forecasts in both levels of forecast dispersion no longer sustain their forecasting superiority when compared to others. Hence, I expect both negative and significant coefficients on PertEXT and PertEXT*DDisp in the post-Reg FD period. Finally, because the impact of the restrictions on privileged access to selective disclosure on accuracy is more evident with analysts included in a high level of dispersion, the negative impact of Reg FD on the association between the frequency of extreme forecasts and forecast accuracy are greater in magnitude for firms in the high dispersion group relative to firms in the low dispersion group. Therefore, in the comparison of the effect of Reg FD on the relation between the extreme forecasts and accuracy for both low and high dispersion groups using Model (1), I predict that the combined coefficient (PertEXT and PertEXT*DRegFD) in high forecast dispersion group is greater in magnitude than it in low forecast dispersion group.

3.5 Sample Selection

I obtain analysts' annual earnings per share forecasts for the period between 1993 and 2011 from the Institutional Brokers Estimate System (I/B/E/S) database. Since exact forecasting dates are important in this research setting, the starting period of the sample, 1993, is approximately correspondent with the date at which I/B/E/S initiated its daily update of analysts' forecasts, a pattern which is consistent with prior research (Cooper et al. 2001). For compatibility, actual reported earnings are also collected from I/B/E/S. The Global Industry Classifications Standard (GICS) codes used to classify each industry are obtained from COMPUSTAT database.[8] I merge the analysts' annual earnings forecasts data with the GICS codes. I impose several restrictions on the data collection process. The sample includes all earnings forecasts issued no earlier than 360 days prior, and one day before the current period earnings announcements date.[9] This requirement helps maximize the sample size and to ensure that all earnings forecasts are released within a one year forecasting period. Also, I eliminate observations in which the code of the analyst equals zero. I remove those earnings forecasts for firms which have a stock price below one dollar and a market value lower than 5 million dollars in order to avoid potential outlier problems. Additionally, I require that at least three analysts follow a firm

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[8] Bhojraj et al. (2003) report that the Global Industry Classifications Standard (GICS) codes are a better measure by which to classify each industry in financial research than other indicators, such as the Standard Industry Classification (SIC) and the North American Industry Classification System (NICS).

[9] I also conducted the test with the forecast sample including earnings forecasts issued no earlier than 11 months prior, and 30 days before the fiscal year end, (a time period which is consistent with Clement (1999). The results are qualitatively similar.

so that the clustered earnings forecasts are defined when there are at least three earnings forecasts gathered on any single day.[10] To include analysts who are actively issuing earnings forecasts, I require that an individual analyst release at least three earnings forecasts for each firm in a given year.[11] Observations with no prior period forecast errors are excluded. To estimate forecast accuracy, I retain the last earnings forecast released by each analyst before the current period earnings announcement date. To avoid the effects of the outlier in the estimation, observations with price-deflated absolute forecast errors lying outside of the first and 99th percentile are excluded.[12] I define the pre-Reg FD period as those years between 1993 and 1999 and the post-Reg FD period as those years between 2001 and 2011 in order to alleviate confounding factors related to the varied adjustments around the passage of Reg FD. Therefore, the total number of analyst-firm-year observations included in the final sample is 263,973, with pre-Reg FD period consisting of 77,239 and post-Reg FD period consisting of 176,566. Panel A in Table 3.2 presents the detail information on the sample selection process. The sample composition by year is also reported in Panel B.

3.6 Results

3.6.1 Descriptive Statistics

Table 3.3 reports the descriptive statistics of the final sample. The distributions of all unstandardized variables are documented in Panel A. The mean frequency of extreme

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[10] When I analyze with different data restrictions (the sample including firms followed by at least five analysts), I obtain statistically consistent results.

[11] Without adding this data restriction or different requirement (at least one forecast or two forecasts per firm in one year forecasting period, overall results remain consistent.

