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Three Essays on Financial Intermediation

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Summary

Financial intermediation plays a central role in connecting capital demanders, i. e. firms, and capital suppliers, i. e. investors. My essays focus on two types of financial intermediaries, namely investment banks, who provide a variety of services for firms and institutional investors, and sell-side security analysts, who analyze and provide information about firms, mainly, to institutional investors. The first essay studies security analysts' cognitive biases in issuing earnings forecasts; the second essay studies analysts' capital expenditure forecasts; and, the third essay studies the underwriting relationship value between investment banks and their client firms.

The first chapter studies how sell-side security analysts are exposed to cognitive biases, specifically belief-persistence and overconfidence biases, and how investors respond to these biases. The belief-persistence bias is analysts' tendency to stick to their prior beliefs. The overconfidence bias is analysts' tendency to overvalue their private information compared to public information (Chen & Jiang 2006). In addition, I propose that analysts' overconfidence bias is more severe when their private information is supported by their prior beliefs. The sensitivity of analysts' overconfidence bias to the consistency between their private information and their prior forecasts is called confidence-enhancement bias. This study makes two contributions. First, it contributes evidences of overconfidence, belief-persistence, and confidence-enhancement biases of securities analysts by analyzing these biases simultaneously. Second, it shows that investors react negatively to analysts' cognitive biases, and suggests that the market demands objective analysts.

To capture the biases, I examine how analysts' earnings forecast formation, which is the incorporation of public information, their private information and their prior earnings forecasts, deviate from the suggestions of the Bayesian decision theory. Public information is measured as the consensus of all outstanding forecasts. A belief-persistence-bias-free analyst would put no additional weight on her prior forecast because the information content of her prior forecast has been incorporated in the consensus. An overconfidence-bias-free analyst would put optimal weights on the public and their private information depending on the information precision. I examine the sample of analysts' annual earnings forecasts in the US market from 1994 to 2010, and find that analysts are subject to these biases. Analysts put an additional weight of 55% instead of 0% on their prior forecasts. Analysts' overconfidence bias, which is measured as the fraction of the difference between real weight and the optimal weight over the real weight on the private information, is 53%

instead of 0%. Analysts' confidence-enhancement bias, the difference in overconfidence bias between supported and unsupported private information, is 15%.

To study the effects of these biases on forecast informativeness, I regress stock abnormal returns around the forecast announcements on forecast deviations from the prior forecasts and the interaction between the forecast revisions and analysts' biases in the previous years. I find that the market reacts more strongly to less overconfident analysts; the difference in forecast informativeness between bottom and top overconfidence bias quintiles is 18% of the average forecast informativeness. The market also reacts more strongly to analysts who are exposed less to the belief-persistence and confidence-enhancement biases. The difference in forecast informativeness between bottom and top belief-persistence (and confidence-enhancement) bias quintiles is around 9% (and 8%) of the average forecast informativeness.

The second chapter studies analysts' capital expenditure (CapEx) forecasts addressing four principal questions: Do CapEx forecasts improve information content of analysts' reports? Which analysts are more likely to issue CapEx forecasts? What are the determinants of CapEx forecast accuracy? And, are CapEx forecasts related to analysts' careers? CapEx forecasts have been overlooked by the academic community despite the fact that CapEx forecasts have become increasingly popular among analysts; in 2011, 57% of analysts issued at least one CapEx forecast on 70% of covered firms. In addition, there exists an extensive literature studying the relationship between managers' CapEx decisions and firm values, which suggests that CapEx information is valuable to investors. Although the direction of the relationship between changes in firm investment levels and changes in firm value is inconclusive, the effects of the firm's investment level on firm value are certain.

First, to assess the information value of CapEx forecasts, I study stock price behavior around analysts' forecasts. I run regressions using forecast informativeness, which is defined as the absolute value of stock cumulative abnormal returns around analysts' report announcements, as the dependent variable. The independent variables are the CapEx forecast dummy variable, the relative CapEx forecast accuracy variable, and control variables. I find that CapEx forecasts significantly improve the reports' information value, and more accurate CapEx forecasts are more valuable to investors than less accurate ones.

Second, I use logistic regression, controlling for firm-year fixed effects, to identify which analysts are more likely to issue CapEx forecasts. I find that frequency of CapEx forecasts is related to certain conditions. Analysts with less experience and working for brokers where issuing CapEx forecasts is a common practice, may have more motivation to issue CapEx forecasts. Working for big brokers, performing well in earnings forecasts, and being voted as star analysts may reduce an analyst's costs of CapEx forecast issuance. Finally, analysts covering fewer stocks and issuing more earnings forecasts on a stock may have more resources allocated to the stock.

Third, similar to earnings forecasts, CapEx forecasts that are issued later in the forecasting period are more accurate than those issued earlier. CapEx forecast accuracy is positively correlated with prior CapEx forecast accuracy, and the analyst' CapEx forecasting experience. In addition, I do not find a robust relationship between CapEx forecast accuracy and contemporary earnings forecast accuracy; the two types of forecasts may require different skills.

Fourth, I use logistic regressions to study the probability of analysts' disappearance from the I/B/E/S database in the following year, and find that analysts, who issue CapEx forecasts, are less likely to leave the profession, and more accurate CapEx forecasters are less likely to leave the profession than less accurate CapEx forecasters.

The third chapter studies the underwriting relationship value between investment banks and their clients. I re-examine the usage of Lehman's collapse on the 15th of September, 2008, to measure the underwriting relationship value, as proposed by Fernando, May, & Megginson (FMM hereafter) in the Journal of Finance (2012). The authors argue that Lehman's clients experienced abnormal returns of nearly 3% below those of other big banks' clients in the seven day period around Lehman's collapse because of the lost underwriting relationship value.

I have three concerns about their methodology. First, Lehman's collapse was not simply a shock to the underwriting industry; it was a shock to the whole economy. There were also other noticeable events around the collapse, e. g. Bank of America's acquisition of Merrill Lynch on the same day and American International Group (AIG)'s credit rating downgrade the day after. Second, firms with different characteristics were affected differently by Lehman's collapse and other events around the collapse. I find that the collapse mostly affected small, young, high market-to-book ratio, and potentially distressed firms, and specific industries. Third, there is a hidden assumption behind FMM's methodology that Lehman's clients and other big banks' clients were similarly affected by the collapse, except that Lehman's clients had additional effects because of their lost underwriting relationship. However, I find that Lehman's clients, on average, were from more severely affected industries compared to the clients of other big banks. Lehman's clients were significantly bigger, younger, more leveraged and closer to potential distress than other big banks' clients.

To measure the marginal effect of being a Lehman client on the firm' stock price reaction to Lehman's collapse, I run ordinary least squared regressions on all the big banks' clients sub-sample. I find that it is invalid to reject the null hypothesis, namely that being a Lehman client has no marginal effect on the stock price reaction to Lehman's collapse. The marginal effect of being a Lehman client drops from -2.7% to -0.9% (i. e. insignificant) after controlling for industry abnormal returns around the collapse, and to -0.3% (i. e. insignificant) after controlling for industry abnormal returns around Lehman's collapse and firm characteristics. To avoid endogeneity issues, the industry abnormal returns are calculated from the abnormal returns of firms, which were neither clients of Lehman nor clients of other big banks.

There are four possible explanations for my finding. First, the underwriting relationship value is minimal. Second, the underwriting relationship value is significant but very short-lived. Third, investment banks have stronger bargaining power, and capture most of the underwriting relationship value. Fourth, the underwriting relationship value between Lehman and its clients might not have been destroyed by the collapse because Lehman's investment banking division was likely to be acquired by other banks. In fact, Barclays declared its interest for Lehman's investment banking division immediately after the collapse.

In conclusion, the first essay shows that sell-side security analysts are subject to overconfidence, confidence-enhancement and belief-persistence biases, while the market demands bias-free analysts. The second paper suggests that capital expenditure (CapEx) forecasts are informative, but costly. Therefore, analysts' motivation and issuing costs affect their decisions to issue capital expenditure forecasts. CapEx issuance and accuracy also reduce the chance of being terminated from the analyst profession. The third paper discards the finding of Fernando et al. (2012) by showing that being a Lehman's equity underwriting client has insignificant marginal effects on the stock price reaction to Lehman's collapse. My essays urge further research on the real effects of analysts' biases, the under-explored area of analysts' CapEx forecasts, and the inconclusive existence of the underwriting relationship value.

Chapter I: Analysts' Cognitive Biases in Earnings Forecasts & Market Response

This paper studies how sell-side security analysts are exposed to cognitive biases, specifically belief-persistence and overconfidence biases, and how investors respond to these biases. My findings suggest the following scenario: Analysts tend to give earnings forecasts close to their prior forecasts on the firms (i. e. belief-persistence bias). At the same time, analysts tend to deviate from the consensus by overweighting the private information (i. e. overconfidence bias). The tendency to deviate from the consensus is stronger when the private information is supported by their prior forecasts (i. e. confidence-enhancement bias). The belief-persistence bias is sensitive to the time distance from the forecast announcement to the earnings announcement, while, the confidence-enhancement bias is sensitive to the dispersion of the public information's constituents. The investors penalize analysts' biases by reacting less strongly to forecasts issued by analysts with higher biases in the previous year. Additionally, I demonstrate that the overconfidence bias is conceptually and empirically distinct from the forecast boldness (i. e. the absolute distance between the forecast and the consensus).

JEL classification: G02, G24

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1 Introduction

Earnings forecasting is one of the main services that sell-side security analysts, who are informational intermediaries between firms and investors, provide to investors. Security analysts collect information from different sources, carry out research, and produce earnings forecasts over the year. Investors expect analysts to give objective and accurate forecasts; however, the forecasts are distorted by analysts' cognitive biases. The biases could be unconsciously controlled by human psychology or motivated by analysts' strategies, e. g. pleasing the firms' managers to gain more informational access or signaling superior ability to gain more recognition[1]. Overconfidence bias, i. e. an analyst believes her information or ability is superior to others, could be the most prominent bias affecting analysts' behavior (Bondt & Thaler 1990). In my paper, the overconfidence bias is

[1] (Lim 2001; Chen & Matsumoto 2006; Ke & Yu 2006; Libby et al. 2007; Jackson 2005)

analysts' tendency to overvalue their private information to the public information and to deviate from the consensus. Another noticeable bias of analysts is belief-persistence bias, which is the tendency for prior beliefs to persist. Prior research documents that financial analysts, as human beings, are subject to these biases[2].

In this paper, I examine these biases by observing how analysts incorporate the public information, private information and their prior earnings forecasts to form their current earnings forecasts. In addition, I study the effects of analysts' overconfidence and belief-persistence biases on the informativeness of earnings forecasts (i. e. the stock price reactions to the forecasts). From the investors' perspective, the biases distort the objectiveness of the forecasts. I conjecture that higher biases are likely to be associated with lower ability, lower trustworthiness and, therefore, lower market reaction to earnings forecasts.

Chen and Jiang (2006) use Bayesian decision theory to examine the overconfidence bias, based on the relationship between real weights and optimal weights that analysts split between public and private information. An analyst is subject to the overconfidence bias if she puts too much weight on her private information than she should do, according to the Bayesian decision theory. Their methodology, not only compares the optimal weights and the real weights that analysts put on the private information, but also discriminates analysts' forecast behavior and information precision. The scenario in their paper is that an analyst is giving out an earnings forecast on a firm based on the public information reflected in the consensus of all outstanding forecasts and her private information, which is not a part of the consensus. My research adopts Chen and Jiang's scenario with a modification. An analyst is giving out an earnings forecast revision, not only based on the public and her private information, but also on her prior beliefs, reflected in her prior forecast on the firm in the same fiscal year. An analyst is subject to the belief-persistence bias if the prior forecast heavily influences the current forecast.

The theoretical and empirical disentangling of the biases presents several challenges. There are many causes leading to analysts' belief-persistence bias, such as cognitive dissonance and strategic optimism, and one of those is overconfidence (Nickerson 1998). An analyst may be overconfident on the precision and accuracy of her prior forecast and believes that the prior forecast contains more information than it is recognized by the public (*ex-ante*). Consequently, she assigns too heavy of a

[2] (Chen & Jiang 2006; Friesen & Weller 2006; Yezegel 2014)

weight on the prior forecast to form the current forecast. I separate these two biases based on an arbitrary assumption that the information contained in the prior forecast is public, i. e. the consensus contains all the information of the prior forecast. Therefore, any additional weight that an analyst puts on the prior forecast is evidence of the belief-persistence bias (Lingle & Ostrom 1981; Sherman & Zehner 1983). This belief-persistence bias is either from *ex-ante* reasons (e. g. unconscious desires to confirm her prior belief or persistently following an optimistic/pessimistic strategy) or *ex-post* reasons (e. g. tendency to search, collect, and over value the information supporting her prior belief or ignore information opposing to her prior belief). The belief-persistence bias is close to the anchoring effect, with the anchor being the prior forecast. Friesen & Weller (2006) add analysts' previous year optimism/pessimism into the Chen and Jiang's scenario, and find evidence of the belief-persistence bias; more optimistic/pessimistic analysts last year tend to be more optimistic/pessimistic this year. Their result predicts that an analyst, in my scenario, puts an additional weight on her prior forecast.

In my model, analysts' forecasts are balanced between three factors: the rational combination of the public and private information, the tendency to keep the forecast close to the prior forecast (i. e. belief-persistence bias), and the tendency to deviate from the consensus (i. e. overconfidence bias). In addition, I propose that the tendency to deviate from the consensus will be stronger if the analyst receives some confidence boost. The agreement between the prior forecast and the private information could provide this confidence boost; as a consequence the analyst would become even more overconfident on her private information, if her private information is supported by her prior forecast (Pyszczynski & Greenberg 1987). This bias is called "*confidence-enhancement bias*", and by definition, the confidence-enhancement bias is an add-on to the overconfidence bias. The confidence-enhancement bias can be viewed as one type of the belief-persistence bias; analysts put more weight on the private information if it is consistent with their prior beliefs. However, it is distinguished from the belief-persistence bias. The prior belief in the belief-persistence bias is the prior forecast, and the belief-persistence bias pulls the current forecast closer to the prior forecast. On the other hand, the prior belief in the confidence-enhancement bias is whether the prior forecast is greater or smaller than the current consensus. I predict that the confidence-enhancement bias will pull the forecasts away from the consensus if the private information is supported by the prior belief.

The analyst's perceived significance of private and public information can also be affected by the belief-persistence bias because she pays more attention on information which is closer to her prior forecast. To simplify, I assume that the effects of the belief-persistence bias, on the collecting and processing information to achieve the private information and the consensus, are implied in the weight put on the prior forecast. The question becomes: How do the belief-persistence, overconfidence, and confidence-enhancement biases affect the weight splitting over the consensus, private information and the prior forecast? The belief-persistence is the misweighting behavior between the prior forecast and the combination of the public and private information. The overconfidence bias is the misweighting behavior between the public and the private information. The confidence-enhancement bias is how the agreement between the prior forecast and the private information affect the weighting behavior between the public and private information. The private information supports her prior belief if both private information and prior forecast are higher or lower than the consensus of available forecasts. The private information opposes her prior belief if one of the two is higher than the consensus and the other is lower than the consensus.

I examine earnings forecasts issued by security analysts from year 1994 to 2010 and have following findings on the existence of overconfidence and belief-persistence biases. Firstly, analysts are exposed to the belief-persistence bias by putting a weight of 55% instead of 0% on her prior forecast to form the current forecast. Secondly, analysts have average overconfidence bias of 53%. The overconfidence bias is defined as the fraction of the real weight subtracted by the optimal weight, over the real weight on the private information. The difference in overweighting between positive and negative private information is 26% (i. e. smaller than 53%), which suggests that analysts are overconfident toward both positive and negative private information. Chen and Jiang do not control for the prior forecast and document that analysts overweight positive private information and underweight negative private information.

There is evidence of belief-persistence-enhancement bias, that the difference in overconfidence bias between supporting forecasts and opposing forecasts is about 15% of the average overconfidence bias. *Supporting forecasts* are forecasts on the same side with prior forecasts with respect to the consensuses, and *opposing forecasts* are forecasts on the opposite side. While the belief-persistence bias is sensitive to the forecasting horizon (i. e. the distance from the forecast to the earnings announcement date), the confidence-enhancement bias is sensitive to the dispersion among outstanding forecasts. There is little information and few forecasts constituting the consensus at the beginning of the forecasting period. An analyst has more room to fulfill her confirmative desire since she can unwind this bias in the future revisions; therefore she tends to stick to her prior belief. On the other hand, a high dispersion within the consensus suggests that analysts are receiving different private information. In that chaos, an analyst has higher demand for the verification of her private information, and the prior forecast becomes more salient to the analyst's confidence in her private information.

My research shows that there is no significant relationship between the belief-persistence bias and analyst's prior accuracy. Capable analysts may have ability to detect unconscious biases, and unwind these biases. In addition, analysts who pursue forecast accuracy put effort to eliminate biases for more accurate forecasts. These capable analysts, however, may become overconfident on their prior forecasts and supporting private information, which increases the belief-persistence bias. Additionally, I document no robust relationships between the belief-persistence bias and other analyst characteristics, such as historical boldness, All-America status, experience, coverage breadth, and size of the brokerage house.

To study the effects of overconfidence, belief-persistence, and confidence-enhancement biases on forecast informativeness (i. e. the reaction of the market around the forecast issuances), I regress three-day buy-and-hold market adjusted abnormal returns around the forecast announcements on forecast deviations from the prior forecast and the interactions between the forecast revisions and analysts' biases in the previous years[3]. The estimated coefficient of the deviation measure the informativeness of the forecasts and the estimated coefficients of the interactions measure how much the previous cognitive biases affect the current forecast informativeness. I measure an analyst's biases in a year from all forecasts issued by the analyst during the year.

I examine the effect of the biases on the earnings forecast informativeness over the period from year 1994 to 2010. I find that market reacts more strongly to less overconfident analysts. The difference in informativeness between bottom and top overconfidence bias quintiles is around 18% of the average informativeness. The overconfidence bias is distinguished from the forecast boldness (i. e. absolute deviation from the consensus). The boldness measurement contains both actual private information and overconfidence bias. An analyst tends to give more bold forecasts if her private information is either reliable or significantly different from the public information. She also tends to give more aggressive revisions if she is subject to the overconfidence bias. I find that analysts' historical boldness increases the market reactions to their forecasts, which implies that investors

[3] (Park & Stice 2000; Clement & Tse 2003; Hilary & Hsu 2013)

appreciate the underlying quality of the bold forecasts more than the risk of the overconfidence bias in those forecasts.

I also find that the market reacts more strongly to analysts exposed less to the belief-persistence and confidence-enhancement biases, although the effects are weaker than the effect of overconfidence bias. The difference in informativeness between bottom and top belief-persistence (and confidence-enhancement) bias quintiles is around 9% (and 8%) of the average informativeness. The effects of the overconfidence and belief-persistence biases on forecast informativeness are even higher than the effect of previous firm-specific accuracy. The market's negative reactions to analysts' cognitive biases suggest that the market demands objective analysts. Investors can recognize the existence of these biases, but they are unable to fully relax the analysts' cognitive biases from the forecasts to obtain the true underlying forecasts; therefore, they undervalue forecasts given by analysts with high biases. The biases also signal low ability to incorporate different information to produce accurate forecasts.

My paper contributes to both psychological and behavioral financial literature. The extant psychological literature documents the belief-persistence bias in a number of professions, such as politics, medicine, and science (Nickerson 1998); however, the belief-persistence bias is not adequately explored in the security analysts setting. . Behavioral financial research mainly focuses on analysts' other biases including optimism[4], overreaction/ underreaction[5], and herding[6] biases. My study contributes evidence of overconfidence, belief-persistence, and confidence-enhancement biases of security analysts by analyzing these biases simultaneously. This paper also contributes to the literature on investors' reactions to security analysts' biases. The rest of the paper is organized as follows. Section 2 studies the existence and properties of the belief-persistence bias. Section 3 studies the relationship between analysts' overconfidence and belief-persistence biases and informativeness of earnings forecasts. I offer concluding remarks in section 4.

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[4] (Butler & Lang 1991; Sinha et al. 1997; Lin & McNichols 1998; Easterwood & Nutt 1999; Lim 2001; Matsumoto 2002; Hong & Kubik 2003; Chen & Matsumoto 2006; Ke & Yu 2006; Libby et al. 2007)

[5] (Bondt & Thaler 1990; Abarbanell & Bernard 1992; Amir & Ganzach 1998; Hilary & Menzly 2006; Gu & Xue 2007)

[6] (Trueman 1994; Hong, Kubik, et al. 2000; Welch 2000; Clement & Tse 2005; Jegadeesh & Kim 2010)

2 Analysts' Cognitive Biases

2.1 Literature Review and Hypotheses Development

Belief-persistence bias happens when a person acquires information over time, and when she tends to put too much weight on the prior information and is reluctant to modify the belief formed earlier (Freedman 1965; Lingle & Ostrom 1981). Belief-persistence bias is one specific case of confirmation bias. In general, the confirmation bias is the tendency that a person has to unintentionally or intentionally prefer information supporting her favored hypotheses or beliefs. A person with confirmation bias tends to find or limit her attention to information supporting her favored hypotheses, and neglects the information supporting alternative possibilities (Koriat et al. 1980; Lingle & Ostrom 1981). She has greater preference and puts more weight on favored information. She requires less evidence to accept and more evidence to reject a favored hypothesis (Pyszczynski & Greenberg 1987).

Although having been extensively studied by philosophers and psychologists, the confirmation bias attracted the interest of the behavioral financial researchers only in the last few decades. In finance, the belief-persistence bias is usually referred to as overconfidence (in prior believes) and conservatism behaviors (Edwards 1982); however, the extant literature mainly focuses on the behavior of investors. The conservatism is consistent with the under-reaction behavior of investors (Fama 1998; Barberis et al. 1998). Investors overestimate precision of private information (i. e. become overconfident) when the public information confirms their prior trades (Daniel et al. 1998). There are few papers examining how security analysts are exposed to the confirmation bias.

Although financial analysts require a great degree of objectiveness, there is no guarantee that analysts are free from the belief-persistence bias. Therefore I would like to validate, under my specific setting that the prior beliefs are reflected in the analysts' prior forecasts, whether analysts are affected by the belief-persistence bias in issuing earnings forecasts. Because analysts acquire information over forecasting period, therefore, I study the belief-persistence bias that analysts tend to put too much weight on their prior forecast and are reluctant to deviate from their prior forecasts.

Hypothesis 1: *Security analysts are subject to the belief-persistence bias by putting too much weight on their prior firm earnings' forecasts.*

Consistent with prior research, I would expect that analysts rely on their prior forecasts too much, while making their current forecasts. Friesen & Weller (2006) find that analysts who were more optimistic (pessimistic) in the previous year tend to be more optimistic (pessimistic) this year. Yezegel (2014) finds that security analysts are affected by the belief-persistence bias by examining analysts' recommendation revisions following quarterly earnings announcements based on the earnings surprise with respect to the consensus of the outstanding forecasts and their prior forecasts. The author states that an analyst puts less weight on the consensus earnings surprise if the reported earnings confirm her prior recommendation.

Chen and Jiang (2006) study how analysts misweight their private information and find that analysts overweight positive private information (i. e. overconfident) and underweight negative private information (i. e. under-confident). On average, they find insignificant misweighting behavior. I would like to reexamine their findings in the presence of belief-persistence bias.

Hypothesis 2: *Security analysts are subject to the overconfidence bias by overweighting their private information.*

Analysts' weighting behavior between their private information and the public information is influenced by external factors, e. g. Chen and Jiang finds that analysts overweight positive private information than negative private information. I conjecture that analysts prefer to deviate from the consensus to signal that they have more information or higher researching ability; therefore, they will overweight the private information more if it has higher validity. Being supported by the prior forecast is a justification for the private forecast, and analysts tend to be more confident on their supported private information. This argument is the basis for the third hypothesis.

Hypothesis 3*: Security analysts are subject to the confidence-enhancement bias by being more confident on private information which is supported by their prior forecasts and less confident on the private information which is not supported by their prior forecasts.*

If the belief-persistence bias exists, I would like to discover factors which influence the belief-persistence bias. Griffin & Tversky (1992) argue that people make decisions based on the strength (extremeness) and weight (predictive validity) of the information. Ones tend to focus on the strength and have insufficient adjustment for the weight. At the beginning of the forecasting period, an analyst tends to be more confident on her prior judgment (i. e. the belief-persistence is stronger) because the strength is high and the weight is low. Desiring to confirm the prior belief, an analyst tends to do that earlier than later during the forecasting period because she has more time to reverse her opinion, if necessary.

Hypothesis 4: *Belief-persistence bias is stronger at the beginning than at the end of the forecasting period.*

When there is high dispersion among outstanding forecasts, analysts are accessing different information or interpreting the information differently. In that confusion, an analyst may wish to find justification for her private information, and the prior forecasts may become more important to her confidence in her private information. Therefore, I would like to validate the following hypothesis.

Hypothesis 5: *Confidence-enhancement bias is stronger when there is higher dispersion among analysts.*

2.2 Testing Methodology

I adopt the Bayesian framework used by Chen and Jiang. At time $\tau - 1$, an analyst gave a forecast of $f_{\tau-1}$ for a firm's earnings (denoted as z). At time τ, she revises her forecast based on the public information contained in the consensus of outstanding forecasts of all analysts including her (denoted as c) and her private information (denoted as y) (Figure 1). If she is bias-free, then she puts optimal weights on those two and her forecast will be $f^{Optimal}$. If she is affected by the overconfidence bias, then she put more weight than the optimal weight on her private information, which makes her forecast to be f as demonstrated on Figure 1. If she is subject to the belief-persistence bias and her prior forecast were $f'_{\tau-1}$ instead of $f_{\tau-1}$, she would have been steered toward $f'_{\tau-1}$, and the forecast would have been f' instead of f.

[Insert Figure 1 about here]

Without loss of generality, I assume that z follows a diffuse zero-mean normal distribution, $c = z + \varepsilon_c$ and $y = z + \varepsilon_y$. In which, $\varepsilon_c \sim N\left(0, \frac{1}{p_c}\right)$ and $\varepsilon_y \sim N\left(0, \frac{1}{p_y}\right)$. The precisions of public and private information are p_c and p_y. If she puts optimal weights on those two, which minimize the expected squared distance from the forecast f to the actual firm's earnings z, the forecast will be the expected value of the actual value conditional on the public and private information by the Bayesian rule.

$$f^{Optimal} = (1 - h).c + h.y = E[z|c, y] \qquad (1)$$

In which, $h \equiv \frac{p_y}{p_y+p_c}$[7].

The optimal weights are not always the weights used by the analyst because she may overvalue the precision of her private information or undervalue the precision of the public information. Assuming that she puts a weight of k on her private information, when k is greater than h, the analyst puts too much weight on the private information and vice versa. Her real forecast is:

$$f = (1-k).c + k.y \tag{2}$$

I substitute y from (2) into (1) to obtain:

$$E[z|c,y] = (1-h).c + h.\left[\frac{f-(1-k).c}{k}\right]$$

$$E[z|c,y] = \frac{k-h}{k}.c + \frac{h}{k}.f$$

$$E[(f-z)|c,y] \equiv E[(FE)|c,y] = \frac{k-h}{k}.(f-c) \equiv \alpha_1.Dev \tag{3}$$

In which, $FE = f - z$, $Dev = f - c$, and $\alpha_1 = \frac{k-h}{k}$.

The intuition of this model is that the deviation of the forecast should not have power to predict the ex-post error of the forecast if the analyst acts rationally. The coefficient estimate $\widehat{\alpha_1}$ in the regression $FE = \alpha_1.Dev + \varepsilon$ converges in probability to $\left(\frac{k-h}{k}\right)$. A positive or negative $\widehat{\alpha_1}$ suggests private information overweighting or underweighting. Therefore, it can be used as a measure of the overconfidence bias. The absence of the intercept presumably assumes that there exist only misweighting behavior.

With the present of the belief-persistence bias, an analyst's realized forecast is a combination of the public information *c*, her private information *y* and her prior forecast. The equation (2) becomes $(1+\theta)f = (1-k).c + k.y + \theta.f_{-1}$, in which f_{-1} is her prior forecast and $\theta/(1+\theta)$ measures the weight put on her prior forecast[8]. The equation (3) becomes $E[(FE)|c,y] = \alpha_1.Dev + (1-\alpha_1).\theta.PriorDev$, in which, $DevPrior = f_{-1} - f$. Consequently, the value $\hat{\theta} =$

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[7] Please refer to Appendix A for a proof

[8] Please refer to Appendix B for further explanation

$\widehat{\alpha_2}/(1-\widehat{\alpha_1})$ obtained from the regression $FE = \alpha_0 + \alpha_1.Dev + \alpha_2.DevPrior + \varepsilon$ measures the belief-persistence bias. A bias-free analyst will correctly incorporate her prior forecast with forecasts of other analysts to form the consensus and her α_2 should be zero.

The confidence-enhancement bias proposes that the agreement between $(f-c)$ and $(f_{-1}-c)$ affect the overconfidence bias. Therefore, the interaction term *Dev*×*Confirm* is included in the equation (3), in which, *Confirm* equals 1 if $(f-c)$ and $(f_{-1}-c)$ having the same signs, and equals 0 otherwise. The equation (3) becomes $E[(FE)|c,y] = \alpha.Dev + (1-\alpha).\theta.DevPrior + \beta.Dev.Confirm$. Subsequently, the estimated coefficient $\hat{\beta}$ from the regression $FE = \alpha_0 + \alpha_1.Dev + \alpha_2.DevPrior + \beta.Dev \times Confirm + \varepsilon$ measures the confidence-enhancement bias.

In addition to informational misweighting biases, there are other biases which are independent from the informational weighting behavior. For example, analysts tend to be more optimistic when the dispersion among analyst forecasts is higher than when the dispersion is lower (Ackert & Athanassakos 1997). These biases in combination with misweighting biases form analysts' behavior. Chen and Jiang also mention these biases as the *"added-bias"*, which is subsumed in the intercept. I extend their models further by allowing the intercept to be a function of the financial environment, firm and analyst characteristics. In addition, I assume that the intercept (including the firm-fixed effects) comes from the analysts' bias behaviors, which is called the *"added-bias"*. The models with the "*added-bias*" are not necessary to have the same results as the models without the "*added-bias*". Friesen & Weller (2006) add belief-persistence bias into the model. They measure the analyst's prior belief by her forecast bias in the previous year.

Chen and Jiang also offer a probability test based on the following argument. If an analyst is free from the overconfidence bias, she will be equally likely to overshoot or undershoot the actual value. If she is overconfident, she will be more likely to overshoot when her private information is higher than the consensus and more likely to undershoot when her information is lower than the consensus. The formal formula is: $\mathbf{1}(sign(FE) = sign(Dev)) = \alpha^* + \varepsilon$. I use (*) to distinguish between linear models and logistic models. The estimated coefficient $\widehat{\alpha^*}$ is a measure of overconfidence bias. Even though the argument is valuable, the probability test is valid only when the "*added-bias*" term is not included in the model. When the "*added-bias*" is included, the *FE* in this logistic regression should be deducted by the intercept α in the equation (3). It would be much more complicated to do that when α is a function of other variables. Therefore, I do not perform this probability test in my analysis.

The "*added-bias*" and overconfidence bias are potentially affected by the environmental characteristics and analyst characteristics; therefore, I control for financial environment characteristics and analyst characteristics in both intercept and interaction terms with *Dev*. Firm characteristics are controlled through firm fixed effect, which capture aggregate effects of all firm characteristics on the regressions. I obtain the overconfidence bias and the belief-persistence bias by running the following model. Following Chen and Jiang, I cluster by industry-year to capture the heteroskedasticity among industries.