[12] Tests are also conducted without the trimming outlier in forecast errors, but results remain consistent.

forecasts is 0.13, suggesting that a few analysts provide extreme earnings forecasts. Also, the distribution of the frequency of extreme forecasts is highly skewed. To extent that the extreme forecasts reflect the analysts' reliance on private information, these results possibly indicate that a number of the analysts might not be able to enjoy the informational advantages generated from private information acquisition. The reported averages of analysts' general and firm experiences are 8.1 years and 4.6 years, respectively. On average, brokerage houses employ roughly 61 analysts. Also, analysts follow an average of 19 firms in approximately three industries and also provide five earnings forecasts per firm in any given year (Sample included only analysts having at least three forecasts for a given firm-year).

The average forecast horizon is measured as 87 days, since all previous forecasts released before the earnings announcement date are included in the final sample. Panel B presents the distribution of all standardized variables based on the methodology of Clement (1999) and Clement and Tse (2005). The transformed values of all variables lie between zero and one. Overall distributions of these standardized variables are consistent with those of the unstandardized variables.[13]

I also document the results gathered from the Pearson correlation analysis among all standardized variables in Table 3.4. The proxy for the reliance on private information, the frequency of extreme forecast, is negatively correlated with the forecast accuracy within the entire sample. The negative correlation probably arises because the relation has dramatically changed between the pre- and post- Reg FD periods. Thus, I also

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[13] Consistent with the studies of Clement (1999), Clement and Tse (2003) and Clement and Tse (2005), I do not require the independent variables to conform to any specific distribution even though the assumption for the hypothesis tests is that the regression error term is normally distributed. (i.e., the distribution of forecast accuracy is conditional on the distributions of the independent variables).

conduct a correlation analysis between those variables before and after Reg FD (Untabulated). Consistent with my expectation, it shows the significantly positive (negative) relation between the frequency of extreme forecasts and forecast accuracy in the pre- (post-) Reg FD period. This result suggests that the impact of analysts' reliance on private information on forecast accuracy changed after the passage of Reg FD. Additionally, this table illustrates that the frequency of extreme forecasts is positively associated with brokerage house size, the number of firm analysts follow, and the forecast frequency, while it is negatively related with analysts' general and firm-specific experiences, the number of industries which the analysts cover, the forecast horizon, and the number of days elapsed since the last forecast by any analyst. The relationships which exist between the forecast accuracy and several of the analysts' characteristics are consistent with the relationships documented in prior literature (Clement and Tse. 2003, Clement and Tse. 2005). Furthermore, correlations among the independent variables are generally low in magnitude (<0.1).

3.6.2 The Impact of Reg FD on the Association between the Frequency of Extreme Earnings Forecasts and Forecast Accuracy

Regression results for the effect of Reg FD on the relationship between the frequency of extreme earnings forecasts and forecast accuracy are reported in Table 3.5. After excluding the interaction term (DRefFD), I run Model (1) using pre- and post-Reg FD observations, respectively. The first two columns present these separate regression results. Then, I conduct the analysis using a full model (with the interaction term) in order to statistically compare the impact of Reg FD on the association between the extreme forecasts and accuracy. The result obtained from the final test is documented in the third column. I run a two dimensional (firm and year) clustered error regression in order to control for both firm-specific effects as well as temporal differences.[14]

Consistent with the first hypothesis (H1), the estimated coefficient of the frequency of extreme forecasts (PertEXT) is positive and statistically significant during the pre-Reg FD period whereas it changes to negative and significant in the post-Reg FD period. Also, consistent with these findings, the results reported in the third column show a positive estimate on PertEXT and a negative estimate on an interaction term (PertEXT * DRegFD). These results indicate that analysts who have a higher tendency of issuing extreme earnings forecasts eventually provide more accurate forecasts compared to analysts who have a lower tendency to issue extreme forecasts before the Reg FD. Whereas these analysts no longer provide better, or even provide worse estimates than others after the Reg FD. In other words, after the loss of their privileged access to management private information, analysts who are more likely to rely on private information to produce earnings forecasts in pre-Reg FD period are no longer able to outperform their peers in post-Reg FD period. Collectively, the findings suggest that a significant portion of the variation in analysts' forecast performance can be attributable to private information acquired from selective disclosure, and not from their innate analyzing skills. The predominant amounts of other explanatory variables are consistent with information gathered in prior research (Clement. 1999, Clement and Tse. 2003, Clement and Tse. 2005). However, the fact that the size of the brokerage house is negatively associated with forecast accuracy in post-Reg FD period most probably arises

[14] Petersen (2009) suggests that a linear regression controlling for correlation in the error terms across time and across firms provides unbiased estimates. This method is robust even if firm-specific effects are not permanent or are varying over time.

because analysts employed in large brokerage house are more significantly affected by the restrictions placed on private access to management.

3.6.3 The Impact of Reg FD on the Association between the Frequency of Extreme Earnings Forecasts and Forecast Accuracy conditional on the Level of Analysts' Forecast Dispersion

Table 3.6 presents the results from the regression which tests how analysts' reliance on private information on forecasting performance differs before and after Reg FD, conditional on the level of the analysts' forecast dispersion. Panel A illustrates the associations which exist between the frequency of extreme earnings forecasts and forecast accuracy for low and high forecast dispersion groups in pre-Reg FD. Before Reg FD, a coefficient on PertEXT is significantly positive for the high forecast dispersion group while it is positive but insignificant for the low forecast dispersion group. Consistent with results obtained from separate regressions, PertEXT has a negative and insignificant coefficient and PertEXT * DDisp has a positive and significant coefficient. The results indicate that in the pre-Reg FD period analysts who rely heavily on private information to forecast earnings issue more precise earnings estimates, particularly in the presence of higher forecast dispersion. This finding is consistent with prior literature (Barron and Stuerke. 1998), suggesting that analysts rely on private information to a greater extent when forecast dispersion is high. Conversely, I show that the relationship between the tendency of extreme forecasts and forecast accuracy changes after Reg FD is enacted. Panel B illustrates the results derived from the same regressions using post-Reg FD observations. I find that analysts who often issue extreme earnings forecasts provide significantly less accurate forecasts after Reg FD for both low and high dispersion groups.

Moreover, the results from the regression analysis with an interaction term indicate that a coefficient on PertEXT is significantly negative and on PertEXT * DDisp is negative and insignificant, which is consistent with my previous results.

Panel C reports the results gathered from testing the impact of Reg FD on the relationship between the tendency of extreme forecasts and the accuracy of analysts following firms in both low and high dispersion groups. PertEXT is significantly positively related with forecast accuracy for both groups, whereas PertEXT * DRegFD is significantly negatively associated with forecast accuracy for both groups. These findings confirm my previous findings that analysts who perform better than their peers because of a heavy reliance on private information in pre-Reg FD period are unable to sustain their superior forecasting performance after losing their privileged access to management in post-Reg FD period. More importantly, the joint test for PertEXT + (PertEXT * DRegFD) between high and low dispersion groups provide evidence to support H2. The results obtained from the joint test indicate a significant difference of the combined coefficient in magnitude between two groups, suggesting that the negative impact of the frequency of extreme earnings forecasts on accuracy in post-Reg FD is more pronounced in the high forecast dispersion group. In sum, the results obtained from further analysis also confirm that the performance differential documented in this study can be attributed to analysts' possession of private information obtained from corporate selective disclosures rather than to their superior information processing skills.

3.7 Conclusion

In this study, I examine whether the performance of analysts who provide more accurate forecasts can be attributed to their privileged access to selective disclosures or to their innate ability in information analysis. To the extent that Reg FD is effectively implemented as it is intended, this paper tests the association between the frequency of extreme earnings forecasts, the proxy for analysts' reliance on private information, and the forecast performances both before and after Reg FD. I find that the frequency of extreme earnings forecasts is positively associated with forecast accuracy in the pre-Reg FD period while it is negatively associated with forecast accuracy in the post-Reg FD period. My findings point out that analysts who rely to a greater extent on private information outperform their peers largely due to their ability to communicate with corporate management.