Model I (OLS Regression with Firm Fixed Effects and Industry-Year Clustering):

$$FE = \alpha_0 + \boldsymbol{\alpha_1 . Dev} + \boldsymbol{\alpha_2 . DevPrior} + A.Controls + \varepsilon$$

In which, *Dev* is the difference between the current forecast and the consensus, *DevPrior* is the difference between the prior forecast and the current forecast, and the "*Controls*" include the distance to earnings announcement (*Horizon*), the dispersion in the consensus (*Dispersion*), the analyst's past accuracy (*ACCURACY*), the analyst's past forecast boldness (*BOLDNESS*), the analyst's All-American status (*STAR*), the analyst's experience (*EXPERIENCE*), number of stocks currently covered by the analyst (*BREADTH*) and size of the analyst's brokerage house (*BROKERSIZE*). The estimated coefficient $\widehat{\alpha_1}$ of *Dev* is the measure for overconfidence bias. A positive $\widehat{\alpha_1}$ suggests overconfidence bias and negative $\widehat{\alpha_1}$ suggests under-confidence bias. Chen and Jiang, and Friesen and Weller suggest a positive $\widehat{\alpha_1}$. The estimation $\hat{\theta} = \widehat{\alpha_2}/(1 - \widehat{\alpha_1})$ measures the belief-persistence bias. Friesen and Weller suggest, and Hypothesis 1 predicts a positive $\hat{\theta}$ and Hypothesis 2 predicts a positive $\widehat{\alpha_1}$.

In order to test the existence of the confidence-enhancement bias (Hypothesis 3), I add the interaction term *Dev*×*Confirm*, along with interaction terms between *Dev* and the "*Controls*", into Model I. In addition, I add the interaction term $Dev \times Positive$ to capture the optimism behavior of the overconfidence bias (Chen & Jiang 2006), in which *Positive* equals 1 if *Dev* is positive and equals 0 otherwise.

Model II (OLS Regression with Firm Fixed Effects and Industry-Year Clustering):

$$FE = \alpha_0 + \alpha_1 . Dev + \alpha_2 . DevPrior + A.Controls + \boldsymbol{\beta_1 . Dev \times Confirm} + \beta_2 . Dev \times Positive + B.Dev \times Controls + \varepsilon$$

In the formula above, the *"Controls"* include *Horizon*, *Dispersion, ACCURACY, BOLDNESS, STAR, EXPERIENCE, BREADTH*, and *BROKERSIZE.* The estimated coefficient $\widehat{\beta_1}$ of the interaction term $Dev \times Confirm$ is a measure of the confidence-enhancement bias. If $\widehat{\beta_1}$ is positive, the overconfidence measures are higher (i. e. the analyst put more weight on the private information) when the private information is supporting her prior belief, and vice versa. Hypothesis 3 predicts a positive $\widehat{\beta_1}$ (i. e. the existence of confidence-enhancement bias on top of the overconfidence bias).

To investigate the relationship between the belief-persistence bias and characteristics (*Horizon, Dispersion,* and *ACCURACY)*, I add the interaction terms between *DevPrior* and $Dev \times Confirm$ with characteristic varibales into Model II.

Model III (OLS Regression with Firm Fixed Effects and Industry-Year Clustering):

$$FE = \alpha_0 + \alpha_1.Dev + \alpha_2.DevPrior + A.Controls + \boldsymbol{B_1.DevPrior} \times \boldsymbol{Controls} + \beta_1.Dev \times Confirm + \beta_2.Dev \times Positive + B_2.Dev \times Controls + \boldsymbol{\Gamma.Dev} \times \boldsymbol{Confirm} \times \boldsymbol{Controls} + \varepsilon$$

In which the Controls includes *Horizon*, *Dispersion, ACCURACY, BOLDNESS, STAR, EXPERIENCE, BREADTH*, and *BROKERSIZE.* I do not separate *Horizon, Dispersion* and *ACCURACY* from the *"Controls"* because the separation causes unnecessary expansion of the regressions' presentation. Hypothesis 4 expects a positive estimated coefficient $\hat{\beta}_{Horizon}$ of the interaction term *DevPrior*×*Horizon*. Hypothesis 5 suggests a positive estimated coefficient $\hat{\gamma}_{Dispersion}$ of the interaction term *Dev*×*Confirm*× *Dispersion.*

2.3 Variables Construction and Data Overview

The dependent variable *FE* stands for "**F**orecast **E**rror", and is defined as the current earnings forecast minus the actual earnings. The key independent variable *Dev* stands for "**Dev**iation from the consensus" and equals to the current forecast minus the current consensus. These variables have unit of $/share. *DevPrior* stands for "**Dev**iation from **Prior** Forecast", and equals to the prior forecast minus the current forecast. *Confirm* equals 1 if the forecast and the analyst's prior forecast are both bigger or both smaller than the consensus and equals 0 otherwise.

The "*Controls"* is a set of financial environment and analyst characteristics at the time of forecasts. *Horizon* is the logarithm of the number of days to the earnings announcements. *Dispersion* is the standard deviation of the forecasts constituting the consensus. This variable measures the degree of agreement among analysts covering the stock at the time of the forecast. $ACCURACY$ is the realized firm-specific accuracy of the analyst in the previous year. It is defined by this equation: $ACCURACY = 1 - (rank(forecast\ absolute\ error) - 1)/(numer\ of\ analysts - 1)$ (Hong and Kubik 2003).*STAR* equals 1 if the analyst is currently voted as an All-American analyst. *EXPERIENCE* is the logarithm of the number of days since her first forecast in I/B/E/S. Finally, *BROKERSIZE* is the logarithm of the number of analysts working for the broker in the current year.

My research uses on analyst forecasts, analyst statuses, and actual earnings per share in the period from 1994 to 2010. The data is obtained from I/B/E/S and collected from Institutional Investors magazines. Since I am interested in the belief-persistence bias, I keep only observations with available prior forecasts. *FE, Dev, DevPrior* and *Dispersion* are suffered from the outlier issue. The range of *FE* is from minus 2 million to 8 million and the range of *Dev* is from minus 5 million to 10 million, which imply there is a high risk of the outlier issue. I winsorize these variables at 1% on both tails to ensure my analysis is not affected by the outliers.

Table 1 presents the descriptive statistics of *FE, Dev, DevPrior, Confirm* and control variables (*ACCURACY, STAR, EXPERIENCE, BROKERSIZE, Dispersion* and *Horizon*) after winsorizing. The final sample includes about 1.1 million of observations. *FE* and *Dev* have ranges of [-1.9; 5.2] and [-1.6; 1.0]. On average, 55% of the revisions are confirmative with the analyst's prior forecasts. This is preliminary evidence of the belief-persistence bias since one would expect an equal chance of obtaining supportive and opposing private information.

[Insert Table 1 about here]

The correlation matrix shows no risk of multicollinearity issue. The correlation between *FE* and *Dev* is approximately equal minus 8%. There are two possible reasons for this: the first reason is that *FE* and *Dev* have V-shaped relationship as documented by Chen and Jiang, the second one is that *FE* and *Dev* are affected by the between-group variation. Figure 2 illustrates how the deviation among groups may distort the correlation between *FE* and *Dev*. In this figure, there are three imaginary firms represented by round, star, and square symbols. Each of them has a positive correlation between *FE* and *Dev*; however, the regression on the pool of uncentered data may end up with a negative correlation as demonstrated. Therefore, the correlation on the pooled sample does not say much about the real correlation between *FE* and *Dev* after controlling for the variance among different firms.

[Insert Figure 2 about here]

The data, actually, urges to control for the variation among firms; Figure 3 illustrates that. This figure presents the overconfidence and belief-persistence bias on the sub-sample of positive and negative *Dev*. The graph on the left is fitted lines from OLS regressions ($FE = \alpha + \beta . Dev + \varepsilon$) on positive and negative *Dev*, and on supporting and opposing forecasts without controlling for firm fixed effects. The graph on the right is fitted lines from the same regressions on the same sub-samples but using centered *FE* and *Dev* at the firm level. The left graph is consistent with one graph presented by Chen and Jiang, and it suggests that analysts are overconfident when *Dev* is positive and underconfident when the *Dev* is negative. Meanwhile, the right graph documents a minimal underconfidence bias in the negative *Dev* sub-sample. Therefore, the data is affected by the between-group variation issue. Additionally, these figures are subject to potential changes after controlling for belief-persistence bias and other control variables.

[Insert Figure 3 about here]

There are two methods to solve this issue: centering variables at the firm level and controlling for firm fixed effects. I adopt the latter one, controlling for firm fixed effects, since it does not only solve the between-group variation issue, but also control for unobservable firm characteristics which may affect the biases. In addition, the fixed effects estimator are consistent, while, centering estimators may produce inconsistent coefficients which lead to incorrect references (Gormley & Matsa 2013)

2.4 Empirical Results

Table 2 demonstrates the existence of the overconfidence and belief-persistence biases. The first column presents results of Model I (i. e. $FE = \alpha_0 + \boldsymbol{\alpha_1 . Dev} + \boldsymbol{\alpha_2 . DevPrior} + A. Controls + \varepsilon$). The estimated coefficients documents the belief-persistence bias of 1.25 (i. e.$\widehat{\alpha_2}/\widehat{\alpha_1}$ or 0.587/(1-0.53)), which means that an analyst puts a weight of 56% (i. e. $1.25/(1 + 1.25)$) on her prior forecast. If she has treated her prior forecast the same as forecasts of other analysts, she would put zero weight on her prior forecast since the consensus has already contained her prior forecast. A positive weight on the prior forecast suggests that the analyst put too much weight on her prior forecast in forming the new forecast. This result supports Hypothesis 1 that analysts are subject to the belief-persistence bias.

[Insert Table 2 about here]

The positive estimated coefficient $\widehat{\alpha_1}$ of the variable *Dev* in Model I suggests that analysts are overconfident. In general, analysts overweight the private information by about 53%. This result supports Hypothesis 2 that analysts are subject to the overconfidence bias. The positive estimated coefficient $\widehat{\beta_2}$ of the interaction term $Dev \times Positive$ in Model II (i. e. $FE = \alpha_0 + \alpha_1.Dev + \alpha_2.DevPrior + A.Controls + \boldsymbol{\beta_1.Dev} \times \boldsymbol{Confirm} + \beta_2.Dev \times Positive + B.Dev \times Controls + \varepsilon$) suggests that analysts optimistically overweight the private information, which is consistent with Chen and Jiang. The difference in overconfidence bias between positive and negative private information is 30%, which is smaller than the average overconfidence bias. Therefore, analysts are overconfident with respect both to negative private information, while Chen and Jiang document a different result, in which analysts are overconfident to positive private information and underconfident to negative private information.

The second column of Table 2 presents results of Model II. The positive estimated coefficient $\widehat{\beta_1}$ of the interaction term *Dev*×*Confirm* suggests that analysts are subject to the confidence-enhancement bias. The confidence-enhancement bias is about 8% which account for 15% (i. e. 0.08/0.53) of the average overconfidence bias. This result is supporting Hypothesis 3 that analysts are affected by the confidence-enhancement bias.

The third column of Table 2 presents results of Model III (i. e. $FE = \alpha_0 + \alpha_1.Dev + \alpha_2.DevPrior + A.Controls + \boldsymbol{B_1.DevPrior} \times \boldsymbol{Controls} + \beta_1.Dev \times Confirm + \beta_2.Dev \times Positive + B_2.Dev \times Controls + \boldsymbol{\Gamma.Dev} \times \boldsymbol{Confirm} \times \boldsymbol{Controls} + \varepsilon$). The positive estimated coefficient of the interaction term $PriorDev \times Horizon$ suggests that the belief-persistence bias is stronger at the beginning of the forecasting period than at the end of the period. The difference in belief-persistence bias between forecasts made at 75 and 25 percentiles of the horizon is about 43% (i. e. 0.27*(5.58 – 4.64)/0.59) of the average belief-persistence bias. This result supports Hypothesis 4. The positive estimated coefficient of the interaction term $Dev \times Confirm \times Dispersion$ suggests that the confidence-enhancement bias is more severe when there is higher dispersion among analysts. The difference in confidence-enhancement bias between forecasts made at 75 and 25 percentiles of the forecast dispersion is also about 30% (i. e. 0.18*(0.16 – 0.03)/0.08) of the average confidence-enhancement bias. This result supports Hypothesis 5.

Finally, the estimated coefficients interactions terms between $DevPrior$, $Dev \times Confirm$, and analysts' characteristic variables reflect the effects of analysts' characteristics on their biases. There are some slightly significant relationships between analysts' characteristics and analysts' biases; however, these relationships are not survived through the robustness checks, and there if no clear theoretical intuition for these relationships. Taking the relationship between analysts' accuracy and belief-persistence bias for an example, a more capable analyst may have ability to recognize the belief-persistence bias within the self and correct it in a rational manner. However, the historical accuracy may create an illusion in the analyst's awareness of the prior forecast's accuracy. Therefore, an analyst who is more accurate in the past may be exposed to the belief-persistence bias more than another analyst who is less accurate in the past.

2.5 Robustness Checks

I perform four robustness checks and the results are summarized in Table 3. Firstly, in the main analysis, I use the forecast error (*FE*), deviation from the consensus (*Dev*), prior forecast deviation (*DevPrior*) and the current forecast dispersion (*Dispersion*) on a "*per share*" basis, and I winsorized those variable at 1% level to solve the heteroskedasticity issue. The differences in number of outstanding shares among firms may be the cause of the issue. I normalize these variables by the stock price to have variables on "*per dollar*" basis by dividing these variables to the stock prices two days before the forecasts. This method may eliminate the variability in the number of shares outstanding, and consequently, reduce the heteroskedasticity. However, the heteroskedasticity issue still remains, and therefore, I winsorize the obtained variables at 1% level. I perform the same analysis and find consistent results. The measures of biases are lower than those in the main analysis. *Horizon* is still the main factor driving belief-persistence bias, while *Dispersion* is the main factor driving confidence-enhancement bias.

[Insert Table 3 about here]

Secondly, Chen and Jiang assign weights on forecasts constituting the consensus proportionally to the inverted time distance to the current moment. Consequently, the time-weighted consensus gets closer to the more current forecasts compared to the equally weighted consensus. They claim that the two measures of the consensus have similar results. I substitute the time-weighted consensus into the equally weighted consensus in the main analysis, and have similar results.

Thirdly, I split the data into two periods: during the boom from 1994 to 2000 (also before the Fair Disclosure Regulations) and during the crises from 2001 to 2010 (also after the Fair Disclosure Regulations). There is no big difference in overconfidence bias between two periods. However, there is an increase in belief-persistence bias during the later period. I conjecture that an analyst gives forecasts based on news collection and news analysis. After the Fair Disclosure Regulations, analysts may emphasize more the news analysis which makes the forecast become more persistent to the prior forecast. Finally, I check whether the fixed effects change the results significantly. I rerun the models in the main analysis without the fixed effects and find that the results are not much different to the main analysis with the firm fixed effects.

3 Analysts' Cognitive Biases and Market's Response

3.1 Literature Review and Hypotheses Development

The information content of the security analysts' reports has been extensively studied. Forecast informativeness is defined as the market's reaction around the forecast announcement in the direction of the forecast revision. Different studies have slightly different definitions of forecast informativeness, e. g. using different window lengths around the forecasts, measuring market reaction per unit or per direction of the deviation, and defining deviation from the prior forecast or from the consensus. The extant literature mostly show positive (negative) abnormal returns for upward (downward) earnings forecast revisions[9]. Stickel (1992) studies the association between forecast informativeness and analysts' status (i. e. analysts who are voted as All-American analysts by institutional investors through surveys conducted by the Institutional Investor magazine). They find that higher-status analysts have greater impact on stock prices than their lower-status peers. Forecasts issued by analysts with better historical track records in earnings forecast accuracy have greater impact on the security prices than analysts with worse historical tract records. This relationship is stock-specific and does not spill-over to other stocks covered by the same analyst (Park & Stice 2000).

There are a limited number of papers investigating the relationship between analysts' biases on the forecast informativeness. Hugon & Muslu (2010) examine how the conservatism (i. e. the difference in analysts' reactions to positive and negative news) affects the forecast informativeness.

[9] (Givoly & Lakonishok 1979; Abdel-Khalik & Ajinkya 1982; Lys & Sohn 1990; Asquith et al. 2005)

They argue that analysts have motivation to please managers by being more optimistic (i. e. exaggerating upward revisions more than downward revisions); however, they also have motivation to keep their reputation by issuing more conservative (i. e. less aggressive) forecast revisions. The authors find that investors react stronger to forecasts given by more conservative analysts.

There are three potential reasons which connect more overconfident analysts with less informative forecasts. First, an analyst with a higher overconfidence bias issues a less accurate forecast revision than another one with a lower overconfidence bias, given the same public and private information. Therefore, the more confident analyst is inferior in terms of forecast accuracy; although, her forecast is not necessary less accurate at the time of earnings announcement. Second, an overconfident analyst exaggerates her private information by giving higher forecasts under positive private information, and giving lower forecasts under negative private information. Consequently, the forecasts will be more volatile, and signal lower forecasting capability. Third, if an analyst is away from the consensus and turns out to be wrong, she will face greater disappointment from investors, and reputation loss. The gain of being away from the consensus but correct in the forecast is less than the loss from being incorrectly away from the consensus. Therefore, on average, the additional deviation from the consensus caused by the overconfidence bias reduces analysts' reputation. These arguments are the basis for the next hypothesis.

Hypothesis 6: *The market reacts less strongly to forecasts issued by more overconfident analysts.*

An analyst with higher belief-persistence bias relies more on her prior belief and deviates less from her prior forecast. Therefore, with the same level of private information, an analyst with higher belief-persistence bias conveys less information to investors than another analyst with lower belief-persistence bias. An analyst with higher belief-persistence may pay insufficient attention to news which is away from their prior forecasts, and in fact, this news is valuable to investors. The belief-persistence bias is associated with lack of ability in making sufficient deviation from the prior forecasts to produce accurate forecasts or negligence to extreme news. I predict that the investors do not favor this bias, and as consequence, they will react less to analysts with high belief-persistence bias in the future. I would like to examine the following hypothesis.

Hypothesis 7: *The market reacts less strongly to forecasts issued by analysts with higher belief-persistence bias.*

The confidence-enhancement bias exaggerates the overconfidence bias when the private information is supported by the prior forecasts and diminishes the overconfidence bias when the private information is not supported by the prior forecasts. The confidence-enhancement bias adds an additional degree of ambiguity to the overconfidence bias and decreases the reliability of the forecasts. Similar to Hugon & Muslu (2010), I would expect that investors prefer objective analysts, and therefore, the confidence-enhancement bias reduces analysts' creditability and decrease market reaction to earnings forecasts.

Hypothesis 8: *The market reacts less strongly to forecasts issued by analysts with higher confidence-enhancement bias.*

The analysts' biases may affect forecast informativeness only if investors recognize the existence of these biases, but do not have the ability to separate the biases from the stated forecasts. Hilary & Hsu (2013) study the relationship between forecasts' consistency (i. e. accuracy of forecasts after cancelling the systematic optimism/pessimism) and forecast informativeness. They find that the consistency is even more important than the accuracy of stated forecasts in determining forecast informativeness. However, the effect of the stated accuracy is still significant after controlling for the de-biased accuracy. The argument is that investors recognize the existence of systematic optimism/pessimism in analysts' forecasts, and partially abandon these biases from the stated forecasts to obtain the "true" forecasts.

3.2 Testing Methodology

The association between abnormal stock returns and forecast revisions has been used to measure the information content of earnings forecasts[10]. A stronger association between abnormal stock returns and forecast revisions indicates more informative forecasts, and vice versa. The basic regression is: $CAR = \alpha_0 + \alpha_1 . Dev$, in which, CAR measures the abnormal stock returns around the forecast issuance date, and *Dev* measures the unexpected forecast revisions. To study the effects of analysts' biases on the forecast informativeness, I add interactions between *Dev* and the interested variables into this model (Clement & Tse 2003; Hugon & Muslu 2010; Hilary & Hsu 2013). The variables of interest are: analysts' overconfidence bias ($OVERCONFIDENCE$), belief-persistence bias

[10] (Givoly & Lakonishok 1979; Stickel 1992; Park & Stice 2000; Clement & Tse 2003; Hugon & Muslu 2010; Hilary & Hsu 2013)

($BELIEF\ PERSISTENCE$), and confidence-enhancement bias ($CONFIDENCE\ ENHANCEMENE$).

The regression results may change dramatically by changing the controls in the regression. Therefore, more controls are applied to minimize the risk of incorrect inferences (i. e. type I error). Firstly, I control for firm-year fixed effects. The firm-year fixed effects will captures all possible firm characteristics variables measured on the annual basis. If I do not control for firm fixed effects, I will have to control for firm characteristic variable such as firm size, book-to-market ratio, beta, institutional holdings, and other variables (Frankel et al. 2006; Hugon & Muslu 2010). Secondly, I control for common used analyst characteristics, which include previous firm-specific accuracy (*ACCURACY*), All-America analyst status (*STAR*), experience (*EXPERIENCE*), and broker size (*BROKERSIZE*)[11]. Thirdly, I control for environmental characteristics which contain the distance to the actual earnings announcement (*Horizon*) [12] and the disagreement among financial analysts (*Dispersion*). Finally, I control for the characteristics of the forecasts, which are usually ignored in the previous literature (e. g., Hugon & Muslu 2010). I control for whether the unexpected forecast revision is positive or negative (*Optimism Dummy*), the magnitude of the revision (*Boldness*), ex-post accuracy of the forecast (*Accuracy Dummy*), and timeliness of the forecast (*Leader-Follower Ratio*).

Before studying the effects of analyst characteristics on forecasts' informativeness, I examine the informativeness of forecasts in isolation, which allows me to study the relative economic significance of the association between analyst characteristics and forecast informativeness. I run the following regression to obtain the average earnings forecast informativeness.

Model IV (OLS Regression with Firm-Year Fixed Effects and Industry-Year Clustering):

$$CAR = \alpha_0 + \boldsymbol{\alpha_1}.\boldsymbol{Dev} + \alpha_2.OVERCONFIDENCE + \alpha_3.BELIEF\ PERSISTENCE + \alpha_4.CONFIDENCE\ ENHANCEMENT + A.Controls + \varepsilon$$

In which, the *"Controls"* include forecast characteristics (*Accuracy Dummy* and *Leader-Follower Ratio*), environmental characteristics (*Horizon, Dispersion*) and analyst characteristics

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[11] (Park & Stice 2000; Stickel 1992; Hugon & Muslu 2010; Hilary & Hsu 2013)

[12] (Sinha et al. 1997; Hilary & Hsu 2013)

(*ACCURACY, STAR, EXPERIENCE,* and *BROKERSIZE*). The estimated coefficient $\widehat{\boldsymbol{\alpha_1}}$ of *Dev* measure the informativeness of the earnings forecasts on average. Prior literature suggests a positive $\widehat{\boldsymbol{\alpha_1}}$ (i. e. forecast revisions are informative).

To study the effect of overconfidence and belief-persistence biases on forecast informativeness, I add interaction terms between *Dev* and analysts' bias variables (i. e. *OVERCONFIDENCE, BELIEF PERSISTENCE, and CONFIDENCE ENHANCEMENT*).

Model V (OLS Regression with Firm-Year Fixed Effects and Industry-Year Clustering):

$$
\begin{aligned}
&CAR = \\
&\alpha_0 + \alpha_1.Dev + \alpha_2.OVERCONFIDENCE + \alpha_3.BELIEF\ PERSISTENCE + \\
&\alpha_4.CONFIDENCE\ ENHANCEMENT + A.Controls + \boldsymbol{\beta_1.Dev} \times \boldsymbol{OVERCONFIDENCE} + \\
&\boldsymbol{\beta_2.Dev} \times \boldsymbol{BELIEF\ PERSISTENCE} + \boldsymbol{\beta_3.Dev} \times \boldsymbol{CONFIDENCE\ ENHANCEMENT} + \\
&\beta_4.Dev \times Optimism\ Dummy + \beta_5.Dev \times Boldness + B.Dev \times Controls + \varepsilon
\end{aligned}
$$

The firm fixed effects capture the effects of firm characteristics on the forecast informativeness (Frankel et al. 2006). The estimated coefficients $\widehat{\boldsymbol{\beta_1}}$, $\widehat{\boldsymbol{\beta_2}}$, and $\widehat{\boldsymbol{\beta_3}}$ of *Dev×OVERCONFIDENCE*, *Dev×BELIEF PERSISTENCE*, and *Dev×CONFIDENCE ENHANCEMENT* measure the effects of these biases on forecast informativeness. Hypothesis 6 predicts a negative $\widehat{\boldsymbol{\beta_1}}$, Hypothesis 6 predicts a negative $\widehat{\boldsymbol{\beta_2}}$**,** and Hypothesis 8 predict a negative $\widehat{\boldsymbol{\beta_3}}$**.**

3.3 Variables Construction

There are some additional variables compared to previous part and some modifications. Firstly, I use three-trading-day accumulative market adjusted abnormal returns surrounding the analyst's forecast revision to measure the reaction of the market. The accumulation period is from one day before to one day after the forecast revision date (Ball & Kothari 1991; Clement & Tse 2003; Hilary & Hsu 2013). Secondly, the forecast revision is defined as the difference between the current forecast and the prior forecast of the same analyst (Park & Stice 2000; Clement & Tse 2003), and this variable is named as "*Dev*". Some people may argue that less aggressive forecasts may stay closer to the prior forecasts; therefore the amount of information per one unit of deviation is mechanically magnified. To capture that, I use another definition of forecast informativeness that measures the total market reaction to the forecast revision instead of the market reaction on one unit of revision (Ball & Kothari 1991). I rerun models V and VI with the optimism dummy (i. e. equals

1 if *Dev* is positive and zero otherwise) instead of deviation as the measure for "*Dev*". To distinguish models with two definitions of informativeness, I denote models with deviation as IV(a) and V(a), and models with the optimism dummy as IV(b) and V(5).

Some other papers use the deviation from the consensus instead of the deviation from the prior forecast (Hugon & Muslu 2010; Hilary & Hsu 2013). The intuitions behind two definitions are different. Using prior forecast, we stand on the analyst's point of view, and the deviation from the prior forecast measures the amount of information sent by the analyst. Using the consensus, we stand on the investors' point of view. The deviation from the consensus is the amount of information received by the investors with an underlying assumption that the consensus is correctly reflect the earnings expectation of the investors. The two definitions produce highly correlated deviations (around 65%). Although the deviation from the prior forecast is used in the main analysis, the deviation from the consensus will be examined in the robustness checks.

Thirdly, I present the constructions of overconfidence, belief-persistence, and confidence-enhancement biases. It is possible that these biases vary from an analyst to another, from a firm to another, and even from a point in time to another. Because of the limitation of the data that many analysts issue few forecasts in a year and few forecasts for a firm, I assume that overconfidence and belief-persistence biases are constants for each analyst; I would calculate these biases on the analyst-firm basis if an analyst produced hundreds of forecasts for a firm in a fiscal year. I use all the forecasts given by an analyst in her entire career to estimate her overconfidence and belief-persistence biases.

To tackle the between-group variation issue, I use the firm centering method instead of including firm fixed effects for two following reasons. The first reason is that it seems to be too much if I put firm fixed effects on each analyst's regression, because, many analysts issue few forecasts on some firms and the fixed effects will capture most of the variation. The second reason is the limitation of the computational power; it would take hours to run thousands of regressions with fixed effects. Before running regressions, I calculate the averages of *FE, Dev, DevPrior, Horizon, Dispersion, ACCURACY, EXPERIENCE* and *BROKERSIZE* for all forecasts given for a firm. Then, I subtract the averages from the corresponding variables. For simplicity, I remain the notations of group centered variables the same as original variables.

For each analyst i, I run two regressions: $FE = \alpha_0 + \boldsymbol{\alpha_1 . Dev} + \boldsymbol{\alpha_2 . DevPrior} + \varepsilon$ and $FE = \alpha_0 + \alpha_2 . DevPrior + \alpha_3 . Confirm + \beta_0 . Dev + \boldsymbol{\beta_1 . Dev} \times \boldsymbol{Confirm} + \varepsilon$. For each analyst i, the estimated coefficient $\widehat{\boldsymbol{\alpha_1}}$ of *Dev* from the first regression measures her overconfidence bias and is denoted as *OVERCONFIDENCE*. Her belief-persistence bias is $\widehat{\boldsymbol{\alpha_2}}/(1-\widehat{\boldsymbol{\alpha_1}})$, and is denoted as *BELIEF PERSISTENCE*. The estimated coefficient $\widehat{\boldsymbol{\beta_1}}$ of *Dev*×*Confirm* from the second regression is the measure for her confidence-enhancement bias (*CONFIDENCE ENHANCEMENT*). These measures, afterward, are classified into quintiles.

Finally, *Accuracy Dummy* is a dummy variable which equals 1 if the forecast is more accurate than the consensus and equals 0 otherwise (Williams 1996; Chen & Jiang 2006). *Optimism Dummy* is a dummy variable which takes the value of 1 if the forecast is above the consensus, and takes the value of 0 otherwise. *Boldness* is the absolute value of the *Dev* variable. *Leader-Follower Ratio* is the logarithm of the average time distances from the forecast to the last two forecasts over average time distances from the forecast to the next two forecasts (Cooper et al. 2001). Environmental characteristics and analyst characteristics (*Horizon*, *Dispersion, ACCURACY, STAR, EXPERIENCE,* and *BROKERSIZE*) share the same constructions with the previous part.

3.4 Empirical Results

Table 3 presents the informativeness of earnings forecast and effects of analyst characteristics on forecast informativeness. The first two columns present the results of model IV(a) and V(a) with the variable *Dev* defined as the deviation from the consensus of the current forecast. The last two columns present Model IV(b) and Model V(b) with the variable *Dev* is defined as the optimism dummy. The first and the third columns present the regression results of Model IV(a) and Model IV(b) (i. e. $CAR = \alpha_0 + \boldsymbol{\alpha_1.Dev} + \alpha_2.OVERCONFIDENCE + \alpha_3.BELIEF\ PERSISTENCE + \alpha_4.CONFIDENCE\ ENHANCEMENT + A.Controls + \varepsilon$). The positive estimated coefficient $\widehat{\beta_1}$ of the variable *Dev* suggests that three days buy-and-hold abnormal returns is positively associated with the forecast revision; in other words, security analysts are informative. On average, *1 cent* increase in the forecast revision is associated with 0.04% increase in the three-day abnormal returns (equivalent to 3.5% *per annum*). The average difference in three-day abnormal returns between upward and downward revisions is nearly 3.4%.

[Insert Table 4 about here]

The second and fourth columns contain the regression results of Model V(a) and Model V(b) ($CAR =$

$\alpha_0 + \alpha_1.Dev + \alpha_2.OVERCONFIDENCE + \alpha_3.BELIEF\ PERSISTENCE +$

$\alpha_4.CONFIDENCE\ ENHANCEMENT + A.Controls + \boldsymbol{\beta_1.Dev \times OVERCONFIDENCE} +$
$\boldsymbol{\beta_2.Dev \times BELIEF\ PERSISTENCE + \beta_3.Dev \times CONFIDENCE\ ENHANCEMENT} +$
$\beta_4.Dev \times Optimism\ Dummy + \beta_5.Dev \times Boldness +\ B.Dev \times Controls + \varepsilon)$. The significantly negative coefficient of the interaction term *Dev×OVERCONFIDENCE* suggests that the higher an analyst's overconfidence bias, the less informative her forecasts. From Model V(a), the difference in the three-day abnormal returns associated with *1 cent* of forecast deviation from the consensus between analysts from the bottom and the top quintiles of the overconfidence bias is 0.0076% (i. e. 0.189*(5-1)/100, equivalent to 0.6% *per annum*). In comparison with the average informativeness, this difference is about 18% of the average informativeness. From Model V(b), the difference in the incremental three-day abnormal returns associated with upward forecasts revisions between analysts from the bottom and the top quintiles of the overconfidence bias is 0.5% (equivalent to 14% of the average incremental three-day abnormal returns associated with upward forecast revisions). These results support Hypothesis 5 that investors react more strongly to analysts affected less by the overconfidence bias.