In addition, given the assumption that the impact of private information on forecasting performance is more distinctive in the presence of high forecast dispersions, I investigate the impact of Ref FD on the associations between the frequency of extreme earnings forecasts and forecast accuracy conditional on the level of forecast dispersions. The results indicate that analysts who have a high frequency of extreme forecasts perform better than those that have a low frequency of extreme forecasts in high forecast dispersion group during the pre-Reg FD period. Conversely, I find that these analysts are not able to outperform their peers in both low and high forecast dispersion groups during the post-Reg FD period. Furthermore, the loss of analysts' forecasting superiority in the post-Reg FD is more pronounced in the presence of high forecast dispersions. In conclusion, these results suggest that access to corporate management is a significant determinant of analysts' forecasting performance.

3.8 Tables for Chapter 3

Table 3.1

Variable Definitions

Accuracy	:	Analyst *i*'s forecast accuracy for firm *j* in year *t*, estimated as the maximum accuracy for analysts following firm j in year t minus the accuracy of analyst *i* following firm *j* in year *t*, divided by the range of accuracy for analysts following firm j in year *t*.
PertEXT	:	The percentage of extreme earnings forecasts for analyst *i* who follow firm *j* in year *t* minus the minimum percentage of extreme earnings forecasts for analysts who follow firm *j* in year *t*, deflated by the range of percentage of extreme earnings forecasts for analysts following firm *j* in year *t*.
GExp	:	Analyst's general experience, measured as the number of years for which analyst *i* has provided at least one forecast in the I/B/E/S in year t minus the minimum number of years of general experience for analysts following firm *j* in year *t*, scaled by the range of general experience for analysts following firm *j* in year *t*.
FExp	:	Analyst's firm-specific experience, calculated as the number of years for analyst *i*' has been following firm *j* in year *t* minus the minimum number of firm experience for analysts following firm *j* in year *t*.
Bsize	:	Brokerage house size, measured as the number of analysts employed by the brokerage employing analysts *i* following firm *j* in year *t* minus the minimum brokerage size for analysts following firm *j* in year *t*, scaled by the range of brokerage size form analysts following firm *j* in year *t*.
NFirm	:	The number of companies analyst *i* follows in year *t*, computed as the number of companies followed by analyst *i* in year t minus the minimum number of companies followed by analysts covering firm *j* in year *t*, deflated by the range in the number of companies followed by analysts following firm j in year *t*.

NIND : The number of industries analyst *i* follows in year *t*, measured as the number of four-digit GICS codes followed by analyst *i* in year t minus the minimum number of industries followed by analysts who cover firm *j* in year *t*, divided by the range in the number of industries followed by analysts who follow firm *j* in year *t*.

Frequency : Forecast frequency, calculated by the number of forecasts made by analyst *i* for firm *j* in year *t* minus the minimum number of forecasts made for firm *j* issued by analysts following firm *j* in year *t*, deflated by the range of forecast frequency of analysts following firm *j* in year *t*.

PriorAccuracy : Prior year forecast accuracy, estimated as maximum accuracy for analysts following firm j in year *t-1* minus the accuracy of analyst *i* following firm j in year *t-1*, divided by the range of accuracy for analysts following firm *j* in year *t-1*.

Horizon : Forecast horizon, calculated as the number of days from the forecasts date to the current period earnings announcement date, for analysts *i* following firm *j* in year *t* minus the minimum forecast horizon for analysts following firm *j* in year *t*, divided by the range of forecast horizons for analysts who follow firm *j* in year *t*.

DaysElapsed : The days elapsed since the last forecasts by any analyst following firm *j* in year *t*, computed as the number of days between analyst *i*'s earnings forecast for firm *j* in year *t* and the most recent preceding earnings forecast for firm *j* by any analysts, minus the minimum number of days between two adjacent forecasts for firm *j* by any two analysts in year *t*, deflated by the range of days between two adjacent earnings forecasts for firm *j* in year *t*.