The significantly negative coefficients of the interaction terms *Dev×BELIEF PERSISTENCE* and *Dev×CONFIDENCE ENHANCEMENT* suggest that the higher an analyst's belief-persistence bias is, the less informative her forecasts are. From Model V(a), the difference in the three-day abnormal returns associated with *1 cent* of forecast deviation from the consensus between analysts from the bottom and top quintiles of belief-persistence bias is 0.004% (i. e. 0.1*(5-1)/100, equivalent to *0.3% per annum*), which is about 9% of the average forecast informativeness. The corresponding difference with respect to the confidence-enhancement bias is 0.004% (i. e. 0.09*(5-1)/100, equivalent to 0.3% *per annum*), which is about 8% of the average forecast informativeness. In total, the difference in forecast informativeness between analysts from the bottom and top quintiles of both belief-persistence and confidence-enhancement biases is 17% of the average forecast informativeness. From Model V(b), the difference in the incremental three-day abnormal returns associated with upward forecasts revisions between analysts from the bottom and the top quintiles of the belief-persistence (confidence-enhancement) bias is 7% (5%) of the average incremental three-day abnormal returns associated with upward forecast revisions. These results support Hypothesis 6 that investors react more strongly to analysts affected less by the overconfidence bias.

To illustrate the economic significance of the effects of the cognitive biases on the forecast informativeness, I calculate the difference in informativeness between the top and the bottom quintiles in previous forecast accuracy from Model V(b). The difference is about 5% (i. e.

0.23*0.8/3.4), which is about a third of the overconfidence bias' effect (14%), less than the belief-persistence bias' effect (7%), and about the confidence-enhancement bias' effect (5%).

Forecasts supporting the prior forecasts are under higher suspicion for the belief-persistence bias than forecast opposing the prior forecasts; consequentially, the supporting forecasts are less informativeness than opposing forecasts. From Model V(b), the difference in forecast informativeness between opposing and supporting forecasts is about 32% (i. e. 1.11/3.42) of the average forecast informativeness. I do not use Model V(a) because with the same level of deviation from the consensus, the deviation from the prior forecast is lower in the supporting forecasts than in the opposing forecasts. Investors react based on the deviation from the consensuses, the supporting forecasts have artificially increased amount of information per one unit of deviation from the prior forecast.

While overconfidence bias accounts how the forecasts irrationally deviate from the optimal level, the traditional boldness (i. e. the difference from the forecast and the consensus) measures the total of underlying informativeness and cognitive biases. On average, the investors react less strongly per unit of deviation, but more strongly in total, as the absolute deviation from the consensus increases. Analysts with higher prior boldness in the prior year also gain more reputation and their forecasts are more informative this year. These results suggest that investors reward the underlying informativeness and penalize the cognitive biases.

The estimated coefficients of the interactions between *Dev* and other control variables are sensible except the analyst status variable. The positive estimated coefficient of *Dev*×*Accuracy Dummy* suggests that ex-post accuracy is associated with the investors' response to the forecasts. The information in the revision may come from the common knowledge or investors may sense the accuracy of the revisions. The positive estimated coefficient of *Dev*×*Leader-Follower Ratio* means that investors react more strongly to more timely forecasts. The negative estimated coefficient of *Dev*×*Optimism Dummy* suggests that investors react more strongly to negative news than positive news. Analysts, in general, tend to overreact to positive news and under-react to the negative news to please the managers (i. e. optimistic overconfidence bias). Therefore, investors recognize this bias and react less to the positive revisions. The positive estimated coefficient of *Dev*×*Horizon* advises that investors have higher demand for the forecast revisions at the beginning of the forecasting period than at the end. At the meantime, the negative estimated coefficient of *Dev*×*Dispersion* advises that investors are more disbelieving on the analysts when they are deviate more from each other. The positive estimated coefficient of *Dev*×*ACCURACY* suggests that more accurate analysts are more informative than less accurate analysts. In addition, analysts covering less stocks and from bigger brokers are more informative. The negative effect of analyst's All-American status on the informativeness is opposing to Stickel (1992).

3.5 Robustness Checks

In the main analysis, I run regressions based on the forecast deviation from the prior forecast issued by the same consensus. However, from the investors' perspective, they may primarily care about the forecast deviation from their current belief, which is measured as the current consensus (Hugon & Muslu 2010; Hilary & Hsu 2013). Therefore, I rerun the analysis on the deviation from the consensus of outstanding forecasts. The average informativeness is smaller than that in the main analysis, which suggests the deviation from the prior forecast is a better measure for the unexpected forecast revision. The effects of cognitive biases on forecast informativeness are also significant in these models.

[Insert Table 5 about here]

Similar to the last section, I separate the sample into the two periods, from 1994 to 2000 and from 2001 to 2010. The earlier period is during the boom of the stock market and before the Fair Disclosure Regulations. The latter period is during volatile stock market with crashes and recoveries, and following the implementation of the Fair Disclosure Regulations Act. My main results primarily hold in both periods. The average informativeness of forecasts during the latter period improved significantly. The estimated coefficient of the deviation in Model IV(a) in the latter (and earlier) period are 4.4 (and 3.5), and the estimated coefficient of the deviation dummy in Model IV(b) is in the latter (and earlier) period 3.8 (and 2.2). During the crises, investors may have an increased demand for professional advice. The effect of the overconfidence bias on forecast informativeness is higher, while the effect of the belief-persistence bias is smaller in the latter period than in the earlier period.

In the calculation of the biases of the main analysis, I use mean-centered *FE, Dev*, and *DevPrior* within firms based on all forecasts given on the firm during the period from 1994 to 2010. This mean-centering method may be forward-looking and distort the results. Therefore, in the next robustness check, I recalculate the biases based on the raw values of *FE, Dev,* and *DevPrior*; then I repeat the main analysis using the obtained biases. The obtained results are consistent with the main analysis. The effect of overconfidence bias on the forecast informativeness is higher, when there is not a big change in the effects of the belief-persistence and confidence-enhancement biases.

Finally, I adopt a more complicated calculation of CAR by controlling for size, book-to-market ratio (B/M) and momentum characteristics of the stock (Daniel et al. 1997; Loh & Stulz 2010). In this check, I also exclude concomitant earnings announcements. The coefficient reduces to 0.1 and is still significant at 5% level. To compute the three-day CAR for an analyst forecast, I create a benchmark portfolio with the same size, B/M, and momentum as the stock. The CAR is defined as the difference between the three-day buy-and-hold cumulative returns of the stock and the cumulative returns of the benchmark portfolio$\left(\text{i. e.} \, CAR_i = \prod_{t=-1}^{1}(1 + R_{it}) - \prod_{t=-1}^{1}\left(1 + R_{it}^{Portfolio}\right)\right)$. The benchmark portfolios are constructed as follows: Each July I assign stocks into 125 portfolios through three steps. I sort stocks into 5 groups based on their size and then, within each group, I sort stocks into 5 sub-groups based on their B/M. Finally, within each sub-group, I sort stocks into 5 portfolios based on their prior 12 months buy-and-hold cumulative returns.

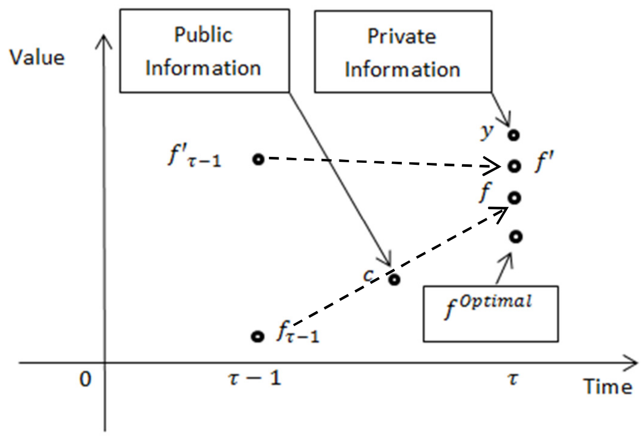
4 Conclusion

This paper studies how sell-side security analysts are affected by cognitive biases, specifically belief-persistence and overconfidence biases. I quantify the extent to which the biases affect analysts by analyzing analysts' misweighting behavior in issuing earnings forecasts. An analyst tends to put too much weight on her prior forecasts, although her prior forecast is already reflected in the consensus (i. e. belief-persistence bias). She tends to believe that her prior forecast is superior to other outstanding forecasts, and deserves higher weight in the construction of the public information, or she tends to emphasize news which is closer to her prior forecasts. Between private information and public information, the analyst tends to overemphasize the importance of her private information and undervalue the public information (i. e. overconfidence bias). In addition, she tends to lay even higher emphasis on the private information when it is supported by her prior forecast (i. e. confidence-enhancement bias).

Secondly, I study how investors react to these cognitive biases of analysts. I measure these biases (i. e. overconfidence bias, belief-persistence bias, and confidence-enhancement bias) for each analyst-year based on all forecasts given by the analyst in the year. I find that analysts with higher cognitive biases issue lower informativeness (i. e. lower market reaction) forecasts in the subsequent year. The effects of the biases on the informativeness are economically and statistically significant. The effect of the overconfidence bias on the forecast informativeness is nearly double the effect of the analyst's firm-specific accuracy on the forecast informativeness. The effect of belief-persistence bias is also greater than the effect of the accuracy.

Even though the research is confirmed by a number of robustness checks, there are some technical limitations. Firstly, there may be some cases where the belief-persistence bias creates direction disagreements between the private information and the realized forecast, and consequently, the inference based on the overconfidence bias is inaccurate. This limitation is difficult to overcome since the private information is unobservable. Secondly, the expected actual earnings, given the available information, may be different from the realized actual earnings because of management's selective disclosure. I tackle this limitation by controlling for firm fixed effects; however, it does not solve the problem entirely. Thirdly, the research is based on the assumption that the distributions of released information and actual earnings are normal, while they are not.

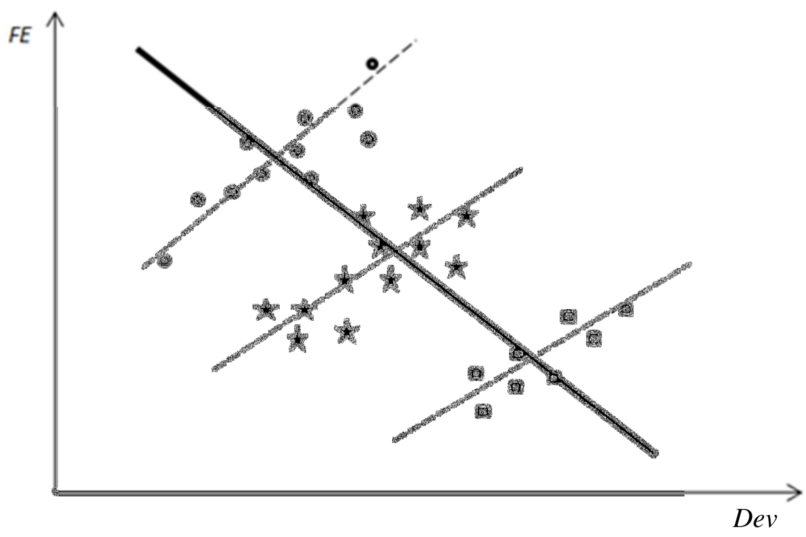
Figure 1: Illustration of Overconfidence and Belief-Persistence Biases in Earnings Forecasts



This figure illustrates overconfidence and belief-persistence biases. An analyst is issuing an earnings forecast based on the consensus c, her private information y, and her prior forecast $f'_{\tau-1}$.

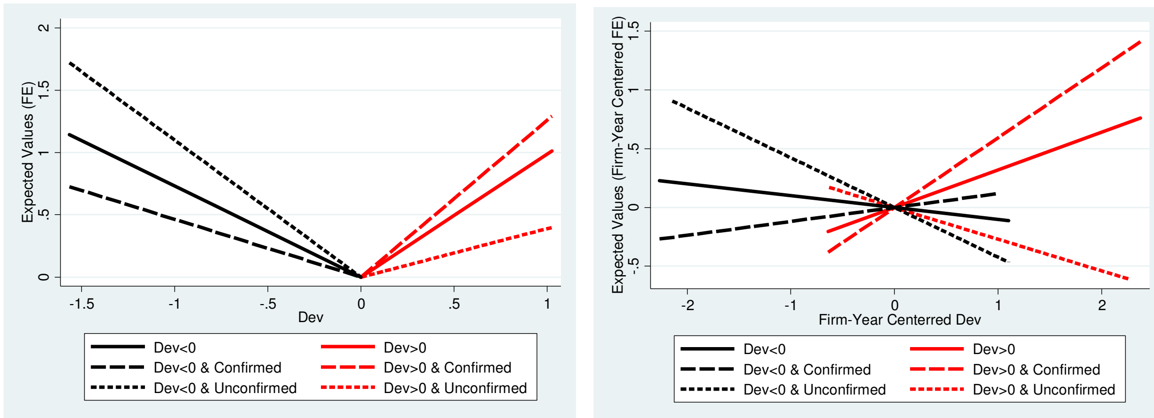
- If she uses optimal weights, she would give a forecast of $f^{\text{Optimal}}$by the Bayes decision theory.
- If she is overconfident on the precision of her private information, she will put more weight on her private information and give a forecast of f.
- If she is subject to the belief-persistence bias and her prior forecast were $f'_{\tau-1}$ instead of $f_{\tau-1}$, she would have been steered toward $f'_{\tau-1}$, and the forecast would have been f' instead of f.

Figure 2: Illustration of the Necessity of Group Centering or Including Fixed Effects



This figure illustrates a possible issue of the observations are not centered within groups (i. e. firm-years or firms). Assume that there are three firms (round, star and square) and the values of FE and Dev are illustrated below. If I run regression $FE = \alpha + \beta.Dev + \varepsilon$ over each firm, I obtain three fitted (dashed) lines with positive slopes. However, if I run the regression on the pooled sample, I obtain one fitted (solid) line with a negative slope. To solve this issue, I must center the observations within groups or include group fixed effects.

Figure 3: Optimistic Overconfidence Bias and Confidence-Enhancement Bias



This figure presents the optimistic overconfidence and confidence-enhancement biases. I run four OLS regressions ($FE = \alpha + \beta. Dev + \varepsilon$) on positive and negative Dev, and on supporting and opposing Dev. The left graph is for the case of no intercept and the right graph is for the case that FE and Dev are centered within each firm-year (i. e. including firm-year fixed effects). The slope is the measure of the overconfidence bias, and it is subject to change when I add belief-persistence bias and control variables into the regressions.

Table 1: Variables Definitions and Descriptive Statistic after Winsorization

Panel 1: Variable Definitions

Variable	Definition
FE	Current Forecast – Actual Earnings
Dev	Current Forecast – Consensus
DevPrior	Prior Forecast – Forecast
Confirm	1 if sign(Current Forecast – Consensus) = sign(Prior Forecast – Consensus) and 0
Horizon	otherwise
Dispersion	the logarithm of the number of days to the actual earnings announcement
ACCURACY	the standard deviation of the forecasts constituting the consensus
	1 – (Rank(abs(Forecast – Actual Earnings)) – 1)/(Number of analysts covering the firm –
BOLDNESS	1) in the prior firm-fiscal year
	1 – (Rank(abs(Forecast – Consensus)) – 1)/(Number of analysts covering the firm – 1) in
STAR	the prior firm-fiscal year
EXPERIENCE	1 if she is currently voted as an All-American analyst and 0 otherwise
BREADTH	the logarithm of the number of days which she appears in I/B/E/S
BROKERSIZE	the logarithm of the number of stocks covered by the analyst in the current year
	the logarithm of the number of analysts working for the broker in the current year

Panel 2: Summary Statistics

	mean	sd	min	p25	p50	p75	max
FE	0.11	0.77	-1.88	-0.08	-0.00	0.12	5.20
Dev	-0.03	0.28	-1.56	-0.07	-0.00	0.04	1.03
PriorDev	0.04	0.32	-0.99	-0.05	0.01	0.08	1.92
Confirm	0.55	0.50	0	0	1	1	1
Horizon	5.00	0.75	0	4.64	5.23	5.58	6.46
Dispersion	0.17	0.30	0	0.03	0.07	0.16	2.07
FIRMSIZE	2.66	0.66	0	2.20	2.77	3.18	4.19
ACCURACY	0.52	0.23	0	0.32	0.50	0.71	1
BOLDNESS	0.50	0.31	0	0.25	0.50	0.75	1
STAR	0.16	0.37	0	0	0	0	1
EXPERIENCE	7.63	0.84	0.69	7.10	7.74	8.27	9.26
BREADTH	2.70	0.55	0	2.48	2.71	3.00	5.07
BROKERSIZE	3.62	1.05	0	3.00	3.81	4.42	5.33
N	1,108,992						

(Continued)

Panel 3: Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12
FE	1												
Dev	2	-.08											
PriorDev	3	.26	-.66										
Confirm	4	.00	.03	-.06									
Horizon	5	.06	.01	-.01	.03								
Dispersion	6	.33	-.21	.29	.06	.08							
FIRMSIZE	7	-.06	.04	-.05	.04	-.02	.00						
ACCURACY	8	.01	-.00	.01	.00	.00	.00	.00					
BOLDNESS	9	.00	-.01	.00	.02	.00	.00	-.00	.24				
STAR	10	-.01	-.01	-.01	.01	-.03	.01	.08	.03	.06			
EXPERIENCE	11	.00	-.00	.00	-.01	-.08	-.01	.03	.02	.09	.21		
BREADTH	12	.00	.00	-.00	-.01	-.03	-.01	.04	.00	.04	.14	.30	
BROKERSIZE	13	.00	-.02	-.01	.03	.01	.01	.08	.03	.05	.37	.03	.03

This table presents the definition and descriptive statistics of dependent and independent variables from 1994 to 2010.

Table 2: Cognitive Biases

	I		II		III	
Dev	0.527 ***	(17.42)	2.716 ***	(9.34)	1.242 ***	(4.30)
DevPrior	0.587 ***	(29.35)	0.561 ***	(22.24)	-1.289 ***	(-6.39)
Dev X Confirm			0.078 ***	(3.25)	0.402	(1.53)
Dev X Positive			0.263 ***	(4.92)	0.265 ***	(5.08)
DevPrior X Horizon					0.267 ***	(9.22)
DevPrior X Dispersion					-0.042	(-1.55)
DevPrior X DFIRMSIZE					0.022	(0.95)
DevPrior X ACCURACY					-0.004	(-0.10)
DevPrior X BOLDNESS					0.009	(0.28)
DevPrior X STAR					0.016	(0.39)
DevPrior X EXPERIENCE					0.025	(1.44)
DevPrior X BREADTH					0.059 ***	(2.69)
DevPrior X BROKERSIZE					0.032 *	(1.92)
Dev X Confirm X Horizon					-0.012	(-0.56)
Dev X Confirm X Dispersion					0.180 ***	(5.42)
Dev X Confirm X FIRMSIZE					-0.007	(-0.27)
Dev X Confirm X ACCURACY					-0.125 *	(-1.67)
Dev X Confirm X BOLDNESS					0.059	(1.20)
Dev X Confirm X STAR					-0.097 *	(-1.82)
Dev X Confirm X EXPERIENCE					-0.021	(-0.88)
Dev X Confirm X BREADTH					-0.031	(-0.88)
Dev X Confirm X BROKERSIZE					-0.035 *	(-1.79)
Firm Fixed Effects	yes		yes		yes	
Unshown Controls	(1)		(2)		(2)	
R2	0.085		0.094		0.099	
N	1,108,992		1,108,992		1,108,992	

t-statistics in parentheses * p<0.1, ** p<0.05, *** p<0.01

(1): Horizon, Dispersion, FIRMSIZE, ACCURACY, BOLDNESS, STAR, EXPERIENCE, BREADTH, & BROKERSIZE

(2): (1) & Confirm, Dev X Horizon, Dev X Dispersion, Dev X FIRMSIZE, Dev X ACCURACY, Dev X BOLDNESS, Dev X STAR, Dev X EXPERIENCE, Dev X BREADTH, & Dev X BROKERSIZE

This table presents regression results of three OLS models with firm fixed effects and clustering by industry-year:

- Model I: $\mathrm{FE} = \alpha_0 + \boldsymbol{\alpha_1}.\,\mathbf{Dev} + \boldsymbol{\alpha_2}.\,\mathbf{DevPrior} + \mathrm{A}.\,\mathrm{Controls} + \varepsilon$
- Model II: $\mathrm{FE} = \alpha_0 + \alpha_1.\,\mathrm{Dev} + \alpha_2.\,\mathrm{PriorDev} + \mathrm{A}.\,\mathrm{Controls} + \boldsymbol{\beta_1}.\,\mathbf{Dev} \times \mathbf{Confirm} + \beta_2.\,\mathrm{Dev} \times \mathrm{Positive} + \mathrm{B}.\,\mathrm{Dev} \times \mathrm{Controls} + \varepsilon$
- Model III: $\mathrm{FE} = \alpha_0 + \alpha_1.\,\mathrm{Dev} + \alpha_2.\,\mathrm{DevPrior} + \mathrm{A}.\,\mathrm{Controls} + \mathbf{B_1}.\,\mathbf{DevPrior} \times \mathbf{Controls} + \beta_1.\,\mathrm{Dev} \times \mathrm{Confirm} + \beta_2.\,\mathrm{Dev} \times \mathrm{Positive} + \mathrm{B_2}.\,\mathrm{Dev} \times \mathrm{Controls} + \boldsymbol{\Gamma}.\,\mathbf{Dev} \times \mathbf{Confirm} \times \mathbf{Controls} + \varepsilon$

In which, FE=Forecast – Actual Earnings, Dev=Forecast – Consensus, DevPrior=Prior Forecast – Forecast, Confirms equals 1 if (Forecast – Consensus) and (Prior Forecast – Consensus) having the same signs and 0 otherwise, and "×" stands for "interaction".

- Overconfidence Bias = Coeff. of Dev (Chen and Jiang predict (+) sign)
- Belief-Persistence Bias = (Coeff. of **DevPrior**)/(Coeff. of **Dev**) (hypothesis 1 predicts (+) sign)
- Confidence-Enhancement = Coeff. of $\mathbf{Dev} \times \mathbf{Confirm}$ (hypothesis 1 predicts (+) sign)
- Effects of Horizon on Belief-persistence Bias = Coeff. of $\mathbf{DevPrior} \times \mathbf{Horizon}$ and $\mathbf{Dev} \times \mathbf{Confirm} \times \mathbf{Horizon}$ (hypothesis 2 predicts (+) signs)
- Effects of Dispersion on Belief-persistence Bias = Coeff. of $\mathbf{DevPrior} \times \mathbf{Dispersion}$ and $\mathbf{Dev} \times \mathbf{Confirm} \times \mathbf{Dispersion}$ (hypothesis 3 predicts (+) signs)
- Effects of ACCURACY on Belief-persistence Bias = Coeff. of $\mathbf{DevPrior} \times \mathbf{ACCURACY}$ and $\mathbf{Dev} \times \mathbf{Confirm} \times \mathbf{ACCURACY}$ (hypothesis 4a and hypothesis 4b predict (-)signs)

Table 3: Robustness Check (Cognitive Biases)

		Overconfidence	Belief Persistence	Confidence Enhancement	Effect of Horizon on Belief Persistence	Effect of Dispersion on Confidence Enhancement
	Main Analysis	53% ***	55% ***	8% ***	25% ***	2% ***
(1)	Divided by Price	43% ***	47% ***	7% ***	18% ***	1% ***
(2)	Time-Weighted Consensus	62% ***	58% ***	7% **	29% ***	2% ***
(3)	1994 – 2000	55% ***	51% ***	5%	37% ***	2% ***
(4)	2001 – 2010	54% ***	56% ***	9% ***	22% ***	2% ***
(5)	No Fixed Effects	47% ***	57% ***	7% **	20% ***	2% ***

This table presents robustness checks for the existence of the cognitive biases and how does the Horizon and Dispersions variables affect these biases.

- (1): I divide the forecast error, deviation from the consensus, the distance from the prior forecast to the current forecast, and dispersion among outstanding forecast by the stock price two days before the current forecast, and perform the same analysis. The results are weaker but similar to the main analysis.
- (2): I use time-weighted consensus instead of the equally weighted consensus. The results are very similar to the main analysis except an increase in the overconfidence bias.
- (3) & (4): I separate the sample into two sub-periods (1994-2000 and 2001-2010). The belief-persistence bias seems to be stronger after the passage of Fair-Disclosure Regulations and during the recessions.
- (5): I exclude the firm fixed effects from the regressions. The results stay aligning with the main analysis.

Table 4: Cognitive Biases and Forecast Informativeness

	IV(a)		V(a)		IV(b)		V(b)	
Dev	4.254	***	10.091	***	2.827	***	1.543	***
	(18.03)		(9.14)		(27.36)		(3.38)	
Dev X OVERCONFIDENCE			-0.189	***			-0.122	***
			(-4.47)				(-7.71)	
Dev X BELIEF PERSISTENCE			-0.100	**			-0.060	***
			(-2.34)				(-3.48)	
Dev X CONFIDENCE ENHANCEMENT			-0.090	***			-0.041	***
			(-2.78)				(-2.68)	
Dev X Accuracy Dummy			2.429	***			1.543	***
			(14.69)				(20.65)	
Dev X Confirm Dummy			0.270	**			-1.108	***
			(2.49)				(-19.70)	
Dev X Optimism Dummy			-4.277	***				
			(-10.33)					
Dev X Boldness			-5.043	***			2.847	***
			(-15.59)				(9.82)	
Dev X Leader-Follower Ratio			0.467	***			0.407	***
			(11.37)				(17.60)	
Dev X Horizon			0.393	***			0.651	***
			(2.74)				(11.84)	
Dev X Dispersion			-1.228	***			-1.995	***
			(-6.11)				(-8.33)	
Dev X ACCURACY			0.490	***			0.230	***
			(2.80)				(3.26)	
Dev X BOLDNESS			0.004				0.277	***
			(0.03)				(4.87)	
Dev X STAR			-1.038	***			-0.604	***
			(-7.75)				(-8.31)	
Dev X EXPERIENCE			0.176	***			0.044	
			(2.58)				(1.30)	
Dev X COVERAGE BREADTH			-1.028	***			-0.905	***
			(-6.28)				(-11.51)	
Dev X BROKERSIZE			0.402	***			0.308	***
			(7.08)				(11.47)	
Firm-Year Fixed Effects	yes		yes		yes		yes	
Unshown Controls	(1)		(1)		(1)		(1)	
R2	0.024		0.043		0.029		0.051	
N	810,068		810,068		959,946		810,068	

t-statistics in parentheses * p<0.1, ** p<0.05, *** p<0.01

(1): OVERCONFIDENCE, BELIEF PERSISTENCE, CONFIDENCE ENHANCEMENT, Accuracy Dummy, Leader-Follower Ratio, Confirm, Horizon, Dispersion, FIRMSIZE, ACCURACY, BOLDNESS, STAR, EXPERIENCE, BREADTH, & BROKERSIZE

This table presents regression results of two OLS models with firm-year fixed effects and clustering by industry-year:

- Model IV: $\mathrm{CAR} = \alpha_0 + \boldsymbol{\alpha_1}.\,\mathbf{Dev} + \alpha_2.\,\mathrm{OVERCONFIDENCE} + \alpha_3.\,\mathrm{BELIEF\ PERSISTENCE} + \alpha_4.\,\mathrm{CONFIDENCE\ ENHANCEMENT} + \mathrm{A.Controls} + \varepsilon$
- Model V: $\mathrm{CAR} = \alpha_0 + \alpha_1.\,\mathrm{Dev} + \alpha_2.\,\mathrm{OVERCONFIDENCE} + \alpha_3.\,\mathrm{BELIEF\ PERSISTENCE} + \alpha_4.\,\mathrm{CONFIDENCE\ ENHANCEMENT} + \mathrm{A.Controls} + \boldsymbol{\beta_1}.\,\mathbf{Dev} \times \mathbf{OVERCONFIDENCE} + \boldsymbol{\beta_2}.\,\mathbf{Dev} \times \mathbf{BELIEF\ PERSISTENCE} + \boldsymbol{\beta_3}.\,\mathbf{Dev} \times \mathbf{CONFIDENCE\ ENHANCEMENT} + \beta_4.\,\mathrm{Dev} \times \mathrm{Optimism\ Dummy} + \beta_5.\,\mathrm{Dev} \times \mathrm{Boldness} + \mathrm{B.Dev} \times \mathrm{Controls} + \varepsilon$

(Continued)

- Models IV(a) and V(a) use deviation from the prior forecast as Dev. The informativeness is measured as the change in market reaction per a unit change in the forecast deviation from the prior forecast.
- Models IV(b) and V(b) use deviation dummy (i. e. equals 1 if the deviation is positive and 0 otherwise) as Dev. The informativeness is measure as the difference in market reactions between positive and non-positive forecast revisions.

For each analyst year, I run two regressions over forecasts given by the analyst in the year: $\mathrm{FE} = \alpha_0 + \boldsymbol{\alpha_1}.\,\mathbf{Dev} + \boldsymbol{\alpha_2}.\,\mathbf{PriorDev} + \varepsilon$ and $\mathrm{FE} = \alpha_0 + \alpha_2.\,\mathrm{PriorDev} + \alpha_3.\,\mathrm{Confirm} + \beta_0.\,\mathrm{Dev} + \boldsymbol{\beta_1}.\,\mathbf{Dev} \times \mathbf{Confirm} + \varepsilon$. The estimated coefficient $\widehat{\boldsymbol{\alpha_1}}$ of Dev from the first regression measures her overconfidence bias and is denoted as OVERCONFIDENCE. Her belief-persistence bias is $\widehat{\boldsymbol{\alpha_2}}/(1 - \widehat{\boldsymbol{\alpha_1}})$, and denoted as BELIEF PERSISTENCE. The estimated coefficient $\widehat{\boldsymbol{\beta_1}}$ of Dev×Confirm from the second regression is the measure for her confidence-enhancement bias (CONFIDENCE ENHANCEMENT). These measures, afterward, are classified into quintiles.

- Informativeness: Coeff. of $\mathbf{Dev}$
- Effect of overconfidence bias on forecast informativeness: Coeff. of $\mathbf{Dev} \times \mathbf{OVERCONFIDENCE}$ (hypothesis 5 predicts (–) sign)
- Effect of belief-persistence bias on forecast informativeness: Coeff. of $\mathbf{Dev} \times \mathbf{BELIEF\ PERSISTENCE}$ (hypothesis 6 predicts (–) sign)
- Effect of confidence-enhancement bias on forecast informativeness: Coeff. of $\mathbf{Dev} \times \mathbf{CONFIDENCE\ ENHANCEMENT}$(hypothesis 6 predicts (–) sign)

In general the cognitive biases decrease the informativeness of future forecasts.

Table 5: Robustness Checks (Cognitive Biases and Forecast Informativeness)

		OVERCONFIDENCE		BELIEF PERSISTENCE		CONFIDENCE ENHANCEMENT	
		Deviation	Deviation Dummy	Deviation	Deviation Dummy	Deviation	Deviation Dummy
(1)	Main Analysis	-0.76%***	-0.49%***	-0.40%**	-0.24%***	-0.36%***	-0.76%***
		(-18%)	(-14%)	(-9%)	(-7%)	(-8%)	(-5%)
(2)	Deviation from Consensus	-0.84%***	-0.50%***	-0.49%**	-0.13%**	-0.07%	-0.84%***
		(-22%)	(-21%)	(-13%)	(-5%)	(-2%)	(-7%)
(3)	1994-2000	-0.33%	-0.29%***	-0.50%**	-0.34%***	-0.45%*	-0.33%**
		(-9%)	(-13%)	(-14%)	(-15%)	(-13%)	(-9%)
(4)	2001-1010	-0.85%***	-0.55%***	-0.39%*	-0.23%***	-0.30%**	-0.85%*
		(-19%)	(-14%)	(-9%)	(-6%)	(-7%)	(-3%)
(5)	No Centering	-0.89%***	-0.61%***	-0.48%***	-0.14%**	-0.28%**	-0.89%**
		(-21%)	(-18%)	(-11%)	(-4%)	(-7%)	(-4%)
(6)	Size-B/M-Momentum	-0.75%***	-0.48%***	-0.33%**	-0.23%***	-0.35%***	-0.15%**
	Adjusted CAR	(-18%)	(-18%)	(-8%)	(-8%)	(-9%)	(-6%)

This table presents robustness checks for effects of the cognitive biases on the forecast informativeness. The above numbers are the differences in informativeness associated with $1 of unexpected revision between the top and the bottom quintiles of cognitive biases. The numbers in parentheses are the ratios of the difference over the average forecast informativeness.

- (1): I use the deviation from the consensus instead of the deviation from the prior forecast
- (2) & (3): I separate the sample into two periods (1994-2000 and 2001-1010) and perform the same analysis as the main analysis on these two sub-samples.
- (4): I calculate biases base on raw values of FE, Dev and DevPrior instead of centered values.
- (5): No centering in the calculation of OVERCONFIDENCE, BELIEF PERSISTENCE, and CONFIDENCE ENHANCEMENT
- (6): I use size-B/M ratio-momentum adjusted cumulative abnormal returns instead of market adjusted cumulative abnormal returns.

Appendix A

Mean-Squared Error (MSE) Minimization

Assume that the forecast, f, is weighted average of the private information, y, and public information, c. The optimal weight h put on y will minimize the expected squared distance between the forecast, f, and the real value, z. If the analyst put a weight of w on y, then the expected squared distance between f and z will be:

$$E[(f-z)^2] = E[(wy+(1-w)c-z)^2] = E\left[\left(w\left(z+\varepsilon_y\right)+(1-w)(z+\varepsilon_c)-z\right)^2\right] =$$

$$E\left[\left(w\varepsilon_y+(1-w)\varepsilon_c\right)^2\right] = w^2E\left[\varepsilon_y^2\right]+(1-w)^2E[\varepsilon_c^2]+2w(1-w)E\left[\varepsilon_y\varepsilon_c\right] =$$

$$\frac{w^2}{p_y}+\frac{(1-w)^2}{p_c} \qquad \text{(assume that y and c are independent)}$$

The optimal weight w=h will minimize $[(f-z)^2]$, such that:

$$\left.\frac{\partial\left(\frac{w^2}{p_y}+\frac{(1-w)^2}{p_c}\right)}{\partial w}\right|_{w=h} = 0 \quad \Rightarrow \quad \frac{h}{p_y}-\frac{(1-h)}{p_c} = 0 \quad \Rightarrow \quad h = \frac{p_y}{p_y+p_c}$$

Bayesian Framework

I assume that z follows a diffuse zero-mean normal distribution and the prior distribution of z is $z \sim N\left(0, \frac{1}{\lambda}\right)$, with $\lambda \approx 0$ because the analyst does not have prior belief on z. The public and private information are expressed as following: $c = z + N\left(0, \frac{1}{p_c}\right)$ and $y = z + N\left(0, \frac{1}{p_y}\right)$.

$$p(z|c,y) \propto p(c,y|z)p(z) \propto exp\left\{-\frac{p_c}{2}(c-z)^2 - -\frac{p_y}{2}(y-z)^2 - \frac{\lambda}{2}z^2\right\}$$

$$\propto exp\left\{-\frac{p_c}{2}(z^2-cz) - \frac{p_y}{2}(z^2-yz) - \frac{\lambda}{2}z^2\right\}$$

$$\propto exp\left\{\frac{1}{2}\left[(p_c+p_y+\lambda)z^2 - 2\left(p_c c + p_y y\right)z\right]\right\}$$

$$\propto N\left(\frac{p_c c + p_y y}{p_c+p_y+\lambda}, Var\right)$$

Then,

$$E(z|c,y) = \frac{p_c c + p_y y}{p_c+p_y+\lambda} \approx \frac{p_c c + p_y y}{p_c+p_y} = \frac{p_c}{p_c+p_y}c + \frac{p_y}{p_c+p_y}y = (1-h)c + hy$$

Appendix B

When the analyst has a prior belief on z, the prior distribution of the actual earnings is $z \sim N\left(f_{-1}, \frac{1}{p_{f_{-1}}}\right)$.

Similarly,

$$p(z|c,y) \propto exp\left\{\frac{1}{2}\left[\left(p_c + p_y + p_{f_{-1}}\right)z^2 - 2\left(p_c c + p_y y + \lambda f_{-1}\right)z\right]\right\}$$

$$\propto N\left(\frac{p_c c + p_y y + \lambda f_{-1}}{p_c + p_y + p_{f_{-1}}}, Var\right)$$

Then in this case, $E(z|c,y) = \frac{p_c}{p_c+p_y+p_{f_{-1}}}c + \frac{p_y}{p_c+p_y+p_{f_{-1}}}y + \frac{p_{f_{-1}}}{p_c+p_y+p_{f_{-1}}}f_{-1}$. It converges to the case in appendix A when $p_{f_{-1}} \to 0$.

Chapter II: Analysts' Additional Effort: Capital Expenditure Forecast Issuance

Capital expenditure (CapEx) forecasts are more and more popular among sell-side security analysts; however, there is virtually no research on these forecasts. This paper fills the gap by studying different aspects of CapEx forecasts and provides four major findings. First, investors react more strongly to analysts' reports containing CapEx forecasts than those without CapEx forecasts, which suggest that CapEx forecasts convey important information to investors. Second, analysts who are from bigger brokers, have less experience, cover fewer stocks, issue more number of earnings forecasts, have higher ex-post earnings forecast accuracy are more likely to issue CapEx forecasts. Analysts are also more likely to issue CapEx forecasts if more of their colleagues issue CapEx forecasts. These results suggest that analysts, who face higher motivation and lower issuing costs, are more likely to issue CapEx forecasts. Third, CapEx forecast accuracy decreases with the distance from earnings announcement, and increases with analysts' experience in CapEx forecasts. Analysts' general experience and quality do not explain analysts' CapEx forecast performance. Finally, analysts who issue CapEx forecasts, especially more accurate CapEx forecasts, are less likely to leave the profession, which is consistent with professional commitment and ability signaling arguments of CapEx forecast issuance.

JEL classification: G24, G31

Keywords: Security Analyst, Capital Expenditures, Forecast, Accuracy, Career

1 Introduction

Producing forecasts is the principal way analysts convey information to investors, demonstrate their abilities or pretend abilities to their existing and potential employers and clients. Almost all analysts issue earnings forecasts for all firms they cover. Some of them desire to enhance the value of their reports by adding other forecasts, such as target price, sales, cash-flow, long-term growth, dividend, and capital expenditure (henceforth, CapEx) forecasts. Since producing these additional forecasts costs time and effort, analysts have to compromise and consider the opportunity costs of this extra work. Analysts without an established reputation would like to gain recognition and develop their reputation by providing supplementary forecasts, while they are not able to imitate high quality analysts by producing forecasts which require too much time, efforts and resources. Supporting this hypothesis, Ertimur & Stubben (2006) propose that producing cash-flow forecasts requires considerably more resources and as a result, analysts from larger brokerage houses are more likely to issue cash-flow forecasts. Ertimur et al. (2009) find that analysts with less established reputation are more likely to issue sales forecasts. This is not surprising because sales forecasting is one aspect of standard earnings forecasting procedure and therefore it requires minimal extra time to include these forecasts in a report.

Although CapEx forecasts are not as popular as other forecasts, such as sales and target price forecasts, they are increasing in popularity among analysts. In 2011, about 57% of analysts issued at least one CapEx forecast and 70% of firms received at least one CapEx forecast. CapEx is an important input of the free-cash-flow valuation model which can directly affect the equity value. The free-cash-flow model is a function of the free cash-flows to firm and weighted average cost of capital$\left(\text{i.e. } Equity\ Value = \sum_{t=1}^{\infty} \frac{FCFF_t}{(1+WACC)^t} - Debt\ Value\right)$. The free cash-flow to firm, $FCFF_t$, is defined as net income, plus net non-cash charges, plus after-tax interest expenses, minus capital expenditure. The weighted average cost of capital, WACC, can also be affected by the capital expenditure through the risk level of new investments.

CapEx forecasts could provide investors with valuable information about the firms and signal analysts' ability. Since producing CapEx forecasts may be costly, some analysts are not issuing CapEx forecasts at all and some others issue CapEx forecasts on selected stocks. This paper studies the value of CapEx forecasts to investors and analyst's career, and the determinants of CapEx forecast issuance and accuracy. Specifically, this paper answers four important questions on CapEx forecasts: (1) Do CapEx forecasts bring additional information to investors? (2) Which analysts are more likely to issue CapEx forecasts? (3) What are determinants of CapEx forecast accuracy? Furthermore, (4) how can CapEx forecasts impact an analysts' career?

Firstly, to assess the information value of CapEx forecasts, I study the stock price behavior around analysts' report announcements. I find that market reacts more strongly to analysts' reports containing CapEx forecasts than those without CapEx forecasts after controlling for firm-year fixed effects and other variables. To illustrate the economic significance, the marginal effect of CapEx forecasts is about 75% of the difference in stock price effects between the third and the first quartiles of ex-post earnings forecast accuracy.

Secondly, to identify which analysts are more likely to issue CapEx forecasts, I use logistic regression to find the marginal effects of analyst characteristics on analysts' probability of issuing

CapEx forecasts, controlling for firm-year fixed effects. The regression results support the argument that issuing CapEx forecasts is beneficial, but costly to analysts. Analysts are more likely to issue CapEx forecasts if the benefits from CapEx forecast issuance increase and/or the costs decrease. Specifically, I find that analysts without established reputation, i. e. those with less broker tenure and firm-specific experience, tend to issue CapEx forecasts to stand out from the crowd. Analysts who have issued CapEx forecasts in the previous year on the same or on another firm and analysts from brokerage houses where CapEx forecasts are popular, are more likely to issue CapEx forecasts. Higher quality analysts, i. e. from bigger brokerage houses, star analysts, and more firm-specific accurate earnings forecasters, are more likely to issue CapEx forecasts. In addition, resource allocation is important to analysts' CapEx forecast decisions. Consistent with Clement (1999), I find that analysts covering more firms are less likely to produce CapEx forecasts. I use the number of earnings forecasts on a firm given by an analyst as a proxy for the resources that analyst is allocating to that firm, and find that the more resources allocated to a firm, the more likely the analyst will issue CapEx forecasts on the firm.

Thirdly, I examine the determinants of CapEx accuracy by regressing relative CapEx forecasts accuracy on characteristics of the forecast and the issuing analyst, controlling for firm-year fixed effects. Similar to earnings forecasts, CapEx forecasts that are issued later in the forecasting period are more accurate than those issued earlier. CapEx forecast accuracy is positively correlated with prior CapEx forecast accuracy, which is consistent with earnings forecasts (Clement 1999; Brown 2001). I also find that experience in CapEx forecasting improves CapEx forecast accuracy; however, the experience in earnings forecasts does not increase CapEx forecast accuracy. In addition, I document a non-robust relationship between CapEx forecast accuracy and contemporary EPS forecast accuracy. The two types of forecasts may require different skills in collecting and processing information.

Finally, I study the probability of analysts' disappearance from the I/B/E/S database next year. I find that CapEx forecast issuance and accuracy reduce the analysts' chance of leaving the financial analyst profession after controlling for year fixed effects and other variables. This result is consistent with Mikhail et al. (1997) who find that more accurate earnings forecasters are unlikely to leave the profession, and Call et al. (2009) who find that analysts issuing cash-flow forecasts and issuing more accurate cash-flow forecasts are less likely to be fired. Analysts who issue CapEx forecasts are 4.4% less likely to leave the profession than those who do not. To illustrate the economic significance, I compare this number with the marginal effects of earnings forecast accuracy on analysts' likelihood of professional discontinuation. Analysts at the third quartile of earnings forecast accuracy are 4.3% less likely to leave the profession than those at the first quartile of earnings forecast accuracy. In addition, the best CapEx forecasters are less likely to leave the profession than the worst CapEx forecasters by 3%.

This paper contributes to the vast literature on analysts' forecasts. Prior literature on security analysts' forecasts focuses extensively on earnings forecasts. Currently, there are a few papers on cash-flows forecasts, long-term growth forecasts, and sales forecasts, while there are virtually none on CapEx forecasts. This is surprising since managers' CapEx decisions are among the most important decisions in a firm and have been studied extensively. This paper fills the gap by studying analysts' CapEx forecasts. The rest of this paper is organized as follows. In section 2, I discuss whether CapEx forecasts bring additional information to investors. In section 3, I identify which analysts are more likely to issue CapEx forecasts. Section 4 studies determinants of CapEx forecast accuracy. Section 5 examines the effects of CapEx forecasts on analysts' career. The final section, section 6, is the conclusion.

2 Information Content of Capital Expenditure Forecasts

Capital expenditure (CapEx) forecasts have become increasingly popular among analysts since 2006. The evolution of CapEx forecasts is illustrated in Figure 1. In 2011, about 57% of analysts issue at least one CapEx forecast on 70% number of firms. Although CapEx forecasts are becoming more popular, these forecasts have not received proper research attention. There is extensive literature studying the relationship between managers' CapEx decisions and firm values. Although there is mixed evidence on the sign of the correlation between changes in firm investment levels and changes in firm value, the effects of investment level on firm value are indisputable, e. g. McConnell (1985). In addition, there is a rich literature on informativeness of earnings forecasts made by sell-side security analysts. The consensus of the studies is that the earnings forecasts contain information about the firm values. Therefore, CapEx forecasts potentially carry information which influences stock prices. Although, there are some papers examining the additional information contribution of supplementary forecasts, CapEx forecasts have been overlooked by the academic community, despite their potential information value.

[Insert Figure 1 about here]

2.1 Related Literature and Hypotheses Development

Literature on relation between capital expenditure and firm values

There have been mixed results on the relationship between CapEx decisions and the value of firms. McConnell (1985) finds that increases (decreases) in planned capital spending of an industrial firm are related to significant market positive (negative) responses. However, they find no similar evidence for public utility firms. Many follow-up studies also document a positive relation between CapEx and abnormal stock returns. Blackwell et al. (1990) and Gobola & Tsetsekos (1992) find negative abnormal stock returns following plant closures, i. e. capital divestment. Woolridge & Snow (1990), Blose & Shieh (1997) and Vogt (1997)) find positive market responses to firms' capital investments. Timothy J. Brailsford & Daniel Yeoh (2010) and Akbar & Stark (2003) also find a positive relation for Australian and UK firms.

On the other hand, other literature reveals mixed or non-significant evidence of the relation between CapEx and firm values. Chung et al. (1998) and Chan et al. (1995) argue that market reaction to a firm's CapEx decisions depend on the quality of the firm's investment opportunities; CapEx positively affects stock prices only if firms take advantage of valuable investment opportunities. Born & Ryan (2000) document a positive relationship if firms have high growth opportunities, but a negative relationship if firms have low growth opportunities. Jensen (1986) suggests an agency problem, in which managers' investment decisions may convey bad signals such as overinvestment, entrenchment and empire-building. Statman & Sepe (1989) argue that firms are reluctant to divest, and that investors recognize divestments as good news; they find consistent empirical evidence to support this argument. Divestures may create value for firms simply by getting rid of unprofitable investments. Afshar et al. (1992) find positive market reactions to divestments and selloffs of UK firms in financial distress. Kalra et al. (1994) discover that firms experience below average returns in the short-term, but above average returns in long-term, after plant closures. Burton et al. (1999) document significant market responses to joint-venture announcements and immediately cash generating projects. Other CapEx announcements insignificantly affect stock prices. Kim et al. (2005) find similar results for Korean firms. Del Brio et al. (2003) find insignificant price reactions to both increases and decreases in CapEx for the Spanish market.

Literature on information value of analysts' forecasts

The information content of security analysts' reports has been extensively studied, with particular on the informativeness of analysts' earnings forecasts. The extant literature mostly documents that upward (downward) earnings forecast revisions are associated with positive (negative) abnormal returns[13], in which, forecasts deviating more from the forecast consensus have higher price impact (Clement & Tse 2005). Some papers study the contribution of analysts' characteristics on the informativeness of earnings forecasts. Stickel (1992) finds that higher-status analysts, i. e. analysts who have been voted as All-America analysts, have greater impact on stock prices than their lower-status peers. Analysts with more accurate historical earnings forecasts have greater impact on the security prices than analysts with less accurate historical forecasts. In addition, Park & Stice (2000) find that the effect of analysts' past accuracy on market reaction is stock-specific and does not spill-over to other stocks covered by the same analyst.

Some authors study the informativeness of analysts' reports in which supplementary forecasts are taken into account. Brav & Lehavy (2003) claim that the market reacts significantly to information contained in analysts' target price forecasts. The market also reacts to the information content of sales forecasts (Ertimur et al. 2003), and sales forecasts amplify the reaction to earnings forecasts (Ertimur et al. 2009; Keung 2010). In the meanwhile, Givoly et al. (2009) document limited market reaction to the information content of cash flow forecasts.

Analysts' CapEx forecasts are meaningless to investors and wasteful to analysts if they convey no additional information. The increasing popularity of CapEx forecasts suggests that such forecasts must be valuable. Therefore, in the first hypothesis, I would like to examine whether the CapEx forecasts actually benefit investors by increasing the information content of the analysts' reports or not. If the CapEx forecasts contain useful information for investors, the more (ex-post) accurate information should receive higher attention from the market, and in consequence, stronger market reaction.

Hypothesis 1(a): *Market reacts more strongly to analysts' reports which include CapEx forecasts than those which do not.*

[13] (Givoly & Lakonishok 1979; Abdel-Khalik & Ajinkya 1982; Lys & Sohn 1990; Asquith et al. 2005)

Hypothesis 1(b): *Market reacts more strongly to CapEx forecasts which are more accurate (ex-post) than less accurate ones.*

2.2 Testing Methodology

Forecast informativeness is usually defined as the unexpected market reaction around the earnings forecast issuance in the direction of the forecast revision[14]. However, the direction of the relation between CapEx forecasts and stock price reactions is vague. An increase or decrease in investment does not create or destroy firm value in an obvious way. I overcome the issue of this ambiguous relationship by studying the absolute cumulative abnormal returns of stocks. I conjecture that additional information of CapEx forecasts would lead to stronger market reaction to analysts' reports.

I use absolute three-trading-day cumulative market adjusted abnormal returns surrounding the analyst's report issuance to measure the unexpected market reaction. The accumulation period is from one day before to one day after the event (Ball & Kothari 1991; Clement & Tse 2003; Hilary & Hsu 2013). To test Hypothesis 1(a), I use the independent variable *CapEx Forecast Dummy*, which equals 1 if the reports include CapEx forecasts and zero otherwise. To test Hypothesis 1(b), I include analysts' ex-post CapEx forecast accuracy, measured by *CapEx Forecast (ex-post) Accuracy,* into the regression. Investors may react differently to earnings forecasts due to the differences in firm characteristics. I include firm-year fixed effects to capture all possible firm characteristics measured on an annual basis.

Model I(a): at forecast level with firm-year fixed effects

$$Absolute\ Abnormal\ Returns = \alpha + \beta_1 * CapEx\ Forecast\ Dummy + \Gamma * Controls + \varepsilon$$

Model I(b): at forecast level with firm-year fixed effects

$$Absolute\ Abnormal\ Returns = \alpha + \beta_1 * CapEx\ Forecast\ Accuracy + \Gamma * Controls + \varepsilon$$

The variables are defined as follows:

<u>Dependent variable:</u>

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14 (Ball & Kothari 1991; Park & Stice 2000; Clement & Tse 2003; Hilary & Hsu 2013)

$Absolute\ Abnormal\ Returns = |\sum_{t=-1}^{t=1}(\text{Stock Return} - \text{Market Return})|$ (Right-winsorized at 1%)

Independent variables:

$$CapEx\ Forecast\ Dummy = \begin{cases} 1 & \text{if analysts' reports include CapEx forecasts} \\ 0 & \text{otherwise} \end{cases}$$

$$CapEx\ Forecast\ Accuracy = \frac{\text{Rank(Absolute CapEx Forecast Error)} - 1}{\text{Number of CapEx Forecasts} - 1}$$

The accuracy measure equals 1 if the forecast is most accurate and 0 if the forecast is least accurate among all CapEx forecasts given on the firm in the current fiscal year. Hypotheses 1(a) and 1(b) predict positive coefficients of *CapEx Forecast Dummy* and *CapEx Forecast Accuracy*.

Control variables:

$$Sales\ Forecast\ Dummy = \begin{cases} 1 & \text{if analysts' reports include sales forecasts} \\ 0 & \text{otherwise} \end{cases}$$

$$Cash - Flow\ Forecast\ Dummy = \begin{cases} 1 & \text{if analysts' reports include CF forecasts} \\ 0 & \text{otherwise} \end{cases}$$

$EPS\ Fcst.Deviation = |\text{Earnings Forecast} - \text{Previous Earnings Forecast}|$ (Winsorized at 1% level)

$$Positive\ EPS\ Fcst. = \begin{cases} 1 & \text{if Earnings Forecast} > \text{Previous Earnings Forecast} \\ 0 & \text{otherwise} \end{cases}$$

$$Distance\ to\ EPS\ Anncmt. = \ln(\text{Earnings Announcement} - \text{Forecast Date})$$

$Dispersion\ of\ EPS\ Fcst. = \text{Std. Dev. (Outstanding Earnings Forecasts)}$ (Winsorized at 1% level)

$EPS\ Fcst.\ L - F\ Ratio = \ln\left(\frac{\text{Average time distance from the last two forecasts}}{\text{Average time distance from the next two forecasts}}\right)$ (Cooper et al. 2001)

$$EPS\ Forecast\ Accuracy = \frac{\text{Rank(Absolute EPS Forecast Error)} - 1}{\text{Number of EPS Forecasts} - 1}$$

$$Number\ of\ Stocks = \ln(\text{number of stocks coverd by the analyst in the current year})$$

$$Analyst\ Firm\ Experience$$
$$= \ln(\text{number of years which the analyst has been covering the firm})$$

$$Analyst\ Experience = \ln(\text{number of years which the analyst has been in I/B/E/S})$$

$$Broker\ Size = \ln(\text{number of analysts working for the brokerage house})$$

$$Lagged\ EPS\ Fcst.Accuracy = \text{EPS Forecast Accuracy of the analyst in the previous year}$$

$$Lagged\ EPS\ Fcst.Boldness = \text{Average}\left[\frac{\text{Rank(EPS Fcst.Deviation)}-1}{\text{Number of EPS Forecasts}-1}\right]\text{ in the previous year}$$

2.3 Data Description

I collect analysts' forecasting information from the I/B/E/S database during the period from 2006 to 2011. The stock returns are extracted from the CRSP database. Information on the All-America analysts is extracted from the Institutional Investor website up to 2010. Table 1 presents the number of analysts issuing at least one CapEx forecast, the number of firms with at least one CapEx forecast, and the number of analyst-firm pairs with at least one CapEx forecast each year. Corresponding values associated with EPS forecasts are also presented for comparison purposes. In 2005, there are as little as 12 CapEx analyst-firm pairs, 11 analysts on 9 firms. In 2006, the number of analyst-firm pairs spiked to about 4,400 CapEx analyst-firms (11.5% of the sample) from nearly 1,000 analysts (24.3% of the sample) on approximately 2,000 firms (39.4% of the sample). The number of CapEx analyst-firms increase to nearly 15,500 (38.1% of the sample) from nearly 2,400 analysts (57.3% of the sample) on approximately 3,100 firms (70.0% of the sample) in 2011.

[Insert Table 1 about here]

Table 2 provides further information on distributions and correlations among variables. There are about 400,000 earnings forecasts from 2006 to 2011, in which about 10% are together with CapEx forecasts. In the meanwhile, 67% and 14% of earnings forecasts are accompanied by sales and cash-flow forecasts. A concern might be that analysts issuing CapEx forecasts may issue sales or cash-flow forecasts as well. However, the correlation between *CapEx Forecast Dummy*, *Sales Forecast Dummy,* and *Cash-Flow Forecast Dummy* are less than 20%, and there is, therefore, no risk of multicollinearity among these variables.

[Insert Table 2 about here]

The absolute cumulative market adjusted abnormal returns from one day before the forecasts to one day after the forecasts are 5.1% on average. The correlation matrix shows a positive correlation between *Absolute Abnormal Returns* and *CapEx Forecast Dummy*, which is consistent with Hypothesis1(a). The correlations among the independent variables display no risk of multicollinearity.

2.4 Empirical Results

Table 3 presents the regression results of Model I(a) and Model I(b). Technically, Model I(b) is run with earnings forecasts which are together with CapEx forecasts; therefore, the number of observations is reduced from nearly 400,000 in Model I(a) to nearly 38,000 in Model I(b). The differences between the number of observations in the regressions and descriptive statistics table are due to firm-year fixed effects.

[Insert Table 3 about here]

The positive coefficient of *CapEx Forecast Dummy* in Model I(a) supports Hypothesis I(a) which suggests that earnings forecasts associated with CapEx forecasts affect stock prices more than those not associated with CapEx forecasts. CapEx forecasts significantly increase the absolute three-day abnormal returns by 0.26%, equivalent to 22% per annum, which is also economically significant. To demonstrate the economic significance, I compare the marginal effects of *CapEx Forecast Dummy* with marginal effects of some other variables which are directly linked to the information content of the earnings forecasts. The effects of adding CapEx forecasts are about 75% of the differential market reaction between earnings forecasts at the third and the first quartiles in deviation from the prior forecasts, and about 72% of the differential market reactions between earnings forecasts at the third and the first quartile of ex-post accuracy. The marginal effect of CapEx Forecast Dummy on market reaction is nearly half of the marginal effects of sales forecasts.

The second column presents the results of Model I(b) which use ex-post CapEx forecast accuracy as the interested independent variable. The coefficient of *Ex-Post CapEx Fcst. Accuracy* is significantly positive at 5% level. The marginal effects of ex-post CapEx forecast accuracy is not as strong as the marginal effects of whether the CapEx forecasts are issued or not. The differential market reactions between forecasts at the third and the first quartile of ex-post CapEx forecast accuracy is about 0.11% (equivalent to 9% per annum). The marginal effects of ex-post CapEx forecast accuracy are about one fourth of marginal effects of ex-post earnings accuracy.

The coefficients of the other control variables have signs consistent with the existing literature. Consistent with Ertimur et al. (2003), Ertimur et al. (2009) and Keung (2010), earnings forecasts associated with sales forecasts are more informative. The negative coefficient of the cash-flow forecast dummy seems to be counter-intuitive; however, this coefficient is insignificant in some of my robustness tests, which is consistent with Givoly et al. (2009).The negative coefficient of *Positive EPS Fcst.* suggests that negative earnings revisions bring more information than positive revisions[15]. The positive coefficient of *EPS Fcst. L-F Ratio* suggests that leaders are more influential than followers (Cooper et al. 2001). Reports issued by more experienced analysts and analysts from bigger brokers have more impact on stock price[16]. Prior earnings forecast accuracy becomes unimportant after controlling for current forecast accuracy. Unlike Stickel (1992), I find that All-America status has a negative impact on market reaction to analysts' reports.

2.5 Robustness Checks

In the first robustness check, I control for concomitant firm events. Following Loh & Stulz (2010), I remove from the sample the earnings forecasts which occur in the three days around firm events, specifically quarterly earnings announcements, because it is difficult to disentangle the price impact of an analyst's forecast and a firm event if they occur at about the same time. The coefficient of the CapEx forecast dummy variable reduces significantly from 0.26 to 0.11 (i. e. reduces by 58%); however, it is still significant at 5% level. At the same time, the effects of other analyst characteristics variables on forecast informativeness are also reduced. For example, the coefficient of the ex-post forecast accuracy variable also reduces from 0.83 to 0.52 (i. e. reduces by 37%).

In the second robustness check, I adopt a more complicated calculation of CAR by controlling for size, book-to-market ratio (B/M) and momentum characteristics of the stock (Daniel et al. 1997; Loh & Stulz 2010). In this check, I also exclude concomitant earnings announcements. The coefficient reduces to 0.1 and is still significant at 5% level. To compute the three-day CAR for an analyst forecast, I create a benchmark portfolio with the same size, B/M, and momentum as the

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[15] (Givoly & Lakonishok 1979; Abdel-Khalik & Ajinkya 1982; Lys & Sohn 1990; Asquith et al. 2005)

[16] (Park & Stice 2000; Stickel 1992; Hugon & Muslu 2010; Hilary & Hsu 2013)

stock. The CAR is defined as the difference between the three-day buy-and-hold cumulative returns of the stock and the cumulative returns of the benchmark portfolio$\left(\text{i. e.}\, CAR_i = \prod_{t=-1}^{1}(1 + R_{it}) - \prod_{t=-1}^{1}\left(1 + R_{it}^{Portfolio}\right)\right)$. The benchmark portfolios are constructed as follows: Each July I assign stocks into 125 portfolios through three steps. I sort stocks into 5 groups based on their size and then, within each group, I sort stocks into 5 sub-groups based on their B/M. Finally, within each sub-group, I sort stocks into 5 portfolios based on their prior 12 months buy-and-hold cumulative returns.

3 Determinants of Capital Expenditure Forecast Issuance

3.1 Related Literature and Hypotheses Development

Ertimur & Stubben (2006) find that analysts from larger brokerage houses, issuing earnings forecasts more frequently but having less accurate prior earnings forecasts are more likely to issue cash-flow forecasts. In contrast, less reputable analysts, who have less experience and are employed by less prestigious brokerage houses, are more likely to issue dis-aggregated earnings forecasts (Ertimur et al. 2009).

In general, there are three motivations for analysts to issue CapEx forecasts. First, analysts are more likely to issue CapEx forecasts when the benefit of issuing or the harm of not issuing CapEx forecasts is higher. Second, analysts are more likely to issue CapEx forecasts when the costs of issuing those forecasts are smaller. Third, analysts are more likely to issue CapEx forecasts when analysts have more resources. Applying these general motivations, I have five predictions.

First, I predict that analysts, who issued CapEx forecasts on the same firm and/or on another firm in the previous year, are more likely to issue CapEx forecasts in the current year. An analyst's employer and clients form expectations from the analyst's past performance, and they are disappointed if they do not receive what they expected. Therefore, the cost of seizing to issue CapEx forecasts is higher than the cost of not issuing CapEx forecasts at all. Analysts, who issued CapEx forecasts before, may have more experience on issuing CapEx forecasts, which lowers the costs of issuing such forecasts in the current year. These analysts may have received more resources from their employer to issue CapEx forecasts.