DRegFD : Dummy variable indicating the post-Reg FD period. DRegFD is equal to 1 (0) if firm-year observations are included in a range between 2001 and 2011 (1993 and 1999).

Dispersion : Forecast dispersion is computed as the standard deviation of the latest consensus earnings per share forecasts for firm *j* in year *t* deflated by stock price.

DDisp : Dummy variable indicating the level of analysts' forecasts dispersion for firm *j* in year *t*. DDisp is equal to 1 (0) if firms are included in group having the highest (lowest) dispersion.

Table 3.2

Sample Selection

Panel A: Sample Selection Procedure

Sample Selection	**Obs Remained**
Analysts' Annual Earnings Forecasts from I/B/E/S between 1993 - 2011	2,311,056
Less:	
Analyst identification code is equal to zero	2,286,603
Forecast horizon is less than 1 day or more than 1 year	2,191,733
Keeping individual analyst's last forecast for each firm in a given year	627,462
No prior-year or current-year forecast errors	410,784
Firms for which the stock price less than $1 or market capital less than $5 mil	406,639
Firms followed by fewer than three analysts	373,890
Analysts issuing fewer than three earnings forecasts per firm in a given year	269,252
Trimming observations with price-deflated absolute forecast errors lying outside of the first and 99th percentile	263,973
Final Analyst-Firm-Year Observations	263,973
Observations in Pre-Reg FD period	77,239
Observations in Post-Reg FD period	176,566

Panel B: Sample Composition by Year

Year	Number of Firm-Year	Number of Firms	Number of Analysts
1993	10144	1750	1388
1994	10009	1879	1495
1995	10625	2029	1626
1996	11045	2171	1725
1997	11349	2340	1917
1998	12262	2379	2098
1999	11805	2266	2196
2000	10168	2025	2081
2001	11047	1976	2069
2002	11142	1943	2022
2003	11966	2024	2115
2004	13911	2152	2243
2005	15915	2407	2414
2006	16967	2548	2439
2007	17430	2653	2483
2008	17473	2555	2458
2009	18414	2509	2437
2010	20369	2528	2518
2011	21932	2594	2765
All Years	263973	7179	9244

Table 3.3

Descriptive Statistics

Panel A: The distribution of unstandardized variables

Variable	Mean	1Q	Median	3Q
Proxy for Accuracy				
ABS_FE	0.006	0.000	0.001	0.005
Proxy for the reliance on private information				
PertEXT	0.130	0.000	0.000	0.250
Control Variables				
GExp	8.151	4.000	7.000	11.000
FExp	4.624	2.000	4.000	6.000
Bsize	60.910	21.000	47.000	91.000
NFirm	18.767	13.000	17.000	22.000
NInd	2.580	1.000	2.000	3.000
Frequency	5.074	3.000	4.000	6.000
PriorAccuracy	0.005	0.000	0.001	0.004
Horizon	86.735	42.000	91.000	109.000
DaysElapsed	8.582	0.000	1.000	8.000

Abs_FE and PriorAccuracy are measured as the absolute forecast error (absolute value of difference between forecast and actual earnings) of analyst *i* for firm *j* in year *t (t-1)*, scaled by stock price.

Panel B: The distribution of standardized variables

Variable	Mean	1Q	Median	3Q
Proxy for Accuracy				
Accuracy	0.608	0.250	0.750	0.972
Proxy for the reliance on private information				
PertEXT	0.267	0.000	0.000	0.500
Control Variables				
GExp	0.425	0.083	0.333	0.750
FExp	0.371	0.000	0.250	0.667
Bsize	0.416	0.069	0.318	0.746
NFirm	0.420	0.101	0.351	0.700
NInd	0.328	0.000	0.167	0.500
Frequency	0.394	0.000	0.333	0.667
PriorAccuracy	0.574	0.143	0.667	0.966
Horizon	0.436	0.035	0.351	0.918
DaysElapsed	0.258	0.000	0.038	0.412

See Table 3.1 for detail variable definitions.

Table 3.4

Pearson Correlations Coefficients (Standardized Variables)

	Accuracy	PertEXT	GExp	FExp	Bsize	NFirm	NInd	Frequency	Prior Accuracy	Horizon	DaysElapsed
Accuracy	1										
PertEXT	-0.0098	1									
	<.0001										
GExp	0.0214	0.0014	1								
	<.0001	0.4623									
FExp	0.0301	0.0092	0.4949	1							
	<.0001	<.0001	<.0001								
Bsize	0.0170	0.0296	0.0314	0.0254	1						
	<.0001	<.0001	<.0001	<.0001							
NFirm	0.0167	0.0186	0.2368	0.1424	0.0724	1					
	<.0001	<.0001	<.0001	<.0001	<.0001						
NInd	-0.0143	-0.0082	0.1277	0.0707	-0.1091	0.3273	1				
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001					
Frequency	0.1178	0.0057	-0.0149	0.0093	0.0640	0.0152	-0.0134	1			
	<.0001	0.0032	<.0001	<.0001	<.0001	<.0001	<.0001				
PriorAccuracy	0.1285	0.0134	0.0136	0.0187	0.0247	-0.0046	-0.0228	0.0440	1		
	<.0001	<.0001	<.0001	<.0001	<.0001	0.0180	<.0001	<.0001			
Horizon	-0.1748	0.0279	0.0238	0.0159	0.0313	0.0137	0.0361	-0.2836	-0.0026	1	
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.1857		
DaysElapsed	-0.0257	-0.0932	0.1388	0.0700	0.0373	0.0513	0.0414	0.1121	-0.0301	-0.1721	1
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	

Table 3.5

The Impact of Reg FD on the Association between the Frequency of Extreme Earnings Forecasts and Forecast Accuracy

$$Accuracy_{i,j,t} = \beta_0 + \beta_1 PertEXT_{i,j,t} + \beta_2 DRegFD_t + \beta_3(PertEXT_{i,j,t} * DRegFD) + \beta_4 GExp_{i,j,t} + \beta_5 FExp_{i,j,t} + \beta_6 Bsize_{i,j,t} + \beta_7 NFirm_{i,j,t} + \beta_8 NInd_{i,j,t} + \beta_9 Frequency_{i,j,t} + \beta_{10} PriorAccuracy_{i,j,t} + \beta_{11} Horizon_{i,j,t} + \beta_{12} DaysElapsed_{i,j,t} + \nu_{i,j,t}$$

VARIABLES	**Pre-RegFD**	**Post-RegFD**	**Full Sample**
PertEXT	0.055***	-0.051***	0.056***
	(<0.01)	(<0.01)	(<0.01)
DRegFD			0.054***
			(<0.01)
PertEXT * DRegFD			-0.107***
			(<0.01)
GExp	0.043***	0.012**	0.023***
	(<0.01)	(0.01)	(<0.01)
FExp	0.032***	0.017***	0.022***
	(<0.01)	(<0.01)	(<0.01)
Bsize	0.060***	-0.009*	0.013
	(<0.01)	(0.08)	(0.13)
NFirm	-0.010*	0.024***	0.013***
	(0.07)	(<0.01)	(<0.01)
NInd	0.006	-0.011**	-0.007*
	(0.18)	(0.03)	(0.06)
Frequency	0.090***	0.058***	0.069***
	(<0.01)	(<0.01)	(<0.01)
PriorAccuracy	0.118***	0.116***	0.118***
	(<0.01)	(<0.01)	(<0.01)
Horizon	-0.154***	-0.164***	-0.160***
	(<0.01)	(<0.01)	(<0.01)
DaysElapsed	-0.036***	-0.075***	-0.063***
	(<0.01)	(<0.01)	(<0.01)
Constant	0.494***	0.618***	0.542***
	(<0.01)	(<0.01)	(<0.01)
Joint Test:			
PertEXT + PertEXT * DRegFD			-0.051***
			(<0.01)
Observations	77,239	176,566	253,805
R-squared	0.061	0.058	0.059
Adj R-square	0.061	0.057	0.058

p-values reported in parentheses are based on firm and year clustered standard errors. Notations ***, **, and * indicate significance at 1, 5, 10 percent significance levels, respectively. See Table 3.1 for detail variable definitions.