Hypothesis 2(a): *Analysts are more likely to issue CapEx forecasts if they have issued CapEx forecasts on the same and/or on another firm in the previous year.*

Second, I predict that an analyst is more likely to issue CapEx forecasts if there are more of her colleagues issuing CapEx forecasts. If issuing CapEx becomes a more common practice within a broker, analysts may face a greater risk of losing their job if they do not issue CapEx forecasts. Analysts may learn the CapEx forecasting skills from their colleagues, who are working for the same broker, and in consequence, reduce the costs of issuing CapEx forecasts. In addition, brokerage houses where issuing CapEx is a common practice might simply offer more resources associated with CapEx forecasts to analysts.

Hypothesis 2(b): *Analysts are likely to issue CapEx forecasts if a high percentage of their colleagues issue CapEx forecasts.*

Third, analysts with less experience are more motivated to issue CapEx forecasts. They are competing with analysts who have been producing analytical reports for many years; therefore, they have to add more items to their reports to increase their reports' quality and visibility. This prediction is consistent with the finding of Ertimur et al. (2009) that less experienced analysts are more likely to issue dis-aggregated earnings forecasts. However, more experienced analysts may face lower CapEx forecast issuing costs, which leads to the higher popularity of CapEx forecast among experienced analysts. These conflicting arguments urge us a test for the following hypothesis.

Hypothesis 2(c): *Inexperienced analysts are more likely to issue CapEx forecasts.*

Fourth, analysts have scarce resources and they have to allocate these resources over the firms they cover. If an analyst covers many stocks, the amount of resources available for each stock is small. Therefore, analysts are more likely to issue CapEx forecasts if they cover fewer firms. In addition, the resources are also allocated unequally among covered firms. The favorite firms receive more attention from analysts and those firms are more likely to receive CapEx forecasts from the analysts. I conjecture that the number of earnings revisions per year is a good proxy for resource allocation, and firms which receive more earnings forecast revisions are more likely to receive CapEx forecasts.

Hypothesis 2(d): *Analysts are more likely to produce CapEx forecasts on firms which receive more resources.*

Finally, high quality analysts, i. e. from bigger brokers, voted as All-America financial analysts, higher earnings forecast accuracy in the same year, are usually given more resources. They may also find issuing CapEx forecasts less costly than low quality analysts. In the consequence, the high quality analysts are more likely to issue CapEx forecasts. However, the reputation argument of Ertimur et al. (2009) predicts that high quality analysts have well established reputation, and they have less motivation to issue additional forecasts. Therefore, I would like to verify those contradicting arguments by testing the following hypothesis.

Hypothesis 2(e): *High quality analysts are more likely to issue CapEx forecasts.*

3.2 Testing Methodology

I use logistic regression to capture the determinants of CapEx forecast issuance. The dependent variable is the probability of an analyst to issue at least one CapEx forecast on the firm in the current year. The interested independent variables are analyst characteristics variables. To control for firm characteristics, which potentially affect analysts' CapEx issuing decisions, I use two types of controls: firm characteristics together with industry-year fixed effects, and firm-year fixed effects. The two regressions are run on analyst-firm-year basis.

Model II (a): at analyst-firm-year level with industry-year fixed effects and clustering for autocorrelation and heteroskedasticity among industries.

$$P(CapEx\ Fcst.Dummmy) = \alpha + \mathrm{B} * Analyst\ Characteristics + \mathrm{C} * Firm\ Characteristics + \varepsilon$$

Model II (b): at analyst-firm-year level with firm-year fixed effects and clustering for autocorrelation and heteroskedasticity among industries.

$$P(CapEx\ Fcst.Dummmy) = \alpha + \mathrm{B} * Analyst\ Characteristics + \varepsilon$$

The analyst characteristic variables are defined as follows:

$$Lagged\ CapEx\ Fcst.Dummy = \begin{cases} 1 & \text{if the analyst issued at least one CapEx forecast on the same firm in the previous year} \\ 0 & \text{otherwise} \end{cases}$$

$$Lagged\ CapEx\ Dummy\ Other\ Firm = \begin{cases} 1 & \text{if the analyst issued at least one CapEx forecast on another firm in the previous year} \\ 0 & \text{otherwise} \end{cases}$$

Hypothesis 2(a) predicts positive coefficients for these variables.

$$Lagged\ Broker\ CapEx\ Ratio = \frac{\text{Number of analysts working for the same broker issuing CapEx forecasts in the previous year}}{\text{Number of analysts working for the same broker in the previous year}}$$

Hypothesis 2(b) predicts a positive coefficient for this variable.

$$Analsyt\ Broker\ Tenure = \ln(\text{No. of years the analyst has been working for the broker})$$

$$Analsyt\ Firm\ Expereince = \ln(\text{No. of years the analyst has been covering the firm})$$

Hypothesis 2(c) predicts negative coefficients for these variables.

$$Number\ of\ EPS\ Fcst. = \ln(\text{No. of EPS forecasts given by the analyst on the firm in the current year})$$

$$Number\ of\ Stocks = \ln(\text{No. of stocks covered by the analyst on the firm in the current year})$$

Hypothesis 2(d) predicts a positive coefficient for $Number\ of\ EPS\ Fcst.$, and a negative coefficient for $Number\ of\ Stocks$.

$$Broker\ Size = \ln(\text{No. of analysts working for the broker in the current year})$$

$$Ex\ Post\ EPS\ Fcst. Accuracy = \frac{\text{Rank(Absolute EPS Forecast Error)}-1}{\text{Number of EPS Forecasts}-1} \text{ in the current year}$$

$$Analyst\ Status = \begin{cases} 1 & \text{if the analyst appear in Institutional Investor magazine last October} \\ 0 & \text{otherwise} \end{cases}$$

Hypothesis 2(e) predicts positive coefficients for these variables.

In Model II (a), I control for size of the firm (*Lagged Market Capitalization*), growth opportunity (*Lagged Book-to-Market Ratio*), managers' cash-in-hand (*Lagged Cash*), profitability (*Lagged Net Income*), historical capital expenditure (*Lagged Capital Expenditure*), and stock market liquidity (*Lagged Share Turnover*). These variables are defined as follows:

Lagged Market Capitalization = ln(share price * number of share outstanding) the end of the most current fiscal year (i. e. ln(prcc_f*csho)).

Lagged Book-to-Market Ratio = ln(book value of common equity / market value of equity) at the end of the most current fiscal year (i. e. ln(ceq/(prcc_f*csho))).

Lagged Cash = cash and short-term investments on total assets at the end of the most current fiscal year (i. e. che/at).

Lagged Net Income = net income on total assets at the end of the most current fiscal year (i. e. ni/at).

Lagged Capital Expenditure = capital expenditure on total assets at the end of the most current fiscal year (i. e. capx/at).

Lagged Share Turnover = ln(number of shares traded in the previous fiscal years / number of shares outstanding at the end of the year) (i. e. ln(cshtr_c/csho))

3.3 Data Description and Empirical Results

In this section, I use sample from 2007 to 2011 for the regression, and retain the year 2006 to calculate analysts' past CapEx performance because CapEx forecasts popularity takes off in 2006. The sample includes 152,441 analyst-firm-years, and 27% of those observations are associated with CapEx forecasts. Panel 1 of Table 4 presents the distribution of analysts' characteristics variables. 20% of analysts have produced CapEx forecasts on the same firm in the previous year, and 43% of them have produced CapEx forecasts on another firm. At a broker level, on average, 43% of analysts working for the broker have issued at least one CapEx forecast in the previous year. An average analyst has nearly 4 years of tenure with the current broker and 3 years of firm-specific experience. Analysts, on average, cover nearly 14 stocks and issue 3.5 forecasts on each stock in a year. Each broker employs 36 analysts on average. Finally, there are nearly 10% of firms covered by star analysts. Note that the average is calculated from observations at analyst-firm-year level; it is subject to change if the average is calculated from observations at analyst-year or broker-year levels instead of analyst-firm-year level.

[Insert Table 4 about here]

Table 5 presents empirical results of Model II(a) and Model II(b). The two models produce very similar results. The first column presents the coefficients associated with analyst characteristics and firm characteristics variables in Model II(a), and the second column presents the marginal effects of these variables on probability of CapEx forecast issuance. The third and the forth columns presents the coefficients and marginal effects of analyst characteristics variables in Model II(b). In general, the regression results suggest that analysts are more likely to issue CapEx forecasts when they have higher potential benefits and lower costs of doing so. Specifically, I have four findings. First, the positive coefficients of *Lagged CapEx Fcst. Dummy* and *Lagged CapEx Dummy Other Firm* are supporting Hypothesis 2(a) that analysts with experience in CapEx forecasts are more likely to issue CapEx forecasts. Analysts who issued CapEx forecasts on the same firm in the previous year are 25% more likely to issue CapEx forecasts on the focal firm this year (from Model II(b)). Analysts who issued CapEx forecasts on other firms are 14% more likely to issue CapEx forecasts on the focal firm this year (from Model II(b)). The positive coefficient of *Lagged Broker CapEx Ratio* is also consistent with Hypothesis 2(b) that broker norms are important to analysts' CapEx forecast decisions. Analysts from brokers at the third quartile of *Lagged Broker CapEx Ratio* (i. e. 65%) are about 20% more likely to issue CapEx forecasts than analysts from brokers at the first quartile of *Lagged Broker CapEx Ratio* (i. e. 14%) (from Model II(b)).

[Insert Table 5 about here]

Second, the coefficients of analysts' broker tenure and firm-specific experience are significantly negative, which demonstrate the validity of Hypothesis 2(c), namely that less experienced analysts are more likely to issue CapEx forecasts. By issuing CapEx forecasts, inexperienced analysts gain more, through the recognition of their employers and investors, than experienced analysts. On average, analysts at the first quartile of broker tenure are 6% more likely to issue CapEx forecasts than those at the third quartile of broker tenure; the similar figure for firm-specific experience is 5% (from Model II(b)). I also use analysts' general experience instead of firm-specific experience in robustness checks and find similar, but weaker effects.

Third, analysts covering less stocks are more likely to issue CapEx forecasts on their covered stocks, and those stocks which are given more earnings forecasts are more likely to be associated with CapEx forecasts. These findings are consistent with Clement (1999)'s limited resource argument embedded in Hypothesis 2(d). The difference in the probability of issuing CapEx forecasts of analysts at the first and the third quartile of number of earnings revisions is 3.5%, and the difference for analysts at the first and the third quartile of the number of covering stocks is 2% (from Model II(b)).

Fourth, I find that higher quality analysts are more likely to issue CapEx forecasts, which is consistent with the ability argument of Hypothesis 2(e). Specifically, analysts from bigger firms, analysts with higher ex-post firm-specific earnings forecast accuracy, and All-America analysts are more likely to issue CapEx forecasts. The findings are also consistent with the resource argument, that high quality analysts are given more resources, and are in consequence, more likely to issue CapEx forecasts. Analysts from the third quartile of broker size are 3% more probable to issue CapEx forecasts than analysts from the first quartile. Analysts in the third quartile of ex-post earnings forecast accuracy are 2% more likely to issue CapEx forecasts than those in the first quartiles of accuracy (from Model II(b)). I also use the past earnings forecast accuracy instead of ex-post accuracy in the robustness checks, but I do not find a significant relationship with the probability of CapEx forecast issuance. Analysts may decide to issue CapEx forecasts when they foresee future information advantages. High status analysts are nearly 3% more likely to issue CapEx forecasts than low status analysts (from Model II(b)).

Model II(a) also offers some insights on the firm characteristics which attract CapEx forecasts. In general, the effects of firm characteristics on the likelihood of CapEx forecast issuance are much smaller than the effects of analyst characteristics. First, the results of Model II(a) suggest that bigger firms and growth firms receive more CapEx forecasts from security analysts. The difference in the likelihood of receiving CapEx forecasts from an analyst between a firm at the third and the first quartiles in size is 1.7% and between a firm at the first and the third quartiles in book-to-market ratio quartiles is 0.7%. Second, firms holding less cash receive more attention on CapEx forecasts than those holding more cash. The difference in the likelihood of receiving CapEx forecasts from an analyst between a firm at the first and the third quartiles in level of cash in the balance sheet is 1.5%. Third, profitable firms receive more CapEx forecasts; however, the result is not economically significant. The difference in the likelihood of receiving CapEx forecasts from an analyst between a firm at the third and the first quartiles in net income is only 0.3%

4 Determinants of Capital Expenditure Forecast Accuracy

4.1 Related Literature and Hypotheses Development on CapEx Forecast Accuracy

Earnings forecast accuracy has been extensively studied for the last two decades. The extant literature documents that earnings forecasts are more accurate if they are produced later in the forecasting period, produced by All America analysts (i. e. star analysts), produced by analysts with more firm-specific experience, produced by analysts with higher prior forecast accuracy, produced by analysts from bigger brokerage houses, or produced by analysts who follow fewer firms and industries[17]. Although Kim et al. (2011) find a significant relationship between earnings forecast accuracy and general experience, Jacob et al. (1999) do not find such a relationship. Clement et al. (2007) suggest that earnings forecast accuracy is associated with innate ability and task-specific experience. Earnings forecast accuracy is increasing with the number of forecasts made during the forecasting intervals (Jacob et al. 1999) and the walk-down pattern (Ke & Yu 2006). Clement & Tse (2005) find that bold forecasts are more accurate. Earnings forecasts which are supplemented with cash flow and sales forecasts are more accurate[18]. Bolliger (2004) studies the European market and reports similar findings to the US market, namely that earnings forecast accuracy is positively related to analysts' firm-specific experience, and negatively related to the number of countries covered by analysts, while there is no relationship with the general experience and brokerage house sizes.

Pae & Yoon (2011) study the relationship between analyst characteristics and cash-flow forecast accuracy, and their results are similar to those of earnings forecast accuracy. They find that cash-flow forecast accuracy is positively associated with cash-flow forecasting frequency, cash-flow forecasting experience and prior cash-flow forecasting performance, while it is negatively associated with the number of companies followed and the forecast horizon.

In general, a forecast is the product of two processes: information collection and information analysis. Both processes can be positively correlated with the ability of analysts and the level of resources allocated to analyze the firm. In addition, the first process can also be improved by the amount of public information available in the market and the analysts' sources to collect non-public information. Although CapEx forecasts are fundamentally different to other types of forecasts, they may share some common determinants. I focus on the effects of analysts' available information, experience, quality, and resources on the accuracy of CapEx forecasts. It is generally agreed in existing studies that earnings forecasts issued closer to the earnings announcements are more accurate than those issued earlier, and I predict that CapEx forecasts behave similarly.

Hypothesis 3(a): *CapEx forecasts produced later in the forecasting period are more accurate than forecasts produced earlier.*

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[17] (O'brien 1988; Stickel 1992; Mikhail et al. 1997; Jacob et al. 1999; Brown 2001; Kim et al. 2011)

[18] (Call et al. 2009; Pae et al. 2007; Keung 2010)

Second, analysts with more firm-specific experience produce better earnings forecasts. Pae & Yoon (2011) find that the cash-flow forecasting quality is also affected by the cash-flow forecasting experience. Therefore, I predict that the CapEx forecasting ability is also positively correlated with the analysts' firm-specific CapEx experience, which is the basis for the following hypothesis.

Hypothesis 3(b): *CapEx forecast accuracy increases with analysts' experience in CapEx forecasting.*

Third, prior research has found that better forecasters in the prior periods tend to produce better forecasts in the subsequent periods. Therefore, I would expect that analysts with more accurate prior CapEx forecasts tend to produce better future CapEx forecasts.

Hypothesis 3(c): *Analysts, who were more accurate in CapEx forecasts in the previous year, produce more accurate CapEx forecasts in the current year.*

Fourth, resources are important for analysts to produce accurate forecasts. Past research has demonstrated that analysts produce more accurate forecasts if they do not split their resources over many stocks, industries, or countries. Therefore, CapEx forecasters are likely to issue better forecasts if they cover fewer stocks. In addition, analysts' concentration of resources on some stocks may cause more accurate CapEx forecasts on those stocks. These arguments serve as the basis for the next hypothesis.

Hypothesis 3(d): *Analysts produce more accurate CapEx forecasts on the firms which receive more resources.*

Finally, the existing literature agrees that high quality analysts, i. e. those from bigger brokerage houses and those that have been voted as All-America analysts, are better at earnings forecasting. I conjecture that those high quality analysts are also better at CapEx forecasting. In addition, I would expect that better earnings forecasters are better CapEx forecasters.

Hypothesis 3(e): *Higher quality analysts issue more accurate CapEx forecasts.*

4.2 Testing Methodology

I use two OLS regression models to examine the determinants of CapEx forecast accuracy. The difference between the two models is that the first model does not include the lagged CapEx forecast accuracy variable as a dependent variable. However it includes the lagged CapEx issuance indicator variables as dependent variables. Model III(b) constrains itself to analysts who have at least two years of CapEx firm-specific experience since it requires past CapEx forecast accuracy data.

Model III(a): at analyst-firm-year level with firm-year fixed effects

$$CapEx\ Fcst.Accuracy = \alpha + \mathrm{B} * Analyst\ Characteristics + \varepsilon$$

Model III(b): at analyst-firm-year level with firm-year fixed effects

$$CapEx\ Fcst.Accuracy =$$
$$\alpha + \beta_1 * Lagged\ CapEx\ Fcst.\ Accuracy + \mathrm{B} * Analyst\ Characteristics + \varepsilon$$

The variables are defined as follows:

<u>To test Hypothesis 3(a)</u>

$$Distance\ to\ EPS\ Anncmt. = \ln(\text{Earnings Announcement} - \text{Forecast Date})$$

Hypothesis 3(a) predicts a negative coefficient for this variable.

<u>To test Hypothesis 3(b)</u>

$$Analsyt\ CapEx\ Expereince = \ln(\text{No. of years the analyst has been issuing CapEx forecasts})$$

Hypothesis 3(b) predicts positive coefficients for this variable.

<u>To test Hypothesis 3(c)</u> (in Model III(b) only)

$$Lagged\ CapEx\ Fcst.Accuracy = \frac{\text{Rank(Absolute CapEx Forecast Error)}-1}{\text{Number of CapEx Forecasts}-1}\ \text{in the previous year}$$

Hypothesis 3(c) predicts positive coefficients for this variable.

<u>To test Hypothesis 3(d)</u>

$$Number\ of\ EPS\ Fcst. =$$
$$\ln(\text{No. of EPS forecasts given by the analyst on the firm in the current year})$$

$$Number\ of\ Stocks = \ln(\text{No. of stocks covered by the analyst in the firm in the current year})$$

Hypothesis 3(d) predicts a positive coefficient for $Number\ of\ EPS\ Fcst.$, and a negative coefficient for $Number\ of\ Stocks$.

To test Hypothesis 3(e)

$$Broker\ Size = \ln(\text{No. of analysts working for the broker in the current year})$$

$$Ex - Post\ EPS\ Fcst. Accuracy = \frac{\text{Rank(Absolute EPS Forecast Error)}-1}{\text{Number of EPS Forecasts}-1} \text{ in the current year}$$

$$Analyst\ Status = \begin{cases} 1 & \text{if the analyst appears in the Institutional Investor magazine last October} \\ 0 & \text{otherwise} \end{cases}$$

Hypothesis 3(e) predicts positive coefficients for these variables.

4.3 Data Description and Empirical Results

Table 6 presents the descriptive statistics of variables used in Model III(a) and Model III(b) at analyst-firm-year level on analysts who produce at least one CapEx forecast on the firm. On average, CapEx forecasters have 2.8 years of experience in CapEx forecasting, and 6.2 years of general experience. Consistent with the determinants of CapEx forecast issuance, CapEx forecasters are covering fewer stocks, issuing more earnings forecasts on the stocks, work in bigger brokerage houses, are more accurate earnings forecasters, and have higher status.

[Insert Table 6 about here]

From the regression results of Model III(a) and Model III(b) presented in Table 7, I obtain five findings. First, the significant negative coefficients of *Distance to EPS Anncmt.* in both models support Hypothesis 3(a), namely that CapEx forecasts given later in the forecasting period are more accurate than those given earlier. The difference in the forecast accuracy score between forecasts issued at the first and the third quartiles of distance to earnings announcements is 6%. Second, analysts significantly improve their CapEx forecast accuracy from their CapEx forecast experience (i. e. supporting Hypothesis 3(b)), but not from their earnings forecast experience (after controlling for their CapEx forecast experience). Analysts in the third quartile of CapEx forecast experience have 2% CapEx forecast accuracy higher compared to those in the first quartile of CapEx forecast experience. Third, analysts' prior firm-specific CapEx forecast accuracy is an important determinant of analysts' current CapEx forecast accuracy. The most accurate CapEx forecasters in the previous year have 10% CapEx forecast accuracy higher than the worst accurate CapEx forecasters.

[Insert Table 7 about here]

Fourth, resource allocation affects analysts' CapEx forecast accuracy. I find that analysts give more accurate CapEx forecasts on firms which are given more earnings forecasts in the same year. This finding is in line with the resource allocation argument of Hypothesis 3(d). However, I do not find any significant effects of coverage breath on CapEx forecast accuracy. Finally, unlike earnings forecasts, there is no robust evidence supporting Hypothesis 3(e), namely that high quality analysts produce more accurate CapEx forecasts. Although I document a positive relationship between earnings forecast accuracy and CapEx forecast accuracy in the same year, this relationship becomes insignificant in the sub-sample of analysts with firm-specific CapEx forecast experience.

5 Capital Expenditure Forecast and Analyst' Job Separation

5.1 Related Literature

Prior research documents positive (negative) career outcomes associated with higher (lower) analysts' forecasting performance. More accurate earnings forecasters are less likely to lose their job (Mikhail et al. 1999) and are more likely to move to high-status brokerage houses (Hong & Kubik 2003). However, Hong & Kubik (2003) also document that analyst optimism is positively related to a successful career, and that optimism is even more important than accuracy when covered firms have underwriting relationships with the analysts' brokerage houses. Hong et al. (2000) find that young analysts are more likely to lose their job for bold and inaccurate earnings forecasts. Clement & Tse (2005) find that analysts covering more firms are more tolerated for inaccurate bold forecasts. Ke & Yu (2006) find that analysts who revise earnings forecasts downward from initial over-optimistic forecasts are less likely to be fired.

Supplementary forecasts are also important to analysts' career. Call et al. (2009) and Pandit et al. (2012) find that cash-flow forecast issuance and accuracy reduce analysts' likelihood of job loss. Pandit et al. (2012) also find that cash-flow forecasts accuracy is more important to analysts' career if firms are covered by more analysts. Ertimur et al. (2009) find that earnings forecast disaggregation assists less reputable analysts to increase their chance of promotion and decrease their chance of demotion or termination. Jung et al. (2012) document those analysts who issue long-term forecasts are less likely to leave the profession or move to smaller brokerage houses.

Similar to other supplementary forecasts, security analysts' CapEx forecasts may signal two things. First, issuing CapEx forecasts may signal analysts' commitment to develop their career as analysts; therefore, these analysts are less likely to leave the profession. Second, issuing CapEx forecasts may signal analysts' ability because, unlike issuing sales forecasts, issuing CapEx forecasts is costly. CapEx forecasts require different skills and procedures compared to other forecasts. Therefore, I predict that the chance of leaving the profession is lower for analysts who are issuing CapEx forecasts. If the ability signaling argument is correct, more accurate CapEx forecasters should be less likely to leave the profession since the signals about their ability are more apparent. These arguments are the basis for the following hypotheses.

Hypothesis 4(a): *CapEx forecast issuers are less likely to leave their profession than other analysts.*

Hypothesis 4(b): *More accurate CapEx forecasters are less likely to leave their profession than less accurate ones.*

5.2 Testing Methodology

I run logistic regressions to find relationships between likeliness of analysts' job loss and analysts' CapEx forecast performance. Model IV(a) includes the analysts' CapEx forecast issuance indicator variable and other control variables. In Model IV(b), the CapEx forecast issuance indicator variable is replaced by the relative CapEx forecast accuracy variable.

Model IV (a): at analyst-year level with year fixed effects

$$Pr(Professional\ Discontinuation) = \alpha + \beta_1 * CapEx\ Fcst.\ Dummy + \Gamma * Controls + \varepsilon$$

Model IV (b): at analyst-year level with year fixed effects

$$Pr(Professional\ Discontinuation) = \alpha + \beta_1 * CapEx\ Fcst.\ Accuracy + \Gamma * Controls + \varepsilon$$

The independent variables are defined as follows:

<u>Interested independent variables</u>

$$CapEx\ Fcst.\ Dummy = \begin{cases} 1 & \text{if the analyst issues at least one CapEx forecast in the current year} \\ 0 & \text{otherwise} \end{cases}$$

$$CapEx\ Fcst.Accuracy = Average\left[\frac{\text{Rank(Absolute CapEx Forecast Error)}-1}{\text{Number of CapEx Forecasts}-1}\right] \text{ in the current year}$$

Hypothesis 4(a) predicts a negative coefficient for $CapEx\ Fcst.\ Dummy$ and Hypothesis 4(b) predicts a negative coefficient for $CapEx\ Fcst.Accuracy$.

<u>Control variables</u>

$$Sales\ Forecast\ Dummy = \begin{cases} 1 & \text{if the analyst issues at least one sales forecast} \\ & \text{in the current year} \\ 0 & \text{otherwise} \end{cases}$$

$$Cash - Flow\ Forecast\ Dummy = \begin{cases} 1 & \text{if the analyst issues at least one cash} - \text{flow forecast} \\ & \text{in the current year} \\ 0 & \text{otherwise} \end{cases}$$

$$EPS\ Forecast\ Accuracy = \text{Average}\left[\frac{\text{Rank(Absolute EPS Forecast Error)}-1}{\text{Number of EPS Forecasts}-1}\right] \text{ in the current year}$$

$$EPS\ Fcst.\ L - F\ Ratio =$$
$$\text{Average}\left[\ln\left(\frac{\text{Average time distance from the last two forecasts}}{\text{Average time distance from the next two forecasts}}\right)\right] \text{ in the current year}$$

$$EPS\ Fcst.Boldness = \text{Average}\left[\frac{\text{Rank(EPS Fcst.Deviation)}-1}{\text{Number of EPS Forecasts}-1}\right] \text{ in the current year}$$

$Walk\ Down\ Score = \text{Average[walk down indicator]}$, in which walk-down indicator equals 1 if the last EPS forecast of the analyst on the firm in the fiscal year is smaller than his last EPS forecast on the same firm in the first half of the fiscal year, and equals 0 otherwise (Ke & Yu 2006; Libby et al. 2007).

$$Number\ of\ Stocks = \ln(\text{number of stocks coverd by the analyst in the current year})$$

$$Number\ of\ EPS\ Fcst. \\ = \ln(\text{No. of EPS forecasts given by the analyst on the firm in the current year})$$

$$Analyst\ Status \\ = \begin{cases} 1 & \text{if the analyst appears in the Institutional Investor magazine this October} \\ 0 & \text{otherwise} \end{cases}$$

$$Broker\ Size = \ln(\text{number of analysts working for the broker in the current year})$$

$Analyst\ Experience = \ln(\text{number of years which the analyst has been in I/B/E/S})$

5.3 Data Description and Empirical Results

I use a sample from 2006 to 2010 because the All-America analysts data is up to 2010, and on average, 15% of security analysts leave the profession each year. Table 8 presents some descriptive statistics of the variables at analyst-year level. There are about 40% of analysts issuing at least one CapEx forecast, nearly 90% of them issuing at least one sales forecast, and only 26% of analysts issuing at least one cash-flow forecast. The correlation among $CapEx\ Fcst.\ Dummy$, $Sales\ Forecast\ Dummy$, and $Cash - Flow\ Forecast\ Dummy$ are less than 30% (the correlation matrix is unreported); therefore, there is no risk of multicollinearity among these variables.

[Insert Table 8 about here]

Table 9 presents regressions results of Model IV(a) and Model IV(b) on 35,906 analyst-years from 2006 to 2010. In the first column, a negative coefficient of *CapEx Fcst. Dummy* suggests that CapEx forecast issuance reduces analysts' chance of leaving their profession. Analysts who issue at least one CapEx forecast are 4.4% less likely to leave the profession than those who do not. This finding is in line with Hypothesis 4(a). This finding is consistent with Call et al. (2009) finding hat analysts who issue cash-flow forecasts are less likely to leave their profession.

[Insert Table 9 about here]

In the third column, the coefficient of *CapEx Fcst. Accuracy* is significantly negative at 10% significance level, which means that more accurate CapEx forecasters are less likely to leave the analyst profession. The most accurate CapEx forecasters are 3% less likely to leave their profession than the least accurate CapEx forecasters. This result is consistent with Mikhail et al. (1999) who document that more accurate earnings forecasters are less likely to leave the profession.

To demonstrate the economic significance of CapEx forecasts' marginal effects on the professional discontinuation likelihood, I further analyze the marginal effects of control variables. Negative coefficients of *EPS Fcst. Accuracy* suggests that more accurate earnings forecasters are less likely to leave the profession than less accurate earnings forecasters. Analysts at the third quartile of earnings forecast accuracy are 4.4% less likely to leave the profession than analysts at the first quartile; this figure is around the marginal effects of the CapEx forecast issuance dummy. The difference in job termination probability between analysts at the third and the first quartiles of coverage breadth is 4.7%, which is a little higher than the marginal effects of the CapEx forecast issuance dummy. Analysts at the third quartile of number of earnings forecasts per stock are 9% less probable to leave their profession than those at the first quartile, which is double of the marginal effects of the CapEx forecast issuance dummy. Furthermore, the marginal effects of All-America analyst status is lower than the marginal effects of CapEx forecast issuance dummy on the job termination probability.

6 Conclusion

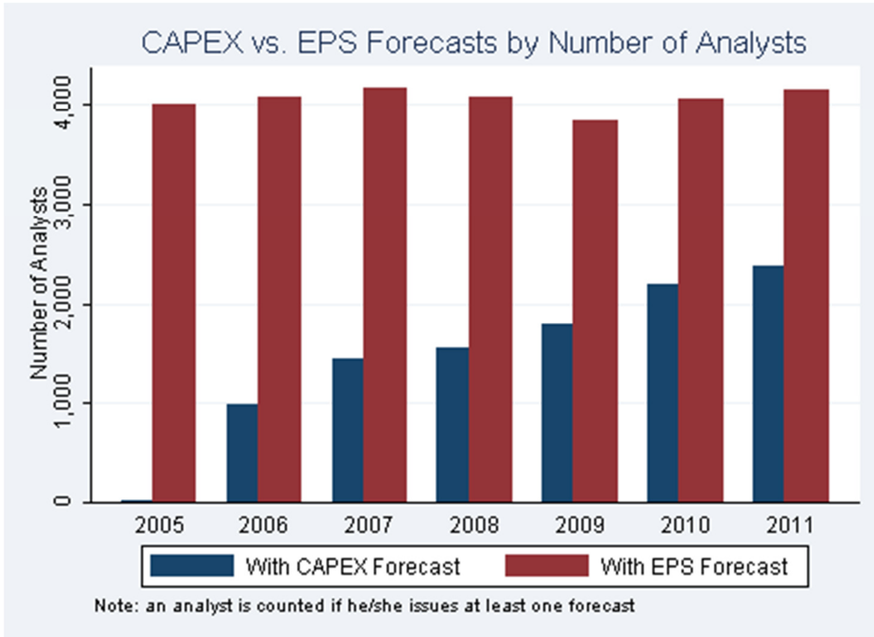
Issuing CapEx forecasts have become a popular exercise among security analysts. At the end of 2011, 57% of analysts were issuing at least one CapEx forecast and 70% of listed firms were given at least one CapEx forecast, despite the fact that CapEx forecasts were first issued only six years ago. I investigate the effects of the CapEx forecasts on the market influence of analysts' reports. I study analysts' characteristics which may affect the likelihood of CapEx forecast issuance and CapEx forecast accuracy. I also examine the impact of CapEx forecast issuance and accuracy on analysts' career.