Table 3.6

The Impact of Reg FD on the Association between the Frequency of Extreme Earnings Forecasts and Forecast Accuracy conditional on Forecast Dispersion

Panel A: Pre-Reg FD period (1993 – 1999)

$$Accuracy_{i,j,t} = \beta_0 + \beta_1 PertEXT_{i,j,t} + \beta_2 DDisp_{j,t} + \beta_3(PertEXT_{i,j,t} * DDisp_{j,t}) + \beta_4 GExp_{i,j,t} + \beta_5 FExp_{i,j,t} + \beta_6 Bsize_{i,j,t} + \beta_7 NFirm_{i,j,t} + \beta_8 NInd_{i,j,t} + \beta_9 Frequency_{i,j,t} + \beta_{10} PriorAccuracy_{i,j,t} + \beta_{11} Horizon_{i,j,t} + \beta_{12} DaysElapsed_{i,j,t} + \nu_{i,j,t}$$

VARIABLES (**Pre-RegFD**)	Low Dispersion	High Dispersion	Full Sample
PertEXT	0.037**	0.040***	0.030**
	(0.01)	(<0.01)	(0.03)
DDisp			0.073***
			(<0.01)
PertEXT * DDisp			0.003
			(0.78)
GExp	0.012	0.022*	0.021***
	(0.10)	(0.06)	(<0.01)
FExp	0.038***	0.004	0.019***
	(<0.01)	(0.59)	(<0.01)
Bsize	0.002	0.038***	0.022***
	(0.76)	(<0.01)	(<0.01)
NFirm	-0.032***	-0.015	-0.022***
	(<0.01)	(0.13)	(<0.01)
NInd	-0.020***	-0.007	-0.019***
	(<0.01)	(0.53)	(<0.01)
Frequency	0.028***	0.073***	0.056***
	(<0.01)	(<0.01)	(<0.01)
PriorAccuracy	0.088***	0.070***	0.079***
	(<0.01)	(<0.01)	(<0.01)
Horizon	-0.121***	-0.305***	-0.220***
	(<0.01)	(<0.01)	(<0.01)
DaysElapsed	-0.074***	-0.071***	-0.076***
	(<0.01)	(<0.01)	(<0.01)
Constant	0.556***	0.686***	0.588***
	(<0.01)	(<0.01)	(<0.01)
Joint Test:			
PertEXT + PertEXT * DRegFD			0.033**
			(<0.01)
Observations	25,400	24,612	56,569
R-squared	0.031	0.118	0.078
Adj R-square	0.031	0.118	0.078

p-values reported in parentheses are based on firm and year clustered standard errors. Notations ***, **, and * indicate significance at 1, 5, 10 percent significance levels, respectively. See Table 3.1 for detail variable definitions.

Panel B: Post-Reg FD period (2001 – 2011)

$$Accuracy_{i,j,t} = \beta_0 + \beta_1 PertEXT_{i,j,t} + \beta_2 DDisp_{j,t} + \beta_3 (PertEXT_{i,j,t} * DDisp_{j,t}) + \beta_4 GExp_{i,j,t} + \beta_5 FExp_{i,j,t} + \beta_6 Bsize_{i,j,t} + \beta_7 NFirm_{i,j,t} + \beta_8 NInd_{i,j,t} + \beta_9 Frequency_{i,j,t} + \beta_{10} PriorAccuracy_{i,j,t} + \beta_{11} Horizon_{i,j,t} + \beta_{12} DaysElapsed_{i,j,t} + \nu_{i,j,t}$$