I find that CapEx forecasts increase the market reaction to financial analysts' reports, and more accurate CapEx forecasts have stronger effects on stock prices. However, CapEx forecasts are also costly to issue; therefore, selective groups of analysts with more motivation and lower costs are more likely to issue CapEx forecasts. Specifically, analysts with less broker tenure and firm-specific experience are more motivated to impress their employers and clients by issuing CapEx forecasts. More experienced analysts in CapEx forecasts and high quality analysts are more likely to issue CapEx forecasts because they may face lower producing costs. The social norm is also an important factor; analysts are more likely to issue CapEx forecasts if their colleagues, who work for the same brokers, are issuing CapEx forecasts.

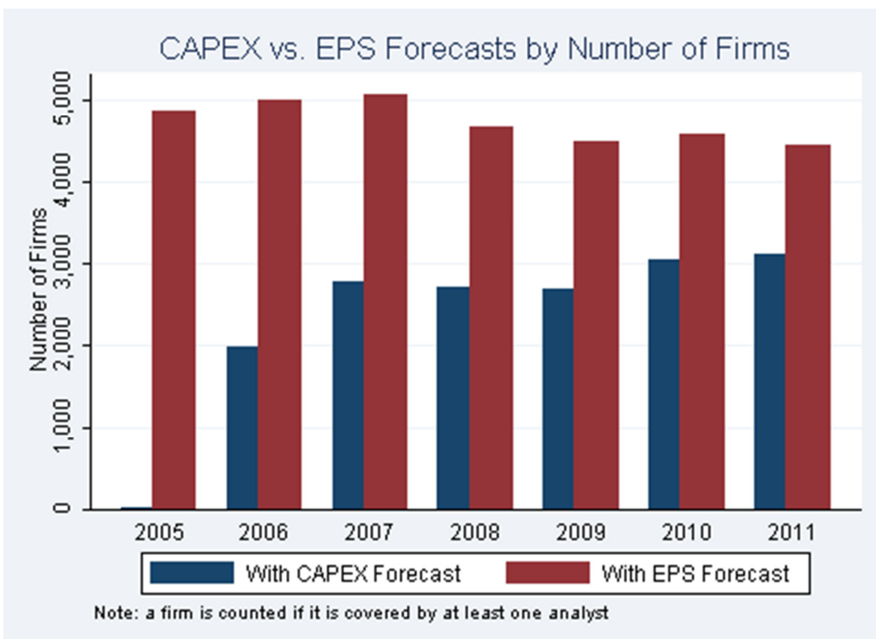
More experienced analysts in CapEx forecasts are more accurate CapEx forecasters. Analysts with more general experience and higher general quality are not necessary better CapEx forecasters. Similar to EPS forecasts, CapEx forecasts issued later in the forecasting period are more accurate than those issued earlier. Furthermore, I find that analysts' CapEx forecast issuance and accuracy are negatively associated with their probability of leaving the financial analyst profession. With regard to the effects of CapEx forecasts on analysts' career, I find that analysts are less likely to leave their profession if they issue CapEx forecasts. The CapEx forecast accuracy is also negatively correlated with the job termination likelihood. The findings are consistent with professional commitment and the ability signaling arguments.

Figure 1: Evolution of CapEx Forecasts

Panel 1: Number of Analysts with CAPEX forecasts and with EPS forecasts

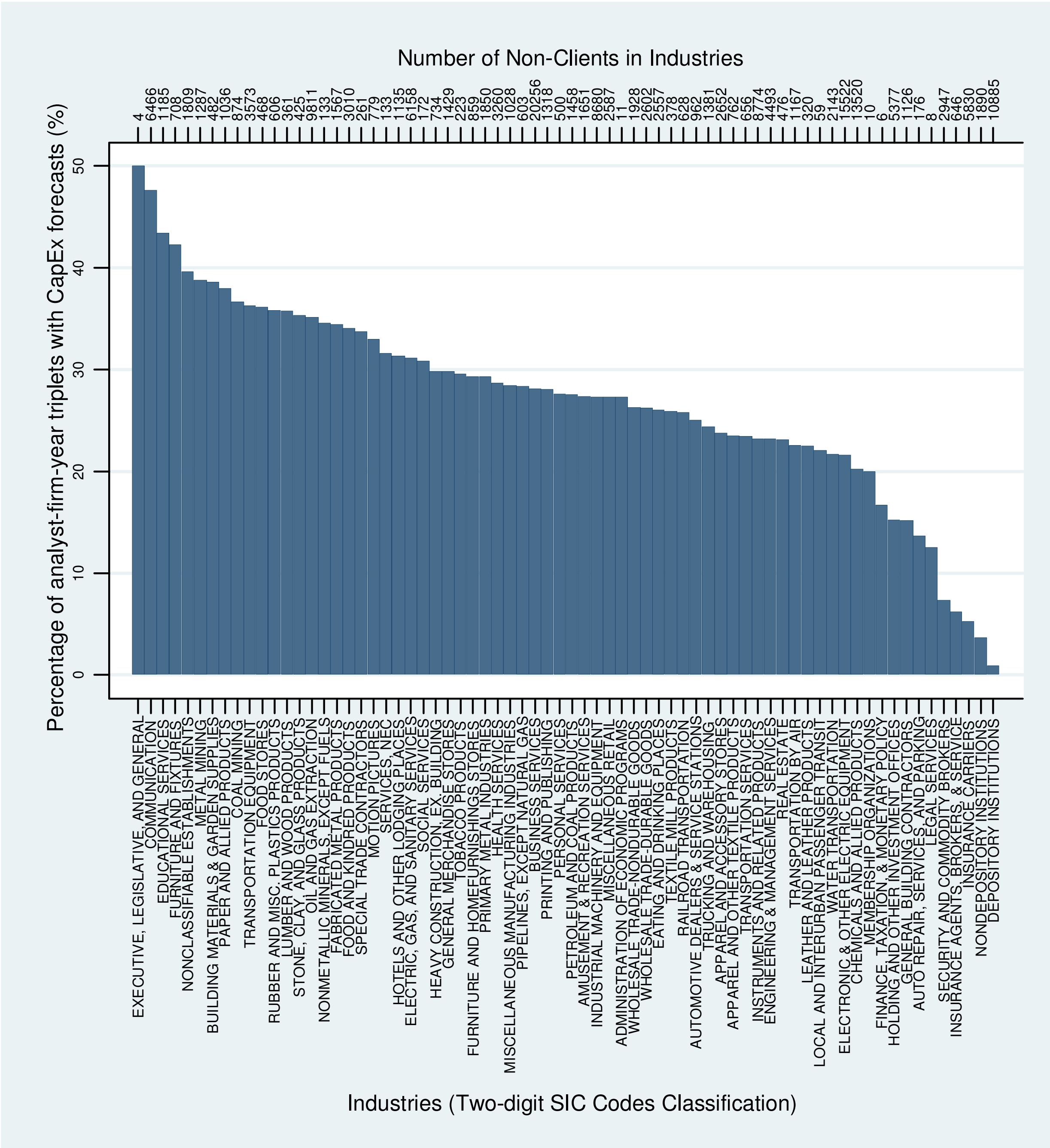


Panel 2: Number of Firms with CAPEX forecasts and with EPS forecasts



This figure presents the evolution of CapEx forecasts from 2005 to 2011. Panel 1 displays the number of analysts in I/B/E/S and number of analysts issuing at least one CapEx forecast by year. The red bar shows the number of analysts that issue at least one annual earnings forecast in the year. The blue bar shows the number of analysts that issue at least one CapEx forecast in that specific year. Panel 2 displays the number of firms covered by at least one analyst and the number of firms which are given at least one CapEx forecast per year. The red bar shows the number of firms which receive at least one annual earnings forecast from all analysts in the year. The blue bar shows the number of firms that receive at least one CapEx forecast from all analysts in that specific year. There is an increasing trend in both graphs.

Figure 2: CapEx Forecasts over Industries



This figure presents the heterogeneity of CapEx forecasts over industries, classified by two-digit SIC codes, from 2006 to 2011. The bars display the percentage of the analyst-firm-year triplets with at least one CapEx forecast over the total number of analyst-firm-year triplets. The upper axis displays the number of analyst-firm-year triplets for each industry. CapEx forecasts are most popular in the communication, educational services, and furniture and fixtures industries. Legal and financial services industries attract the least CapEx forecasts.

Table 1: Evolution of CapEx Forecasts

Year	Number of Analyst-Firms With EPS Forecasts	Number of Analyst-Firms With CAPEX Forecasts	Number of Analysts With EPS Forecasts	Number of Analysts With CAPEX Forecasts	Number of Firms With EPS Forecasts	Number of Firms With CAPEX Forecasts
2005	36,589	12 (0.03%)	4,001	11 (0.27%)	4,847	9 (0.19%)
2006	38,334	4,397 (11.47%)	4,074	988 (24.25%)	4,985	1,965 (39.42%)
2007	39,674	7,571 (19.08%)	4,166	1,453 (34.88%)	5,060	2,778 (54.90%)
2008	38,252	8,491 (22.20%)	4,068	1,549 (38.08%)	4,664	2,710 (58.10%)
2009	36,732	10,055 (27.37%)	3,836	1,782 (46.45%)	4,479	2,688 (60.01%)
2010	39,834	13,574 (34.08%)	4,050	2,185 (53.95%)	4,558	3,035 (66.59%)
2011	40,660	15,479 (38.07%)	4,152	2,378 (57.27%)	4,427	3,099 (70.00%)

This table presents a comparison between EPS forecasts and CapEx forecasts in three levels: analyst-firm, analyst, and firm levels. The second column presents the number of analyst-firm pairs with at least one EPS forecast, the third column presents the number of analyst-firm pairs with at least one CapEx forecast, and the numbers in parenthesis present the ratio between the two. Similarly, the forth column shows the number of analysts who issue at least one EPS forecast, the fifth column shows the number of analysts who issue at least one CapEx forecast, and the numbers in parenthesis shows the ratio between the two. The sixth column presents the number of firms which receive at least one EPS forecast, the seventh column presents the number of firms which receive at least one CapEx forecast, and the numbers in parenthesis present the ratio between the two. There is a significantly increasing trend in all three levels. From 2006 to 2011, CapEx forecast rate increased from 11% to 38% in the analyst-firm level, from 24% to 57% in the analyst level, and from 39% to 70% in the firm level.

Table 2: Descriptive Statistics (Forecast Level)

Panel 1: Distribution

	mean	sd	min	p25	p50	p75	max
Absolute Abnormal Returns	5.13	5.52	0	1.40	3.29	6.79	29.73
CapEx Forecast Dummy	0.10	0.30	0	0	0	0	1
Sales Forecast Dummy	0.67	0.47	0	0	1	1	1
Cash-Flow Forecast Dummy	0.14	0.35	0	0	0	0	1
Ex-Post CapEx Fcst. Accuracy	0.52	0.32	0	0.25	0.53	0.80	1
EPS Fcst. Deviation	0.18	0.30	0	0.03	0.07	0.19	2.01
Positive EPS Fcst.	0.51	0.50	0	0	1	1	1
Distance to EPS Anncmt.	5.12	0.58	0	4.72	5.25	5.61	6.02
Dispersion of EPS Fcst.	0.21	0.34	0.01	0.05	0.10	0.21	2.36
EPS Fcst. L-F Ratio	-0.01	1.95	-4.65	-1.31	0	1.33	4.64
Ex-Post EPS Fcst. Accuracy	0.53	0.28	0	0.30	0.53	0.76	1
Number of Stocks	2.74	0.51	0	2.56	2.77	3.04	4.60
Lagged EPS Fcst. Accuracy	0.55	0.28	0	0.33	0.56	0.78	1
Lagged EPS Fcst. Boldness	0.50	0.16	0	0.39	0.49	0.60	1
Analyst Firm Experience	1.47	0.60	0.69	1.10	1.39	1.95	3.40
Analyst Experience	2.03	0.64	0.69	1.61	2.08	2.48	3.40
Analys Status	0.14	0.35	0	0	0	0	1
Broker Size	3.68	1.03	0	3.04	3.78	4.54	5.26
N	399,192						

Panel 2: Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Absolute Abnormal Returns	1																
CapEx Forecast Dummy	2	.03															
Sales Forecast Dummy	3	.11	.19														
Cash-Flow Forecast Dummy	4	-.04	.16	.03													
EPS Fcst. Deviation	5	.12	-.00	-.04	.02												
Positive EPS Fcst.	6	-.06	.03	.03	-.00	-.11											
Distance to EPS Anncmt.	7	.02	.00	.04	-.01	.05	.03										
Dispersion of EPS Fcst.	8	.05	-.02	-.09	.07	.62	-.06	.06									
EPS Fcst. L-F Ratio	9	.00	-.02	-.03	.02	-.01	-.02	-.05	-.02								
Ex-Post EPS Fcst. Accuracy	10	.04	.03	.04	-.01	.01	.01	-.41	-.03	-.00							
Number of Stocks	11	-.03	-.02	-.05	-.01	.01	-.00	-.01	.02	.02	.01						
Lagged EPS Fcst. Accuracy	12	.00	.00	.01	.00	-.00	-.00	-.01	.02	.00	.04	.00					
Lagged EPS Fcst. Boldness	13	.00	.00	.00	.00	.01	-.00	.00	.01	.05	-.02	.02	-.08				
Analyst Firm Experience	14	-.07	-.00	-.05	-.00	.00	.01	-.05	.01	.01	.02	.13	.02	.08			
Analyst Experience	15	-.03	.00	-.02	-.02	-.00	.01	-.03	-.00	.01	.01	.25	-.00	.05	.57		
Analyst Status	16	-.06	-.00	-.02	.02	.00	.01	-.03	.02	.03	.00	.13	.01	.05	.16	.16	
Broker Size	17	-.03	.03	.10	.05	-.03	.01	-.02	-.01	.09	-.00	.13	.02	.04	-.01	-.01	.34

This table presents descriptive statistics for variables used in Model I(a) and Model I(b) over the period from 2006 to 2011 with nearly 400,000 forecasts. Panel 1 and Panel 2 present the distributions and correlation matrix of the variables.

- Absolute Abnormal Returns: absolute three days cumulative market adjusted returns of stocks around analysts' forecasts (in % and right-winsorized at 1% level)
- CapEx Forecast Dummy: equals 1 if CapEx forecasts are included in analysts' reports and 0 otherwise
- Sales Forecast Dummy: equals 1 if sales forecasts are included in analysts' reports and 0 otherwise
- Cash-Flow Forecast Dummy: equals 1 if cash-flow forecasts are included in analysts' reports and 0 otherwise
- EPS Fcst. Deviation: absolute deviations from analysts' prior forecasts (winsorized at 1% level)
- Positive EPS Fcst.: equals 1 if earnings forecasts are revised upward and 0 otherwise

(Continued)

- Distance to EPS Anncmt.: distance from the forecast to the earnings announcement (logarithm)
- Dispersion of EPS Fcst.: standard deviation of available earnings forecasts (winsorized at 1% level)
- EPS Fcst. L-F Ratio: leader-follower ratio of the earnings forecast
- Ex-Post EPS Fcst. Accuracy: ex-post accuracy of the earnings forecast
- Number of Stocks: number of stocks covered by the analyst in the current year (logarithm)
- Lagged EPS Fcst. Accuracy: firm-specific earnings forecast accuracy of the analyst in the previous year
- Lagged EPS Fcst Boldness: firm-specific earnings forecast boldness of the analyst in the previous year
- Analyst Firm Experience: number of years in which the analyst has been following the firm (logarithm)
- Analyst Experience: number of years in which the analyst has been in I/B/E/S
- Analyst Status: equals 1 if the analyst has been voted as an All-America analyst recently and 0 otherwise
- Broker Size: number of analysts working for the broker in the current year (logarithm)

Detailed variable definitions are presented in subsection 2.2.

The absolute three-day cumulative abnormal returns are about 5% on average. There are only 10% of analysts' reports containing CapEx forecasts, while this number for sales and cash-flow forecasts are 67% and 14%. The correlation matrix does not display any risk of multicollinearity.

Table 3: Information Content of CapEx Forecasts (Forecast Level)

	Model I(a)		Model I(b)	
CapEx Forecast Dummy	0.257	***		
	(8.99)			
Ex-Post CapEx Fcst. Accuracy			0.224	**
			(2.29)	
Sales Forecast Dummy	0.638	***	0.583	***
	(17.12)		(3.82)	
Cash-Flow Forecast Dummy	-0.083	**	-0.111	*
	(-2.54)		(-1.71)	
EPS Fcst. Deviation	2.118	***	2.169	***
	(14.97)		(8.17)	
Positive EPS Fcst.	-0.108	***	-0.279	***
	(-2.71)		(-3.05)	
Distance to EPS Anncmt.	-0.012		0.099	
	(-0.16)		(0.89)	
Dispersion of EPS Fcst.	0.431	**	1.005	***
	(2.55)		(3.21)	
EPS Fcst. L-F Ratio	0.036	***	0.036	**
	(5.04)		(2.12)	
Ex-Post EPS Fcst. Accuracy	0.825	***	0.877	***
	(13.45)		(6.26)	
Number of Stocks	0.014		0.075	
	(0.75)		(1.36)	
Lagged EPS Fcst. Accuracy	-0.060	**	-0.073	
	(-2.24)		(-0.85)	
Lagged EPS Fcst. Boldness	0.153	***	-0.094	
	(4.12)		(-0.62)	
Analyst Firm Experience	0.013		-0.006	
	(0.87)		(-0.10)	
Analyst Experience	0.056	***	0.146	**
	(3.94)		(2.23)	
Analyst Status	-0.044	*	-0.232	**
	(-1.96)		(-2.40)	
Broker Size	0.048	***	0.144	***
	(3.69)		(3.69)	
Constant	3.511	***	2.596	***
	(9.11)		(3.78)	
Firm-Year Fixed Effects	yes		yes	
R2	0.019		0.017	
N	399,192		37,822	

This table presents regression results of Model I(a) and Model I(b) over the period from 2006 to 2011.

- **Model I(a):** $\text{Absolute Abnormal Returns} = \alpha + \beta_1 * \text{CapEx Forecast Dummy} + \Gamma * \text{Controls} + \varepsilon$
- **Model I(b):** $\text{Absolute Abnormal Returns} = \alpha + \beta_1 * \text{CapEx Forecast Accuracy} + \Gamma * \text{Controls} + \varepsilon$

These models include firm-year fixed effects. Positive coefficients of CapEx Forecast Dummy and Ex-Post CapEx Fcst. Accuracy suggest that the market reacts more strongly to analysts' reports containing CapEx forecasts and even stronger to ex-post accurate CapEx forecasts. The results support Hypothesis 1(a) and Hypothesis 1(b). * p<0.1, ** p<0.05, *** p<0.01, t-statistics in parentheses.

Table 4: Descriptive Statistics (Analyst-Firm-Year Level)

Panel 1: Distribution

	mean	sd	min	p25	p50	p75	max
CapEx Fcst. Dummy	0.27	0.44	0.00	0.00	0.00	1.00	1.00
Lagged CapEx Fcst. Dummy	0.19	0.39	0.00	0.00	0.00	0.00	1.00
Lagged CapEx Dummy Other Firm	0.42	0.49	0.00	0.00	0.00	1.00	1.00
Lagged Broker CapEx Ratio	0.43	0.28	0.00	0.13	0.49	0.65	1.00
Analyst Broker Tenure	1.32	0.77	0.00	0.69	1.39	1.95	3.40
Analyst Firm Experience	1.09	0.78	0.00	0.69	1.10	1.61	3.40
Number of EPS Fcst.	1.25	0.68	0.00	0.69	1.39	1.79	5.18
Number of Stocks	2.63	0.65	0.00	2.40	2.71	3.00	4.60
Broker Size	3.59	1.04	0.00	2.94	3.66	4.48	5.26
Ex-Post EPS Fcst. Accuracy	0.50	0.30	0.00	0.25	0.50	0.75	1.00
Analyst Status	0.09	0.29	0.00	0.00	0.00	0.00	1.00
Lagged Market Capitalization	7.65	1.77	1.25	6.38	7.54	8.86	13.13
Lagged Book-to-Market Ratio	-0.84	0.83	-10.71	-1.29	-0.77	-0.30	2.82
Lagged Cash	0.19	0.22	0.00	0.03	0.10	0.26	1.00
Lagged Net Income	0.02	0.17	-9.20	0.00	0.04	0.08	4.83
Lagged Capital Expenditure	0.06	0.08	-0.15	0.01	0.03	0.07	2.01
Lagged Share Turnover	14.56	0.87	7.32	14.10	14.64	15.13	17.89
N	108,825						

Panel 2: Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
CapEx Fcst. Dummy	1																
Lagged CapEx Fcst. Dummy	2	.53															
Lagged CapEx Dummy Other Firm	3	.47	.53														
Lagged Broker CapEx Ratio	4	.41	.38	.54													
Analyst Broker Tenure	5	-.06	.06	.10	-.04												
Analyst Firm Experience	6	-.02	.16	.10	.04	.43											
Number of EPS Fcst.	7	.06	.11	.07	.02	.11	.23										
Number of Stocks	8	-.04	.02	.13	.04	.30	.21	.19									
Broker Size	9	.06	.06	.06	.07	.08	.00	.08	.13								
Ex-Post EPS Fcst. Accuracy	10	.04	.02	.03	.04	-.00	.02	.17	.04	.02							
Analyst Status	11	.02	.03	.03	-.01	.15	.18	.09	.15	.29	.02						
Lagged Market Capitalization	12	.08	.07	.03	.00	.05	.19	.13	-.03	.15	-.00	.16					
Lagged Book-to-Market Ratio	13	-.07	-.04	-.07	-.01	.04	.07	.04	.06	-.01	.01	.01	-.20				
Lagged Cash	14	-.05	-.05	-.02	.02	-.07	-.13	-.08	-.09	-.08	-.00	-.08	-.25	-.34			
Lagged Net Income	15	.06	.05	.04	-.00	.04	.06	.05	-.01	.06	-.00	.03	.33	-.04	-.28		
Lagged Capital Expenditure	16	.10	.09	.11	.02	-.04	-.04	.09	.02	-.04	.00	-.00	.02	-.06	-.15	.05	
Lagged Share Turnover	17	.05	.07	.08	.08	-.01	.10	.14	.08	-.00	.01	.04	.12	-.01	.05	.06	.10

This table presents descriptive statistics for variables used in Model II(a) over the period from 2007 to 2011 with more than 150,000 analyst-firm-year observations.

- CapEx Fcst. Dummy: equals 1 if the analyst issue at least one CapEx Forecast on the firm in the current year and 0 otherwise
- Lagged CapEx Fcst. Dummy: equals 1 if the analyst issue at least one CapEx forecast on the firm in the previous year and 0 otherwise
- Lagged CapEx Fcst. Other Firm: equals 1 if the analyst issue at least one CapEx forecast on any firm other than the focal firm in the previous year and 0 otherwise
- Lagged Broker CapEx Ratio: number of analysts issuing at least one forecasts over number of analysts working for the broker in the previous year (to measure the social norm)

(Continued)

- Analyst Broker Tenure: number of years in which the analyst has been working for the broker (logarithm)
- Analyst Firm Experience: number of years in which the analyst has been following the firm (logarithm)
- Number of EPS Fcst.: number of earnings forecast given by the analyst on the firm (logarithm)
- Number of Stocks: number of stocks covered by the analyst in the current year (logarithm)
- Broker Size: number of analysts working for the broker in the current year (logarithm)
- Ex-Post EPS Fcst. Accuracy: ex-post accuracy of the earnings forecast
- Analyst Status: equals 1 if the analyst has been voted as an All-America analyst recently and 0 otherwise
- Lagged Market Capitalization: market value of the common shares at the end of the most current fiscal year (logarithm)
- Lagged Book-to-Market Ratio = book value over market value of common shares at the end of the most current fiscal year (logarithm).
- Lagged Cash = cash and short-term investments on total assets at the end of the most current fiscal year
- Lagged Net Income = net income on total assets at the end of the most current fiscal year
- Lagged Capital Expenditure = capital expenditure on total assets at the end of the most current fiscal year

Detailed variable definitions are presented in the subsection 3.2.

There are 27% of analyst-firm-years are associated with CapEx forecasts, while this figure for the previous year is only 20%. There are about 43% of analysts issuing at least one CapEx forecast in a year.

Table 5: Capital Expenditures Forecast Issuance (Analyst-Firm-Year Level)

	Model II(a)		Marg. Effects		Model II(b)		Marg. Effects	
Lagged CapEx Fcst. Dummy	1.789	***	0.222	***	1.748	***	0.245	***
	(41.49)		(37.81)		(83.66)		(27.18)	
Lagged CapEx Dummy Other Firm	1.079	***	0.134	***	1.006	***	0.141	***
	(23.21)		(25.12)		(46.84)		(23.27)	
Lagged Broker CapEx Ratio	2.810	***	0.350	***	2.947	***	0.413	***
	(36.79)		(34.85)		(68.08)		(30.29)	
Analyst Broker Tenure	-0.328	***	-0.041	***	-0.336	***	-0.047	***
	(-11.60)		(-10.99)		(-27.06)		(-19.88)	
Analyst Firm Experience	-0.418	***	-0.052	***	-0.402	***	-0.056	***
	(-14.95)		(-15.43)		(-30.77)		(-20.13)	
Number of EPS Fcst.	0.199	***	0.025	***	0.228	***	0.032	***
	(9.06)		(8.93)		(15.18)		(14.33)	
Number of Stocks	-0.282	***	-0.035	***	-0.256	***	-0.036	***
	(-10.29)		(-10.61)		(-16.04)		(-11.54)	
Broker Size	0.127	***	0.016	***	0.132	***	0.019	***
	(5.50)		(5.44)		(14.20)		(16.82)	
Ex-Post EPS Fcst. Accuracy	0.290	***	0.036	***	0.259	***	0.036	***
	(9.30)		(9.25)		(9.38)		(9.46)	
Analyst Status	0.199	***	0.025	***	0.202	***	0.028	***
	(2.80)		(2.76)		(6.72)		(6.29)	
Lagged Market Capitalization	0.057	***	0.007	***				
	(7.62)		(7.66)					
Lagged Book-to-Market Ratio	-0.060	***	-0.007	***				
	(-2.96)		(-2.96)					
Lagged Cash	-0.504	***	-0.063	***				
	(-4.56)		(-4.59)					
Lagged Net Income	0.346	***	0.043	***				
	(3.89)		(3.85)					
Lagged Capital Expenditure	0.157		0.020					
	(0.92)		(0.91)					
Lagged Share Turnover	-0.008		-0.001					
	(-0.45)		(-0.45)					
Constant	-3.004	***						
	(-10.68)							
Industry-Year Fixed Effects	yes							
Firm-Year Fixed Effects					yes			
Pseudo-R2	0.369				0.367			
N	108,825		108,825		120,355		120,355	

This table presents the regression results of Models II(a) and II(b) over the period from 2007 to 2011.

Model II(a): $\text{P(CapEx Fcst. Dummmy)} = \alpha + \text{B} * \text{Analyst Characteristics} + \text{C} * \text{Firm Characteristics} + \varepsilon$

This model includes industry-year fixed effects to capture effects of firm characteristics, and clustering by industry-year to capture heteroskedasticity and autocorrelation among industries

Model II(b): $\text{P(CapEx Fcst. Dummmy)} = \alpha + \text{B} * \text{Analyst Characteristics} + \varepsilon$

This model includes firm-year fixed effects to capture effects of firm characteristics, and clustering by industry-year to capture heteroskedasticity and autocorrelation among industries

- Hypothesis 2(a) predicts positive coefficients of Lagged CapEx Fcst. Dummy, Lagged CapEx Fcst. Other Firm, and Lagged CapEx Fcst. Other Firm
- Hypothesis 2(b) predicts negative coefficients of Analyst Broker Tenure and Analyst Firm Experience
- Hypothesis 2(c) predicts a positive coefficient of Number of EPS Fcst.

(Continued)

- Hypothesis 2(d) predicts a negative coefficient of Number of Stocks
- Hypothesis 2(e) predict positive coefficients of Broker Size, Ex-Post EPS Fcst., and Analyst Status

The table also demonstrates that bigger firms, growth firms, profitable firms, and firms with less cash attract more CapEx forecasts. * $p<0.1$, ** $p<0.05$, *** $p<0.01$, t-statistics in parentheses.

Table 6: Descriptive Statistics of Analysts with CapEx Forecasts (Analyst-Firm-Year Level)

Panel 1: Description

	mean	sd	min	p25	p50	p75	max
Ex-Post CapEx Fcst. Accuracy	0.50	0.35	0	0.20	0.50	0.80	1
Lagged CapEx Fcst. Accuracy	0.52	0.35	0	0.24	0.50	0.83	1
Distance to EPS Anncmt.	4.72	0.81	0	4.48	4.70	5.28	6.16
CapEx Experience	1.02	0.58	0	0.69	1.10	1.39	1.95
Analyst Experience	1.82	0.85	0	1.39	1.95	2.40	3.40
Number of EPS Fcst.	1.32	0.65	0	1.10	1.39	1.79	3.83
Number of Stocks	2.59	0.66	0	2.40	2.71	3.00	4.25
Broker Size	3.70	0.99	0	3.09	3.78	4.52	5.13
Ex-Post EPS Fcst. Accuracy	0.51	0.29	0	0.28	0.50	0.75	1
Analyst Status	0.11	0.31	0	0	0	0	1
N	35,906						

Panel 2: Correlation Matrix

		1	2	3	4	5	6	7	8	9
Ex-Post CapEx Fcst. Accuracy	1									
Lagged CapEx Fcst. Accuracy	2	.11								
Distance to EPS Anncmt.	3	-.15	-.04							
CapEx Experience	4	.04	.03	-.01						
Analyst Experience	5	.03	.03	-.02	.52					
Number of EPS Fcst.	6	.04	.01	-.10	.19	.19				
Number of Stocks	7	.02	.01	-.00	.33	.35	.19			
Broker Size	8	.01	-.01	-.03	.06	.01	.06	.21		
Ex-Post EPS Fcst. Accuracy	9	.05	.01	-.10	.05	.06	.14	.06	.01	
Analyst Status	10	.01	-.00	-.04	.09	.17	.10	.16	.29	.02

This table presents descriptive statistics for variables used in Model III(a) and Model III(b) over the period from 2007 to 2011 with nearly 36,000 analyst-firm-year observations.

- Ex-Post CapEx Fcst. Accuracy: ex-post accuracy of the CapEx forecast
- Lagged CapEx Fcst. Accuracy: accuracy of the CapEx forecast in the previous year
- Distance to EPS Anncmt.: distance from the forecast to the earnings announcement (logarithm)
- CapEx Experience: number of years in which the analyst has been issuing CapEx forecasts (logarithm)
- Analyst Experience: number of years in which the analyst has been in I/B/E/S (logarithm)
- Number of EPS Fcst.: number of earnings forecast given by the analyst on the firm (logarithm)
- Number of Stocks: number of stocks covered by the analyst in the current year (logarithm)
- Broker Size: number of analysts working for the broker in the current year (logarithm)
- Ex-Post EPS Fcst. Accuracy: ex-post accuracy of the earnings forecast
- Analyst Status: equals 1 if the analyst has been voted as an All-America analyst recently and 0 otherwise

Detailed variable definitions are presented in subsection 4.2.

Table 7: Capital Expenditure Forecast Accuracy (Analyst-Firm-Year Level)

	Model III(a)		Model III(b)	
Lagged CapEx Fcst. Accuracy			0.101	***
			(10.64)	
Distance to EPS Anncmt.	-0.073	***	-0.093	***
	(-20.89)		(-14.99)	
CapEx Experience	0.027	***	0.036	**
	(4.87)		(2.58)	
Analyst Experience	0.002		0.007	
	(0.47)		(1.12)	
Number of EPS Fcst.	0.012	***	0.041	***
	(2.79)		(5.00)	
Number of Stocks	-0.001		0.002	
	(-0.19)		(0.21)	
Broker Size	0.000		-0.004	
	(0.10)		(-0.85)	
Ex-Post EPS Fcst. Accuracy	0.047	***	0.013	
	(5.71)		(1.01)	
Analyst Status	0.002		-0.013	
	(0.20)		(-1.06)	
Constant	0.771	***	0.788	***
	(35.34)		(18.46)	
Firm-Year Fixed Effects	yes		yes	
Pseudo-R2	0.030		0.056	
N	35,906		14,643	

This table presents regression results of Model III(a) and III(b) over the period from 2007 to 2011.

- **Model III(a):** $\text{CapEx Fcst. Accuracy} = \alpha + \text{B} * \text{Analyst Characteristics} + \varepsilon$
- **Model III(b):** $\text{CapEx Fcst. Accuracy} = \alpha + \beta_1 * \text{Lagged CapEx Fcst. Accuracy} + \text{B} * \text{Analyst Characteristics} + \varepsilon$

These models include firm-year fixed effects to capture effects of firm characteristics.

- Hypothesis 3(a) predicts a negative coefficient of Distance to EPS Anncmt.
- Hypothesis 3(b) predicts a positive coefficient of CapEx Experience
- Hypothesis 3(c) predicts a positive coefficient of Lagged CapEx Fcst. Accuracy
- Hypothesis 3(d) predicts a positive coefficient of Number of EPS Fcst. and a negative coefficient of Number of Stocks
- Hypothesis 3(e) predicts positive coefficients of Broker Size, Ex-Post EPS Fcst. Accuracy, and Analyst Status

* p<0.1, ** p<0.05, *** p<0.01, t-statistics in parentheses.

Table 8: Descriptive Statistics (Analyst-Year Level)

Panel 1: Description

	mean	sd	min	p25	p50	p75	max
Professional Discontinuation	0.15	0.36	0	0	0	0	1
CapEx Fcst. Dummy	0.41	0.49	0	0	0	1	1
CapEx Fcst. Accuracy	0.48	0.26	0	0.33	0.50	0.63	1
Sales Forecast Dummy	0.89	0.31	0	1	1	1	1
Cash-Flow Forecast Dummy	0.26	0.44	0	0	0	1	1
EPS Fcst. Accuracy	0.50	0.18	0	0.40	0.51	0.60	1
EPS Fcst. L-F Ratio	-0.20	0.89	-4.60	-0.75	-0.22	0.33	4.50
EPS Fcst. Boldness	0.50	0.11	0	0.44	0.50	0.55	1
Walk-Down Score	0.20	0.22	0	0	0.17	0.31	1
Number of EPS Fcst.	1.27	0.51	0	0.99	1.34	1.61	4.08
Number of Stocks	2.06	0.93	0	1.61	2.30	2.71	4.60
Analys Status	0.06	0.25	0	0	0	0	1
Broker Size	3.44	1.18	0	2.71	3.53	4.38	5.26
Analyst Experience	1.55	0.88	0	0.69	1.61	2.20	3.37
N	16,289						

Panel 2: Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12
Professional Discontinuation	1												
CapEx Fcst. Dummy	2	-.13											
Sales Forecast Dummy	3	-.03	.25										
Cash-Flow Forecast Dummy	4	-.03	.24	.09									
EPS Fcst. Accuracy	5	-.28	.07	.02	-.01								
EPS Fcst. L-F Ratio	6	-.06	-.01	-.02	.04	.07							
EPS Fcst. Boldness	7	.04	-.01	-.00	.03	-.15	.11						
Walk-Down Score	8	-.07	.04	.06	-.02	.14	.00	.00					
Number of EPS Fcst.	9	-.37	.09	.00	.11	.27	.11	.04	.11				
Number of Stocks	10	-.25	.13	.09	-.05	.09	.03	-.04	.08	.21			
Analys Status	11	-.08	.03	.05	.01	.05	.07	.03	.04	.16	.18		
Broker Size	12	-.03	.04	.15	.02	.04	.21	.04	.01	.12	.14	.25	
Analyst Experience	13	-.09	.07	.05	-.01	.04	-.00	.03	.07	.18	.38	.17	-.01

This table presents descriptive statistics for variables used in Model IV(a) and Model IV(b) over the period from 2006 to 2010 with more than 16,000 analyst-year observations and turn-over rate is 15% per year.

- Professional Discontinuation: equals 1 if the analyst is not in I/B/E/S in the following year and 0 otherwise
- CapEx Forecast Dummy: equals 1 if the analyst issues at least one CapEx forecast this year and 0 otherwise
- Sales Forecast Dummy: equals 1 if the analyst issues at least one sales forecast this year and 0 otherwise
- Cash-Flow Forecast Dummy: equals 1 if the analyst issue at least one cash-flow forecast this year and 0 otherwise
- CapEx Fcst. Accuracy: average forecast accuracy of all CapEx forecasts given by the analyst this year
- EPS Fcst. Accuracy: average forecast accuracy of all earnings forecasts given by the analyst this year
- EPS Fcst. L-F Ratio: average leader-follower ratio of all earnings forecasts given by the analyst this year
- EPS Fcst Boldness: average forecast boldness of all earnings forecasts given by the analyst this year
- Walk-Down Score: walk-down rate over all firms covered by the analyst this year
- Number of EPS Fcst.: average number of earnings forecast given by the analyst per stock (logarithm)
- Number of Stocks: number of stocks covered by the analyst in the current year (logarithm)
- Broker Size: number of analysts working for the broker in the current year (logarithm)
- Analyst Status: equals 1 if the analyst has been voted as an All-America analyst recently and 0 otherwise

(Continued)

Detailed variable definitions are presented in subsection 5.2.
The table shows that 41% of analysts are issuing at least one CapEx forecast, while the percentage of analysts issuing at least one sales (or cash-flow) forecast is 89% (or 26%). On average, analysts walk-down on 20% of the covered firms, issue 3.6 earnings forecasts per stock, cover 7.8 stocks, are from broker size of 31 analysts, and have 4.7 years of experience.

Table 9: Professional Discontinuation (Analyst-Year Level) 2006-2010

	Model IV(a)	Marg. Eff.	Model IV(b)	Marg. Eff.
CapEx Fcst. Dummy	-0.542***	-0.044***		
	(-9.15)	(-9.18)		
CapEx Fcst. Accuracy			-0.564***	-0.030***
			(-3.21)	(-3.21)
Sales Forecast Dummy	0.165**	0.013**	0.109	0.006
	(2.07)	(2.07)	(0.28)	(0.28)
Cash-Flow Forecast Dummy	-0.029	-0.002	-0.092	-0.005
	(-0.47)	(-0.47)	(-0.90)	(-0.90)
EPS Fcst. Accuracy	-2.656***	-0.216***	-2.794***	-0.148***
	(-19.76)	(-19.17)	(-10.00)	(-9.61)
EPS Fcst. L-F Ratio	-0.047*	-0.004*	-0.139**	-0.007**
	(-1.80)	(-1.80)	(-2.53)	(-2.52)
EPS Fcst. Boldness	0.129	0.011	0.447	0.024
	(0.70)	(0.70)	(1.15)	(1.15)
Walk-Down Score	0.018	0.001	0.095	0.005
	(0.17)	(0.17)	(0.47)	(0.47)
Number of EPS Fcst.	-1.799***	-0.146***	-1.334***	-0.071***
	(-33.39)	(-32.39)	(-12.35)	(-12.26)
Number of Stocks	-0.525***	-0.043***	-0.622***	-0.033***
	(-18.19)	(-17.84)	(-10.85)	(-10.51)
Analys Status	-0.487***	-0.040***	0.029	0.002
	(-2.83)	(-2.85)	(0.12)	(0.12)
Broker Size	0.111***	0.009***	0.086*	0.005*
	(5.15)	(5.14)	(1.93)	(1.92)
Analyst Experience	0.114***	0.009***	0.026	0.001
	(3.83)	(3.81)	(0.45)	(0.45)
Constant	1.739***		0.601	
	(10.63)		(1.11)	
Year Fixed Effects	yes		yes	
Pseudo R2	0.25		0.19	
N	16,289	16,289	6,030	6,030

This table presents regression results of Model IV(a) and IV(b) over the period from 2006 to 2010.

- **Model IV (a):** $\Pr(\text{Professional Discontinuation}) = \alpha + \beta_1 * \text{CapEx Fcst. Dummy} + \Gamma * \text{Controls} + \varepsilon$
- **Model IV (b):** $\Pr(\text{Professional Discontinuation}) = \alpha + \beta_1 * \text{CapEx Fcst. Accuracy} + \Gamma * \text{Controls} + \varepsilon$

These models include year fixed effects.

- Hypothesis IV(a) predicts a negative coefficient of CapEx Forecast Dummy
- Hypothesis IV(b) predicts a negative coefficient of CapEx Fcst. Accuracy

Analysts who issue CapEx forecasts are 4.4% less likely to leave the profession than those who do not. The most accurate CapEx forecasters are 3% less likely to leave the profession than those issuing less accurate CapEx forecasts. Consistent with prior research, more accurate earnings forecasters, leaders, more active analysts, and higher status analysts are less likely to leave the profession.

* p<0.1, ** p<0.05, *** p<0.01, t-statistics in parentheses.

Chapter III: Does Lehman's Collapse Confirm Equity Underwriting Relationship Value?

This paper re-examines the question of the underwriting relationship value proposed by Fernando, May & Megginson in the Journal of Finance (2012). The authors find that Lehman's underwriting clients had abnormal returns of nearly 3% below the abnormal returns of comparable banks' underwriting clients in the seven day period around Lehman's collapse. Additionally, they argue that the fell in market valuation came from the underwriting relationship value destroyed by the collapse. I show that these clients reacted differently to Lehman's collapse mainly because they were in different industries and were characteristically different. Lehman's clients belonged to more affected industries and had characteristics which were associated with more severe side-effects of the collapse than clients of other big banks. Specifically, the marginal effect of being a Lehman client reduces from -2.7% to around -0.3% (i. e. insignificant) after controlling for industry and firm characteristics. This means that it is invalid to reject the null hypothesis, namely that being a Lehman's client has no marginal effect on the stock price reaction to Lehman's collapse.

JEL classification: G24, G01

Keywords: Lehman Brothers, Collapse, Underwriting Relationship, Market Reactions

1 Introduction

The Lehman bankruptcy was a shock to the underwriting services industry because Lehman was a major underwriting services provider, occupying the sixth position in total proceeds from global debt, equity and equity-related transactions in 2008. Fernando et al. (2012) (FMM hereafter) try to measure the magnitude of the firms' portion in the value created from the equity underwriting relationship by comparing the reactions to the collapse between Lehman's former equity underwriting clients (Lehman's clients hereafter) and former clients of the other top 10 underwriters (other big banks' clients hereafter), namely Merrill Lynch, Goldman Sachs, Morgan Stanley, JP Morgan, Citibank, UBS, Credit Suisse, Deutsche Bank, Bank of America, and Wachovia. They argue that the value created from the equity underwriting relationship between Lehman and former Lehman's clients vanished with the collapse, while this did not happen to other banks and their clients. The average seven-day cumulative abnormal returns in the period from five days before the event to one day after the event obtained from Fama-French-Carhart four-factor model (*CAR7* hereafter) of Lehman's clients and other big banks' clients were -4.85% and -1.91%; the difference between these two values was nearly -3%, which is statistically and economically significant. The results remain even after excluding firms with a lending relationship to Lehman. FMM claim that this -3% is mostly due to the value of the equity underwriting relationship destroyed by the collapse.

I have three concerns about their methodology. First, Lehman's collapse was not simply a shock to the underwriting industry; it was a shock to the whole economy. It was the most remarkable event of the credit crunch period (2007-2009). The S&P 500 index went down by 4.7% in the day of the bankruptcy announcement, the 15th of September 2008. In addition, there were multiple events happening around that fateful 15th of September. During the weekend before the event, Bank of America's acquisition of Merrill Lynch was announced (Sorkin 2008). On the day after the event, the 16th of September 2008, the large insurer American International Group (AIG)'s credit rating was downgraded, which required the company to supply additional collaterals, pushing AIG close to default if it could not find additional liquidity. The credit crisis had truly begun with an additional drop of 4.5% in the S&P 500 index the day after, the 17th of September, 2008.

Second, firms with different characteristics were affected differently by Lehman's collapse and other events around the collapse. I study how different industries were affected by Lehman's collapse. I calculate average abnormal returns of firms in industries classified by two-digit SIC codes, excluding Lehman's and other big bank's clients, and observe that different industries responded differently to the collapse. Some industries experienced significant negative abnormal returns around the collapse, e. g. metal mining, coal mining, oil and gas extraction, and local and interurban passenger transit, while some other industries experienced positive abnormal returns or were not significantly affected by the collapse. In addition, Tong & Wei (2010) use Lehman's collapse as an event study to examine the effects of the credit crunch on firms over 24 emerging countries. The estimated coefficients of their control variables indicate that bigger and less levered firms are less affected by the collapse. FMM's cross-sectional analysis of Lehman's clients also points out that younger, smaller and more financially constrained clients were more affected by the collapse than others.

Third, there is a hidden assumption behind FMM's methodology that Lehman's clients and other big banks' clients were similarly affected by the collapse, except that Lehman's clients had additional effects because of their lost underwriting relationship. However, if Lehman's clients were not comparable with other big banks' clients in term of firm characteristics, then FMM's results may not be correct. Therefore, I would like to examine the following null hypothesis, taking into account the characteristics of the banks' clients.

Null hypothesis: *Being Lehman's client had no marginal effect on the stock's reaction to Lehman's collapse.*

The extant literature has different views on the relationship between firms and their investment banks, which partially support and reject the null hypothesis. There are many papers suggesting that the relationship between investment banks and their clients creates values through different channels. Investment banks may play a monitoring role to constrain their clients' managers from value-destroying decisions (Hansen & Torregrosa 1992). Investment banks also may create value through their relationship with institutional investor networks[19]. Some authors argue that firms experience switching costs when they move from an underwriter to another one[20], although Krigman et al. (2001) document a high frequency of underwriter switching among client firms. On the other hand, there are papers showing that the underwriting relationship is short-lived[21], which would suggest that Lehman's collapse had little effect on firms which have had an underwriting relationship with Lehman in the distant past.

In addition, Lehman's collapse was not a total evaporation of the bank. Lehman Brothers went bankrupt because it held large positions in sub-prime and low-rated mortgage tranches in structured finance. Meanwhile, the investment-banking division was profitable and was a likely candidate for acquisition by other banks, e. g. Barclays and Bank of America, in case of a bank collapse. In fact, only one day after the bankruptcy filing of Lehman, Barclays declared its interest in the investment-banking and trading divisions (Teather & Clark 2008). Barclays would retain the inherited relationship between Lehman and its former clients after the acquisition. Therefore, Lehman's clients would not lose all the value, if there was any, of their relationship with Lehman.

I reexamine Lehman's collapse from a different angle, namely that the bank's collapse and other events around the collapse affected every firm in the economy. I examine whether Lehman's clients were more affected due to their lost relationship, and I have three findings. First, by running a regression of the *CAR7* on characteristic variables over the firms which had no underwriting relationship with any big bank controlling for industry abnormal returns, I find that the event

[19](Benveniste & Spindt 1989; Cornelli & Goldreich 2001; Ritter & Welch 2002)
[20](Burch et al. 2005; Ellis et al. 2000)
[21](Ellis et al. 2000; Schultz & Zaman 1994; Aggarwal 2000; Corwin et al. 2004)

affected mostly small, young, high market-to-book ratio, and potentially distressed firms. This finding is consistent with FMM and Tong & Wei (2010).

Second, I use t-tests to compare characteristics of Lehman's clients and other big banks' clients and find that Lehman's clients, on average, were from more severely affected industries compared to the clients of other big banks. For example, nearly 16% of Lehman's clients (compared to 7% of other big banks' clients) were in the oil and gas extraction industry and this industry was severely harmed by the collapse of Lehman. In addition, Lehman's clients were, on average, significantly bigger, younger, more levered and closer to potential distress than other big banks' clients.

Third, I find no significant evidence to reject the null hypothesis after controlling for the client firms' industries and characteristics. Industry abnormal returns played a crucial role in explaining the difference in average the *CAR7* of Lehman and other big banks' clients. Characteristic variables also had contribution to explain that difference. To illustrate the importance of industry factor, I exclude the oil and gas extraction industry and calculate the difference between average abnormal returns of Lehman and other big banks' clients. Surprisingly, the difference is only -1.3% and statistically insignificant, while the difference is -2.7% and statistically significant if the oil and gas extraction industry is included. To formally test the null hypothesis, I use the ordinary linear regression (OLS) method to capture the marginal effect of being Lehman's clients, controlling for industry abnormal returns and firm characteristics. The regression includes the dependent variable of seven-day abnormal returns, i. e. the *CAR7*, of Lehman and other big banks' clients and the independent variable *LehmanClient*, which equals to 1 if the firm was Lehman's client and equals zero otherwise. After controlling for industry abnormal returns, but not firm characteristics, the marginal effect of being Lehman client drops from -2.7% to -0.9% and becomes insignificant. To avoid endogeneity issues, I define the industry abnormal returns based on firms which were not Lehman's clients, nor other big banks' clients. When I control for industry abnormal returns and firm characteristics, the marginal effect decreases further to about -0.3% and it is not significant.

Using a number of setting modifications in the robustness checks, I find that the difference in the *CAR7* between Lehman's clients and other big banks' client is economically significant if Lehman's clients are not clients of any other big banks. Due to the small number of observations, it is not statistically significant.

My paper contributes to the existing literature in two dimensions. Firstly, it contributes to the literature on the effects of financial shocks on the economy. Some industries were heavily affected by the collapse while others were not, and less reputable and more risky firms were hit harder by the event. Secondly, it discards the finding of FMM that Lehman's clients reacted more strongly to the Lehman's collapse than other big banks' clients because of the destroyed relationship value. My results are consistent with studies showing that the value of market making provided by underwriters is short-lived[22]. Nevertheless, my paper does not reject the existence of underwriting relationship value, nor rejects the significance of clients' share in this value. The insignificant reaction of Lehman's clients to the bank's collapse may be because the value of their relationship was not destroyed.

The rest of the paper is organized as follows. Section 2 presents the cumulative abnormal stock returns around Lehman's collapse. Section 3 discusses the effects of Lehman's collapse on non-Lehman-client firms. Section 4 illustrates the differences between Lehman and other big banks' clients and tests the marginal effects of being a Lehman client on the stock price reaction to the collapse. I discuss some robustness checks in section 5, and the conclusion comes at the end.

2 Cumulative Abnormal Stock Returns around Lehman's Collapse

2.1 Cumulative Abnormal Returns Calculation

I use the Fama-French-Carhart four-factor model to calculate the *CAR7* of firms. FMM use five methods, namely the Fama-French-Carhart four-factor model, the Fama-French three-factor model, the capital market model, the size-book-to-market matched model and the industry-size matched model, which provide similar results when evaluating the difference in abnormal returns between Lehman's and other big banks' clients. I use the four-factor model for the detailed analysis because it is the most advanced model for capital asset pricing among models used by FMM. Other selected models are used in the robustness check section. For each stock i, I run the following regression:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i R_{M,t} + s_i SMB_t + h_i HML_t + u_i UMD_t + \varepsilon_{i,t}$$

The setting in the regression is similar to FMM. R_{it} is the return of stock i at day t minus risk-free rate on day t, $R_{M,t}$ is market premium on day t, and SMB_t,HML_t, UMD_t are the returns to the small-minus-big (*SMB*), high-minus-low (*HML*), and up-minus-down (*UMD*) portfolios to capture size, book-to-market, and return momentum effects, respectively. Parameters α_i, β_i, s_i, h_i, and u_i are

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[22](Ellis et al. 2000; Schultz & Zaman 1994; Aggarwal 2000; Corwin et al. 2004)

estimated using data from day minus 290 to day minus 31 (day zero is the event date, the 15th of September 2008). Abnormal returns of stock i during the event window, i. e. the event window is from day minus 5 to day plus 1, are calculated from the following equation:

$$AR_{it} = R_{it} - R_{f,t} - \left(\hat{\alpha}_i + \hat{\beta}_i R_{M,t} + \hat{s}_i SMB_t + \hat{h}_i HML_t + \hat{u}_i UMD_t\right)$$

After having abnormal returns for every single day in the event window for all stocks, abnormal returns are summed over seven days (from day minus 5 to day plus 1) for each stock to obtain seven-day cumulative abnormal return for stock i, which is denoted as *CAR7* for short.

2.2 Data

The share price and daily stock returns data are extracted from CRSP. I keep firms with at least 30 data points in the pre-event window (-290,-31) (the event date, day zero, is the 15th of September 2008) and with all 7 data points in the event window (-5, +1). The characteristics data of these firms is taken from Compustat and I keep the firms which do not miss the total assets variable or the CUSIP code. I extract only common stock deals from data on equity underwriting deals, which are obtained from Thomson Reuters. Data of risk free rate, market premium, small-minus-big, high-minus-low, and up-minus-down, is taken from Kenneth R. French's website.

[Insert Table 1 about here]

Table 1 illustrates the process of data refining. From the CRSP data of 6,832 firms and Compustat data of 9,865 firms, I use CUSIP codes to obtain 4,667 matched firms. From Thomson Reuters, 2,568 firms had at least one common equity underwriting deal with at least one of top eleven banks, namely Merrill Lynch, Goldman Sachs, Morgan Stanley, JP Morgan, Citibank, UBS, Credit Suisse, Deutsche Bank, Bank of America, Wachovia and Lehman Brothers, in ten years before the bankruptcy date. 442 firms of those were Lehman clients and 2,146 firms were clients of the other top ten banks. However, only 249 Lehman clients and 999 other big banks' clients are matched with CRSP and Compustat data. The data of other firms are not available because they went bankrupt or delisted or the data from Compustat is incomplete. Following FMM, I exclude firms with SIC code beginning with 6 (financial firms) and 49 (utility firms), and firms with missing data to calculate characteristic variables. 3,289 firm observations are left, in which 173 former Lehman's clients and 716 former clients of other top 10 underwriters. These numbers are slightly different from those of FMM because of the following three main reasons: first, I define a firm as an equity underwriting client of a bank if the bank is one of the managers in at least one of common equity issuances;

second, I do not exclude firms with material financial exposure to Lehman; and third, some firms have missing data.

2.3 Overview of the CAR7

At first glance, Lehman's clients and clients of other big banks had different cumulative abnormal returns. Table 2 presents descriptive statistics of the *CAR7* of three subsets of the sample: Lehman's clients, other big banks' clients and other firms. On average, the *CAR7* of Lehman's clients were the smallest (-4.6%), the *CAR7* of other big banks' clients were the highest (-1.9%) and the *CAR7* of other firms are in between (-3.5%). If the Lehman bankruptcy is viewed as a shock to the underwriting industry, ones could interpret that the firms, which are more likely to need the underwriting services from Lehman, will be more severely affected by the collapse. Lehman's former clients were most likely to use services from Lehman again and former clients of other banks were least likely to use services from Lehman because they already had a relationship with other reputable banks. However, this hypothesis stands only when the differences in the *CAR7* between the two groups are significant after controlling for firm characteristics.

[Insert table 2 about here]

3 Effects of Lehman's Collapse on Lehman's Non-Client Firms

Lehman's collapse was not only a shock to the underwriting industry, but also to the whole economy. To study the effects of the collapse, which are not due to the loss of the underwriting relationship, I study the share price reaction of Lehman's non-clients to the collapse. Lehman's non-clients are defined as firms which did not have any equity underwriting deals with Lehman Brothers within the 10 year period before the collapse. Although some of Lehman's non-clients could be potential equity underwriting clients of Lehman, the stock price reactions of these firms to the collapse were not due to any loss of established relationships.

3.1 Testing Methodology

I run ordinary least squares (OLS) regressions on firms which are not Lehman's former clients. On the left hand side of the regression, I use the 7-day cumulative abnormal price returns to capture the effects of Lehman's collapse on firms, and on the right hand side, I use multiple firm characteristics as explanatory variables. Different industries might be exposed to different risk factors, which create heteroskedaticity in the standard errors between industries. I run two similar models: the first one controls for heteroskedasticity between industries, and the second one controls for both industry fixed effects and heteroskedaticity. I use two-digit SIC codes to classify firms into industries.

Model I(a): OLS regression, controlling for between industry heteroskedasticity
$CAR7_i = \alpha + \Gamma * CHARACTER_i + \varepsilon_i$

Model I(b):OLS regression, controlling for industry fixed effects and between industry heteroskedasticity
$CAR7_i = \alpha + \Gamma * CHARACTER_i + \varepsilon_i$

$CHARACTER_i$ is a set of characteristics variables of Lehman's non-client *i*, which includes: logarithm of firms' market capitalization (*MarketValue*), logarithm of firms' number of days appearing in CRSP (*Age*), market-to-book ratio of firms' values (*MarketToBook*), net of firms' debts (i. e. long-term and short-term debts) to cash over market values (*NetLeverage*), Altman's Z-Score (*ZScore*), and financial distress dummy (*DistressDummy*). The details of these variables are described in Appendix Table 1. A significantly positive estimated coefficient Γ suggests that firms, which had a lower value of the corresponding characteristic variable, were more fragile to the shock and vice versa. If the estimated coefficient is insignificant, we can conclude that there was no significant relation between the corresponding characteristics variable and the stock price response to the shock.

3.2 Data Description

Table 3 presents descriptive statistics of characteristics of firms which have no underwriting relationship with Lehman. These firms had an average of -3.1% abnormal stock returns in the 7 day period around Lehman's collapse. The average size, age, book-to-market ratio, and net leverage of these firms were about $850 million, 10 years, 1.8 times, and 0.1%. Lehman's non-client firms had an average Altman's Z-Score of 6.1, and 17% of these firms were at the risk of financial distress (i. e. the Z-Score is below 1.8). The correlation matrix in Panel B of this table shows no risk of multicollinearity.

[Insert table 3 about here]

3.3 Regression Results

Table 4 presents regression results of the *CAR7* on firm characteristics including firm size, firm age, market-to-book ratio, net leverage and distress dummy. Model I(a) in the first column controls for heteroskedasticity between industries, and Model I(b) in the second column controls for industry fixed effects and heteroskedasticity between industries. The two models agree on all the signs of the estimated coefficients. Firstly, the positive estimated coefficients of *MarketValue* and *FirmAge* suggest that smaller and younger firms were more affected by the collapse, which is consistent with FMM and Tong & Wei (2010). The difference in the *CAR7* between firms at the third and the first quartiles in size and age were 3.6% and 1.3%.

[Insert table 4 about here]

Secondly, the negative estimated coefficient of *MarketToBook* suggests that firms with higher market-to-book ratios were more affected by the collapse. These firms were growth firms and the collapse severely damaged their prospective growth opportunities. Firms at the first quartiles of market-to-book ratio experienced 1.3% higher in*CAR7* than firms at the third quartiles of market-to-book ratio. Finally, firms closer to potential financial distress were hit harder by the collapse; on average, firms in potential financial distress had 2.6% lower *CAR7* compared to firms further away from potential financial distress. Meanwhile, Alman's Z-Score has statistically insignificant capability in explaining the stock price reactions to the collapse; the *DistressDummy* variable proves its dominance over *ZScore* in this context.

4 Effects of Lehman's Collapse on Lehman and Other Big Banks' Clients

This section firstly analyzes the differences in industry allocation and firm characteristics between Lehman and other big banks' clients. After that, I study the marginal effects of being Lehman's clients on the stock price reaction to the collapse, controlling for industry and firm characteristics. The previous section demonstrated that firms with different characteristics reacted differently to the collapse. Therefore, controlling for firm characteristics is necessary when we study the value of the underwriting relationship.

4.1 Testing Methodology

I use ordinary least squares (OLS) linear regressions to find the marginal effect of being Lehman's clients on the *CAR7* of stocks. I perform a cross-sectional regression among firms which are common equity underwriting clients of Lehman and other top ten underwriters. I run five models with different levels of control. The general form of these models is: $CAR7_i = \alpha + \beta *$

$LehmanClientDummy_i + \Gamma * CONTROL_i + \varepsilon_i$, where $LehmanClientDummy_i$ equals 1 if firm i is a former equity underwriting client of Lehman and 0 otherwise.

Model II(a): OLS regression, controlling for between industry heteroskedasticity
$CAR7_i = \alpha + \beta * LehmanClientDummy_i + \varepsilon_i$

Model II(b): OLS regression, controlling for between industry heteroskedasticity
$CAR7_i = \alpha + \beta * LehmanClientDummy_i + \Gamma * CHARACTER_i + \varepsilon_i$

Model II(c): OLS regression, controlling for between industry heteroskedasticity
$CAR7_i = \alpha + \beta * LehmanClientDummy_i + \gamma * IndustryAbnRet + \varepsilon_i$

Model II(d): OLS regression, controlling for between industry heteroskedasticity
$CAR7_i = \alpha + \beta * LehmanClientDummy_i + \Gamma * CHARACTER_i + \gamma * IndustryAbnRet + \varepsilon_i$

Model II(e): OLS regression, controlling for industry fixed effects and between industry heteroskedasticity
$CAR7_i = \alpha + \beta * LehmanClientDummy_i + \Gamma * CHARACTER_i + \varepsilon_i$

$CHARACTER_i$ is a set of control variables which include some firm characteristics variables: size (*MarketValue*), age (*FirmAge*), market-to-book ratio (*MarketToBook*), net leverage (*NetLeverage*), Altman's Z-Score (*ZScore*), and distress dummy (*DistressDummy*). The Lehman bankruptcy is an exogenous event to firms' characterisitcs, thus eliminating endogeneity issues in these models.

The 7-day cumulative industry abnormal returns variable (*IndustryAbnRet*) is calcualted as the average of the *CAR7* of all non-client firms (those are not former clients of any big banks) in the industry to isolate the underwriting relationship value from the effects of Lehman's collapse. This variable is a good proxy for the effects of the collapse excluding the effects of the underwriting relationship destroyed, and it is exogenous to the effects of the collapse due to the loss of the underwriting relationship. *IndustryAbnRet* does not perfectly capture the effects of the collapse excluding the lost underwriting relationship on big banks' clients due to the differences in firm characteristics between client and non-client firms.

Model II(a) does not contain any control variable, and the estimated coefficient $\hat{\beta}$ is the same as the difference in the *CAR7* between Lehman and other big banks' clients in a simple t-test. This model controls for between industry heteroskedasticity, which leads to a lower significance level. Model

II(b) controls for firm characteristics, Model II(c) controls for industry abnormal returns, and Model II(d) controls for both firm ccharacteristics and industry abnormal returns. The industry abnormal returns variable (*IndustryAbnRet*) does not capture all the industry related effects of the collapse; therefore, I controls for industry fixed effects in Model II(e). The industry fixed effects may be endogenous because they partially capture the loss of underwriting relationship of Lehman's clients.