VARIABLES (**Post-RegFD)**	Low Dispersion	High Dispersion	Full Sample
PertEXT	-0.040***	-0.076***	-0.038***
	(<0.01)	(<0.01)	(<0.01)
DDisp			0.090***
			(<0.01)
PertEXT * DDisp			-0.040***
			(<0.01)
GExp	0.001	0.018*	0.009*
	(0.87)	(0.07)	(0.07)
FExp	0.008*	0.011	0.010**
	(0.09)	(0.12)	(0.05)
Bsize	-0.003	-0.028***	-0.016***
	(0.42)	(<0.01)	(<0.01)
NFirm	-0.004	0.026***	0.012***
	(0.58)	(<0.01)	(<0.01)
NInd	-0.019***	-0.007	-0.014***
	(<0.01)	(0.12)	(<0.01)
Frequency	0.022***	0.063***	0.046***
	(0.01)	(<0.01)	(<0.01)
PriorAccuracy	0.080***	0.116***	0.098***
	(<0.01)	(<0.01)	(<0.01)
Horizon	-0.108***	-0.244***	-0.172***
	(<0.01)	(<0.01)	(<0.01)
DaysElapsed	-0.075***	-0.088***	-0.082***
	(<0.01)	(<0.01)	(<0.01)
Constant	0.603***	0.702***	0.607***
	(<0.01)	(<0.01)	(<0.01)
Joint Test:			
PertEXT + PertEXT * DDisp			-0.078***
			(<0.01)
Observations	59,691	55,993	115,684
R-squared	0.026	0.103	0.070
Adj R-square	0.026	0.103	0.070

p-values reported in parentheses are based on firm and year clustered standard errors. Notations ***, **, and * indicate significance at 1, 5, 10 percent significance levels, respectively. See Table 3.1 for detail variable definitions.

Panel C: The Impact of Reg FD in Low and High Level of Forecast Dispersion

$$Accuracy_{i,j,t} = \beta_0 + \beta_1 PertEXT_{i,j,t} + \beta_2 DRegFD_t + \beta_3(PertEXT_{i,j,t} * DRegFD) + \beta_4 GExp_{i,j,t} + \beta_5 FExp_{i,j,t} + \beta_6 Bsize_{i,j,t} + \beta_7 NFirm_{i,j,t} + \beta_8 NInd_{i,j,t} + \beta_9 Frequency_{i,j,t} + \beta_{10} PriorAccuracy_{i,j,t} + \beta_{11} Horizon_{i,j,t} + \beta_{12} DaysElapsed_{i,j,t} + \nu_{i,j,t}$$

VARIABLES	**Low Dispersion**	**High Dispersion**
PertEXT	0.037***	0.042***
	(0.01)	(<0.01)
DRegFD	0.038***	0.048***
	(<0.01)	(<0.01)
PertEXT * DRegFD	-0.077***	-0.117***
	(<0.01)	(<0.01)
GExp	0.005	0.020***
	(0.22)	(0.01)
FExp	0.018***	0.009*
	(<0.01)	(0.10)
Bsize	-0.001	-0.007
	(0.76)	(0.44)
NFirm	-0.013**	0.012
	(0.05)	(0.10)
NInd	-0.020***	-0.009**
	(<0.01)	(0.03)
Frequency	0.024***	0.066***
	(<0.01)	(<0.01)
PriorAccuracy	0.083***	0.102***
	(<0.01)	(<0.01)
Horizon	-0.112***	-0.262***
	(<0.01)	(<0.01)
DaysElapsed	-0.076***	-0.083***
	(<0.01)	(<0.01)
Constant	0.563***	0.666***
	(<0.01)	(<0.01)
Joint Test:		
Diff [(*Low Dispersion:* PertEXT+PertEXT*DRegFD) – (*High Dispersion:* PertEXT+PertEXT*DRegFD)]		-0.035***
		(<0.01)
Observations	85,091	80,605
R-squared	0.028	0.106
Adj R-square	0.028	0.106

p-values reported in parentheses are based on firm and year clustered standard errors. Notations ***, **, and * indicate significance at 1, 5, 10 percent significance levels, respectively. See Table 3.1 for detail variable definitions.

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