If β is significantly negative, we can assert that Lehman's clients were more affected by the collapse than clients of other big banks. It is consistent with FMM and β can be interpreted as the marginal effect of being Lehman's clients on the *CAR7*. If β is significantly positive, then Lehman clients are less affected by the collapse than clients of other big banks. However, it is counter-intuitive and is unlikely to be the case. If β is insignificant, I cannot reject the null hypothesis that Lehman and other big banks' clients were equally affected by Lehman's collapse. An insignificant β will go against FMM's findings and there could be a number of explanations for that. Clients might receive insignificant shares from value created by underwriting relationship, or the value of the relationship did not vanish due to the collapse, or the value created by the relationship with Lehman was not significant.

Before applying data into the models, it is worthy to compare the characteristics of Lehman's and other big banks' clients. Specifically, I examine the difference in industry allocation and firm characteristics of the two groups of clients.

4.2 Variation of the CAR7 over Industries and Industry Allocation of the Big Banks' Clients

Figure 1 illustrates the variation in reaction among industries and the allocation of Lehman and other big banks' clients over industries. The top half of Figure 1 presents the average of *CAR7* over non-client firms (i. e. those are neither clients of Lehman nor clients of other big banks) in each industry classified by two-digit SIC code. There is a huge variation among industries. Coal mining (SIC code 12), oil and gas extraction (SIC code 13), metal mining (SIC code 10), general building contractors (SIC code 15), and local and interurban passenger transit (SIC code 41) industries are the most affected industries. While some other industries were unaffected by the collapse such as transportation by air (SIC code 45), lumber and good products (SIC code 24), agricultural services (SIC code 7), building materials & garden supplies (SIC code 53), and furniture and home furnishings stores (SIC code 57). The industry abnormal returns are calculated as average of the *CAR7* over non-client firms, and the number of non-client firms is presented at the upper border of the figure. Industries with very few number of constituents may have unreliable industry abnormal returns.

[Insert Figure 1 about here]

The bottom half of Figure 1 presents allocations of Lehman and other big banks' clients over industries. The most noticeable difference lies in the oil and gas extraction industry (two-digit SIC code 13). About 16% of Lehman's clients were in this industry while only 7% of other big banks' clients were in this industry, and, this industry was heavily affected by the collapse with industry abnormal returns of around -16%.

Table 5 presents the t-test results between Lehman and other big banks' clients before and after excluding firms in this industry. After excluding firms in this industry the absolute average difference between two groups drops from 2.7% (significant) to 1.3% (insignificant). This early result confirms the importance of controlling for industry and potentially firms' characteristics when we assess the marginal effect of being Lehman's clients on the *CAR7*.

[Insert table 5 about here]

4.3 Characteristics of Lehman and Other Big Banks' Clients

Table 6 presents descriptive statistics of the *CAR7,* firm characteristics, and industry abnormal returns of Lehman's and other big banks' clients. These firms had abnormal returns of -2.4% around the collapse, while the average industry abnormal returns were around -4.1%, and 19% of them were Lehman's former clients. On average, big banks' clients had $1.5 billion in capitalization, 7 years of listing age, 2 times of market-to-book ratio, and 2% of net leverage. In addition, the average Altman's Z-Score was 5.8 and 21% of the big banks' clients were at potential financial distress. The correlation matrix in Panel B does not show any risk of multicollinearity; the highest correlation is 0.5 between market-to-book ratio and Z-Score.

[Insert table 6 about here]

Panel C of Table 6 illustrates that the characteristics of Lehman's clients and clients of other big banks were significantly different. Leman's clients carried characteristics related to more severe effects from the collapse. Specifically, they were significantly younger, had higher leverage, were closer to potential distress, and concentrated in industries which have lower industry abnormal returns compared to other big banks' clients. The only exception was that Lehman clients were bigger and bigger firms were less affected by the collapse. Lehman clients, on average, were 40% bigger and 17% younger than their peers. Lehman clients were bearing more risk than other big banks' clients. Lehman clients had significantly higher market net leverage, 10% compared to -0.4% of other big banks' clients. Lehman's clients were less in red zone of potential distress compared to their peers; 31% of Lehman's clients had Z-Scores lowers than 1.8, while only 20% of other big banks' clients had Z-Scores lower than that level. Finally, Lehman's clients concentrated on industries which are more affected by the shocks. The average seven-day cumulative abnormal returns of industries where the Lehman clients in was -5.6% while that of other big banks' clients was only -3.7%.

4.4 Marginal Effect of Being Lehman' Clients on the CAR7

Table 7 presents the regression results of 5 models with the same dependent variable, *CAR7,* and independent variable of interest *LehmanClient* and different sets of control variables. The estimated coefficient of the *LehmanClient* variable represents the marginal effect of being Lehman's clients on *CAR7*. Model II(a) uses no control variables and has virtually the same estimated coefficients as a simple t-test. However the significance level is changed because the between industry heteroskedasticity is controlled. The marginal effect is -2.7% and significant at 10% level; this result is in line with FMM. Model II(b) controls for characteristic variables including market value, firm age, market-to-book ratio, net leverage, Z-Score and distress dummy. Model II(c) controls for industry abnormal returns, and Model II(d) controls for both industry abnormal returns and firm characteristics. Model II(e) is similar to Model II(d), but controls for industry fixed effects instead of industry abnormal returns.

[Insert table 7 about here]

The insignificant estimated coefficient of *LehmanClient* in Model II(b), II(c), II(d), and II(e) suggests that being a Lehman's client did not exert a significant marginal effect on *CAR7.* In Model II(b), controlling for firm characteristics, the marginal effect of *LehmanClient* decreases from -2.7% to about -2.1% and is statistically insignificant. The firm characteristics variables together explain around -0.6% of stock abnormal returns of Lehman's clients. The marginal effect of *LehmanClient* declines dramatically to -0.9 (i. e. statistically and economically insignificant) when the industry abnormal returns are controlled for. Firms' industrial allocations singularly can explain -1.8% of the abnormal returns. After controlling for both industry abnormal returns and firm characteristics, the marginal effect of *LehmanClient* drops to around 0.3%, which is minimal. The estimated coefficient of *LehmanClient* is even positive in Model II(e). However, this positive estimated coefficient cannot be interpreted as an underwriting relationship gain to the Lehman's clients because the industry fixed effects partially capture the underwriting relationship loss.

The estimated coefficient of *IndustryAbnRet* in Model II(d) has the value of 0.95, which suggests that the stock prices of big banks' clients exhibited similar behavior to stock prices of non-client firms in response to the collapse. In addition, the signs of the estimated coefficients of other control variables are ,in general, consistent with those of the characteristic model (table 5) and cross-sectional analysis in FMM. The estimated coefficients of market value and firm age have positive signs and estimated coefficients of net leverage and distress dummy have negative signs, although the significance level changes from one model to another.

4.5 Interaction Effects between Lehman's Client Dummy Variable and Firm Characteristics

In this sub-section, I study the interaction effects between Lehman's client dummy (*LehmanClient*), and industry and firm characteristics (*IndustryAbnRet* and *CHARACTER*). The interaction terms will capture the differences in the sensitivity of the *CAR7* to firm characteristics between Lehman and other big banks' clients. I run two models as follows.

Model III(a): OLS regression, controlling for between industry heteroskedasticity

$$CAR7_i = \alpha + \beta * LehmanClient_i + \Gamma * CHARACTER_i + \gamma * IndustryAbnRet + \Phi * LehmanClient_i \, X \, CHARACTER_i + \phi * LehmanClient_i \, X \, IndustryAbnRet + \varepsilon_i$$

Model III(b): OLS regression, controlling for industry fixed effects and between industry heteroskedasticity

$$CAR7_i = \alpha + \beta * LehmanClient_i + \Gamma * CHARACTER_i + \Phi * LehmanClient_i \, X \, CHARACTER_i + \varepsilon_i$$

$CHARACTER_i$ is a set of control variables which include some firm characteristic variables: firm's capitalization (*MarketValue*), firm's age (*FirmAge*), firm's market-to-book ratio (*MarketToBook*), firm's net leverage (*NetLeverage*), firm's Altman's Z-Score (*ZScore*) and distress dummy (*DistressDummy*).

[Insert table 8 about here]

Table 8 presents regression results of Model III(a) and Model III(b). $CHARACTER_i$ and $IndustryAbnRet$ are not shown in the table to save space. The negative estimated coefficient of net leverage suggests that the *CAR7* of Lehman's clients were much more sensitive to net leverage than the *CAR7* of other big banks' clients. The difference in *CAR7* between Lehman's clients at the first and the third quartiles in net leverage is 0.7%, while this number for other big banks' clients is almost zero. The estimated coefficients of other interaction terms remain insignificant. Although being Lehman's clients had no significant marginal effects on the stock price, Lehman's clients with high leverage were hit harder by the collapse than comparable other big banks' clients.

In an unreported regression, I include the interaction terms between *LehmanClient* and industry dummies basing on 1-digit SIC codes to capture the effects of being Lehman's clients on stock price reaction to the collapse over different industries. I do not find any significant interaction effects, which suggests that there is no specific industry in which the underwriting relationship loss was significantly more than other industries.

5 Robustness Check

I perform a number of robustness checks by altering settings over four dimensions. For the first dimension, different models of calculating cumulative abnormal returns are used, namely the Fama-French three-factor model and the capital market model. I also use actual cumulative returns as dependent variable. In this setting, I control for market risk premium, i. e. coefficient of market premium in the capital market model over the pre-event window (-290;-31), and momentum, i. e. average returns in the pre-event window (-290;-31), (Whited & Wu 2006; Tong & Wei 2010) in addition to industry abnormal returns and firm characteristics. For my second dimension, three levels of relationship are used: firms have Lehman as a lead manager at least once within the 10 years before the collapse, firms have Lehman as a lead manager in the last equity issuance before the collapse, and firms have Lehman as the only big lead manager within the 10 years before the collapse. If firms have relationships with other big banks, i. e. firms have alternatives to Lehman, then they will be less affected by the loss of equity relationship.

For the third dimension, I use two definitions of equity underwriting clients. The first one is that a firm is a client of a bank if it has at least one common stock underwriting deal with the bank in ten years before Lehman's collapse. The second one is that a firm is a client of a bank if it uses any of the following services of the bank: common stock underwriting, convertible underwriting, equity private placements and equity pipeline & registrations. Depending on definitions used, the sets of Lehman's and other big banks' clients change. Finally, for the forth dimension, I use two horizons of relationships: 10 years and 5 years. I cannot further shorten the horizon due to limitations in the sample size.

[Insert table 9 about here]

Table 9 demonstrates that the marginal effects of being Lehman's clients are statistically insignificant in every setting. These marginal effects are also economically insignificant except firms that had equity deals with Lehman, and no equity deals with other big banks. It is potential evidence that firms are affected more by an underwriter's collapse if the firm lacks existing relationships with other banks. The number of those firms, however, are only 47 and 35 for 10-year and 5-year horizons, and I cannot draw a statistically significant conclusion.

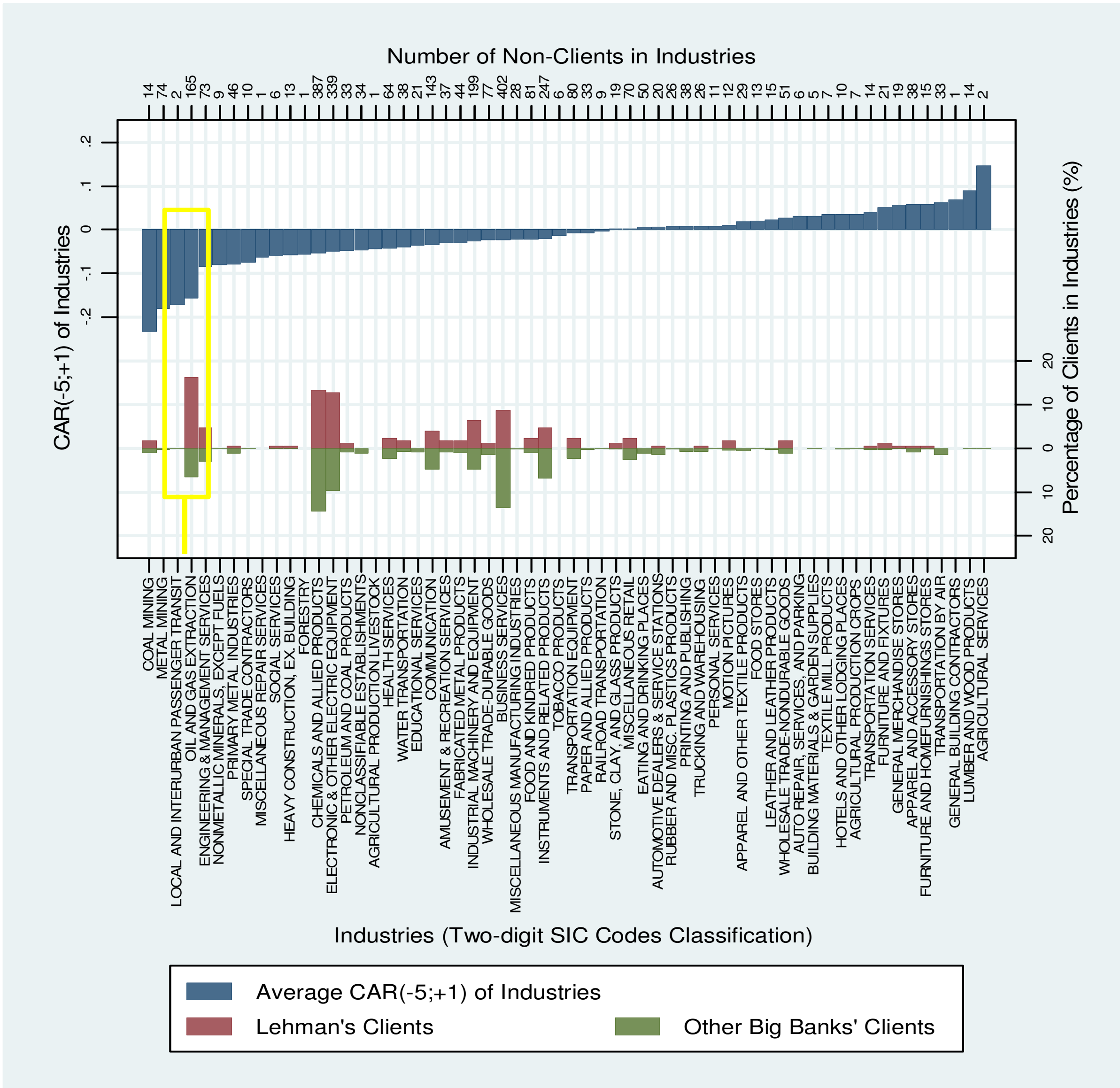
6 Conclusion

This paper reexamines the valuation of underwriting relationships using Lehman's collapse as an exogenous shock. Fernando et al. (2012) argue that Lehman's former clients had relationships with Lehman, and the value of these relationships was destroyed by Lehman's collapse, while the relationships between other banks and their clients remained unaffected by Lehman's collapse. They empirically document that Lehman's clients experienced lower stock price abnormal returns around the collapse compared to other big banks' clients; however, they do not take into account the differences in characteristics of Lehman's and other big banks' clients.

I study the effects of the collapse (and other events around the collapse) on firms which were not Lehman's clients and find that some industries were more affected by the collapse than others. Stocks of small, young, growth and potentially distressed firms experienced worse abnormal returns around the event. In addition, Lehman's clients bear many characteristics associated with greater damage by the collapse. Lehman's clients were younger, highly levered, closer to potential financial distress, and from more affected industries. The marginal effect of being a Lehman's client on the stock price reaction to the collapse was insignificant after controlling for the differences in characteristics between Lehman's and other big banks' clients. Nevertheless, I find the stock price abnormal returns of Lehman's clients were sensitive to leverage, while other big banks' clients are not.

Although my findings suggests that Lehman's collapse does not significantly affect its former clients more than comparable firms, my findings do not reject the existence of the underwriting relationship value. There are three possible explanations for my findings: the relationship was short lived, the investment banks captured the majority of the relationship value, or the collapse did not destroy the relationship value. My paper urges further research in capturing the value of the relationship between investment banks and their clients, and how the value is distributed among parties.

Figure 1: Industry Abnormal Returns and Firm Allocations



This figure illustrates significant deviation in abnormal returns around Lehman's collapse over different industries and allocations of Lehman and other big banks' clients over industries. The upper half of the figure displays average CAR(-5;+1) of firms in industries over two-digit SIC codes classification. The averages are calculated from firms having no equity underwriting relationship with any big banks. Some industries are heavily affected by the collapse such as metal mining (SIC code 10), coal mining (SIC code 12), oil and gas extraction (SIC code 13), and local and interurban passenger transit (SIC code 41). The lower half of the figure displays allocations of Lehman and other big banks' clients over industries. The y-axis on the right hand side presents percentage of firms being allocated in each industry for Lehman's clients (above and in red) and other big banks' clients (below and in green). The graph illustrates the differences in industrial allocations between two groups. The most significant difference is that around 16% of Lehman's clients were in oil and gas extraction industry while around 7% of other big banks' clients were in this industry and this industry was highly affected by the collapse.

Table 1: Data Filtering Process

Types of firms ➔	Lehman's Clients	Other big banks' Clients		All
Sources of data ➔	Thomson Reuters		CRSP	Compustat
Number of firms extracted	422	2,146	6,832	9,865
Merge CRSP with Compustat			4,667	
Merge with Thomson Reuters	249	999	4,667	
Delete utility and financial firms	189	769	3,498	
Delete firms with missing data	173	716	3,289	

This table presents the data filtering process. There are nearly 7,000 firms on CRSP at the time of Lehman's collapse with at least 30 data points in the pre-event windows (-290;-31) and nearly 10,000 firms on Compustat with non-missing total assets. I match these two samples by using 8-digit CUSIP codes. About 4,700 firms are matched. I define a firm as Lehman's client (or other big banks) if it has Lehman (or other big banks) as a lead manager in at least one common stocks deal in 10 years before the collapse. There were nearly 700 Lehman clients and 3,800 clients of other big banks in Thomson One data base, in which around 250 Lehman's clients and around 1,000 other big banks' clients are matched with CRSP and Compustat by using 6-digit CUSIP codes. The unmatched clients might have gone bankrupted or delisted. After excluding financial and utility firms and firms with missing data, I have 173 Lehman's clients, 716 clients of other big banks and 2,400 non-client firms.

Table 2: Descriptive Statistics of CAR(-5;+1) over Sub-Samples

Firms	N	mean	sd	min	p25	p50	p75	max
Lehman's Clients	173	-4.58	0.13	-0.71	-0.11	-0.03	0.03	0.31
Other Banks' Clients	716	-1.9	0.13	-1.11	-0.09	-0.02	0.04	1.19
Non-Clients	2,400	-3.54	0.11	-0.66	-0.07	-0.01	0.05	0.32
Total	3,289	-3.24	0.13	-1.11	-0.09	-0.02	0.04	1.19

This table presents distributions of CAR(-5;+1) of Lehman's clients, other big banks' clients and other firms. On average, Lehman's clients, other big banks' clients and other firms had average CAR(-5;+1) of -4.6%, -1.9% and -3.5%, respectively.

Table 3: Descriptive Statistics of Lehman's Non-Clients

Panel A: Distributions

	mean	sd	min	p25	p50	p75	max
CAR7	-3.09	12.64	-111.37	-8.45	-1.51	3.80	119.25
MarketValue	6.74	2.08	1.26	5.26	6.54	8.09	13.86
FirmAge	8.22	1.12	4.48	7.59	8.41	8.99	10.32
MarketToBook	0.60	0.58	-0.77	0.18	0.50	0.93	3.85
NetLeverage	0.00	0.25	-1.84	-0.12	0.00	0.14	0.78
ZScore	6.07	9.06	-1.77	2.20	3.56	6.11	66.37
DistressDummy	0.17	0.38	0	0	0	0	1
IndustryAbnRet	-3.50	4.83	-23.46	-5.09	-2.61	-2.10	14.60
N	3,253						

Panel B: Correlation matrix

		1	2	3	4	5	6	7
CAR7	1							
MarketValue	2	.18						
FirmAge	3	.17	.22					
MarketToBook	4	-.08	.13	-.18				
NetLeverage	5	.04	.31	.18	-.12			
ZScore	6	-.07	-.09	-.23	.49	-.25		
DistressDummy	7	-.09	-.02	-.03	-.24	.29	-.27	
IndustryAbnRet	8	.38	.02	.14	-.16	.09	-.13	-.05

This table presents descriptive statistics of firms which are neither client of Lehman nor of other big banks. Panel A presents distributions of variables and Panel B presents correlation coefficients among variables. The average size, age, book-to-market ratio, and net leverage of Lehman's non-clients were about $850 million, 10 years, 1.8 times, and 0.1%. Lehman's non-client firms had average Altman's Z-Score of 6.1, and 17% of these firms were at the risk of financial distress (i. e. the Z-Score is below 1.8). Please refer to Appendix Table 1 for definitions of variables.

Table 4: Effects of Lehman's Collapse on Lehman's Non-Client Firms

	Model I(a)		Model I(b)	
MarketValue	1.07	***	1.26	***
	(6.7)		(9.1)	
FirmAge	1.23	***	0.93	***
	(3.5)		(3.3)	
MarketToBook	-2.06	***	-1.67	***
	(-3.1)		(-2.8)	
NetLeverage	-1.02		-1.39	
	(-0.6)		(-0.9)	
ZScore	-0.02		0.02	
	(-0.3)		(0.8)	
DistressDummy	-3.48	***	-2.55	**
	(-3.4)		(-2.6)	
Constant	-18.51	***	-18.00	***
	(-5.6)		(-8.1)	
Industry Fixed Effects	no		yes	
R2	0.07		0.06	
N	3,122		3,122	

This table presents the results of regression of Lehman's non-client firms with dependent variable CAR(-5,+1). Model I(a) controls for market value, age, market-to-book ratio, net leverage, Z-Score, and financial distress dummy. Model I(b) further controls for industry fixed effects. Firms that are smaller, younger, with higher market-to-book ratios, and closer to potential distress were more affected by the collapse. * p<0.1, ** p<0.05, *** p<0.01, and t-statistics in parentheses. Please refer to Appendix Table 1 for definitions of variables.

Table 5: Oil and Gas Extraction Industry Exclusion

	Lehman's Clients	Other Banks' Clients	Difference	t-statistics
CAR7	-4.6	-1.9	-2.7***	(-2.7)
CAR7 (SIC-code 13 Excluded)	-2.5	-1.2	-1.3	(-1.3)

This table presents the difference in CAR(-5;+1) between Lehman and other big banks' clients. The difference is -2.7% and significant. However if I exclude oil and gas extraction industry (two-digit SIC code 13) – 28 Lehman's clients and 36 other big banks' clients are excluded – the difference drops to -1.3% and becomes insignificant. * p<0.1, ** p<0.05, *** p<0.01.

Table 6: Descriptive Statistics of Lehman and Other Big Banks' Clients

Panel A: Distributions

	mean	sd	min	p25	p50	p75	max
CAR7	-2.42	11.78	-71.17	-7.69	-1.18	4.79	31.50
LehmanClient	0.19	0.40	0	0	0	0	1
MarketValue	7.29	1.50	1.62	6.28	7.15	8.22	12.30
FirmAge	7.84	1.08	5.27	7.04	8.01	8.55	10.32
MarketToBook	0.68	0.57	-0.42	0.24	0.59	1.01	3.56
NetLeverage	0.02	0.27	-1.20	-0.13	0.01	0.18	0.78
ZScore	5.79	8.15	-1.77	1.95	3.27	5.80	66.37
DistressDummy	0.21	0.41	0	0	0	0	1
IndustryAbnRet	-4.08	5.03	-23.46	-5.55	-3.54	-2.10	14.60
N	889						

Panel B: Correlation matrix

		1	2	3	4	5	6	7	8
CAR7	1								
LehmanClient	2	-.09							
MarketValue	3	.07	.09						
FirmAge	4	.10	-.07	.40					
MarketToBook	5	.01	.02	.09	-.18				
NetLeverage	6	-.03	.15	.44	.19	-.21			
ZScore	7	-.02	-.01	-.11	-.23	.50	-.32		
DistressDummy	8	-.13	.13	.00	.03	-.29	.37	-.31	
IndustryAbnRet	9	.40	-.15	-.06	.00	.00	.02	.06	-.12

Panel C: Differences between Lehman's clients and other big banks' clients

	Lehman's Clients	Other Banks' Clients	Difference	t-statistics
MarketValue	7.55	7.22	0.33 ***	(2.62)
FirmAge	7.69	7.88	-0.20 **	(-2.16)
MarketToBook	0.70	0.68	0.02	(0.45)
NetLeverage	0.10	-0.00	0.10 ***	(4.53)
ZScore	5.60	5.84	-0.23	(-0.34)
DistressDummy	0.32	0.19	0.14 ***	(4.01)
IndustryAbnRet	-5.63	-3.70	-1.92 ***	(-4.56)

This table presents descriptive statistics of the LehmanClient dummy and control variables. Panel A presents distributions of variables and Panel B presents correlation coefficients among variables. Panel C presents the differences in characteristics of Lehman's clients and other big banks' clients. On average, Lehman's clients were bigger, younger, higher levered, more in financial distress, and in more affected industries compared to other big banks' clients. We would expect that Lehman and other big banks' clients are affected differently by the collapse due to their characteristic differences. * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Please refer to Appendix Table 1 for definitions of variables.

Table 7: Effects of Lehman's Collapse on Lehman and Other Big Banks' Clients

	Model II(a)	Model II(b)	Model II(c)	Model II(d)	Model II(e)
LehmanClient	-2.69 *	-2.05	-0.90	-0.34	0.33
	(-1.8)	(-1.5)	(-0.9)	(-0.3)	(0.4)
MarketValue		0.44		0.83 ***	1.01 ***
		(1.2)		(2.9)	(3.9)
FirmAge		0.73		0.59 *	0.41
		(1.4)		(1.9)	(1.1)
MarketToBook		-0.19		-0.02	-0.48
		(-0.2)		(-0.0)	(-0.6)
NetLeverage		-1.21		-4.03 **	-1.59
		(-0.6)		(-2.5)	(-1.0)
ZScore		-0.06		-0.10	-0.11 *
		(-0.8)		(-1.5)	(-1.8)
DistressDummy		-3.82 **		-2.18 *	-3.26 ***
		(-2.4)		(-1.9)	(-3.5)
IndustryAbnRet			0.93 ***	0.95 ***	
			(8.1)	(8.1)	
Constant	-1.90 *	-9.61 **	1.55 **	-8.06 ***	-11.45 ***
	(-2.0)	(-2.5)	(2.1)	(-2.7)	(-4.0)
Industry Fixed Effects	no	no	no	no	yes
R2	0.01	0.04	0.16	0.19	0.04
N	889	889	889	889	889

This table presents the results of regressions with dependent variable CAR(-5;+1) over the sub-sample of Lehman and other big banks' clients. The estimated coefficient of LehmanClient represents the marginal effects of being Lehman's clients on CAR(-5;+1). Model II(a) has no control variable (i. e. equivalent to t-test), the marginal effect is -2.7% and significant. Model II(b) controls for firm characteristics, and the marginal effect reduces to -2.1% and it is not significant. Model II(c) controls for only average abnormal returns of non-clients in the industries, and the marginal effect drops dramatically to -0.9% . Model II(d) controls for firm characteristics and industry abnormal returns, and the marginal effect is almost zero. Model II(e) controls for firm characteristics and industry fixed effects, and produces similar results. Therefore, we cannot reject the null hypothesis that Lehman's and other big banks' clients were equally affected by Lehman's collapse. All of these models are controlled for between industry heteroskedasticity. * p<0.1, ** p<0.05, *** p<0.01, and t-statistics in parentheses. Please refer to Appendix Table 1 for definitions of variables.

Table 8: Interaction Effects

	Model III(a)		Model III(b)	
LehmanClient	-7.57		-5.79	
	(-1.1)		(-1.0)	
MarketValue	0.87	***	0.91	***
	(2.7)		(3.0)	
FirmAge	0.37		0.35	
	(1.1)		(0.9)	
MarketToBook	-0.27		-0.62	
	(-0.2)		(-0.6)	
NetLeverage	-2.47		0.47	
	(-1.4)		(0.3)	
ZScore	-0.08		-0.08	
	(-1.0)		(-1.1)	
DistressDummy	-2.73	*	-3.84	***
	(-1.8)		(-3.2)	
IndustryAbnRet	0.95	***		
	(6.5)			
LehmanClient X MarketValue	0.02		0.80	
	(0.0)		(0.9)	
LehmanClient X FirmAge	0.95		0.16	
	(1.4)		(0.2)	
LehmanClient X MarketToBook	0.40		-0.01	
	(0.2)		(-0.0)	
LehmanClient X NetLeverage	-10.74	*	-13.30	**
	(-2.0)		(-2.4)	
LehmanClient X ZScore	-0.12		-0.13	
	(-1.3)		(-1.5)	
LehmanClient X DistressDummy	2.38		2.29	
	(1.1)		(1.3)	
LehmanClient X IndustryAbnRet	-0.05			
	(-0.3)			
Constant	-6.39	*	-10.12	***
	(-2.0)		(-3.4)	
Industry Fixed Effects	no		yes	
R2	0.20		0.05	
N	889		889	

This table presents the results of regressions with dependent variable CAR(-5;+1) over the sub-sample of Lehman's and other big banks' clients. The independent variables include Lehman's client dummy, industry abnormal returns, firm characteristics, and interactions between Lehman's client dummy and characteristic variables. The estimated coefficients of characteristic variables are not shown to save space. The significantly negative coefficient of LehmanClient X NetLeverage suggests that Lehman's clients with high leverage were affected more than other big banks' clients with similar leverage level. * p<0.1, ** p<0.05, *** p<0.01, and t-statistics in parentheses.

Table 9: Robustness Check

	Lehman's clients		Lehman's clients in the last deals		Lehman's client and not client of any other big bank	
4-factor model	-0.4%	-0.3%	-0.1%	-0.1%	-0.6%	-0.4%
	0.0%	0.3%	0.3%	0.3%	-1.6%	-1.4%
3-factor model	-0.7%	-0.7%	-0.4%	-0.4%	-1.0%	-1.0%
	-0.3%	-0.3%	0.0%	-0.1%	-2.0%	-1.9%
CAMP model	-0.8%	-0.9%	-0.5%	-0.5%	-1.0%	-0.8%
	-0.4%	-0.4%	-0.1%	-0.2%	-2.0%	-1.7%
Cumulative returns	-0.8%	-0.9%	-0.5%	-0.6%	-1.2%	-1.0%
	-0.3%	-0.4%	-0.1%	-0.3%	-2.3%	-2.2%

I organize each Model Type – Relationship Level pair as following:

	10 years	5 years
Common stock deals	x	x
All equity deals	x	x

This table presents the marginal effect of being a Lehman's client with 4 directional modifications.

- I use 3 models to calculate abnormal returns, namely the Fama-French-Carhart four-factor model, the Fama-French three factor-model, the capital model, and the cumulative returns. Model types are organized by rows.
- I use 3 levels of relationship: firms have Lehman as a lead manager at least once within the 10 years before the collapse, firms have Lehman as a lead manager in their last equity issuance before the collapse, and firms have Lehman as the only big lead manager within the 10 years before the collapse. Relationship levels are organized by columns.
- I use 2 definitions of relationship: a firm is a bank's client if it has at least one common stock deal with the bank within the 10 years before the collapse, and a firm is a bank's client if it has at least one equity deal (common stock, private placement, convertible, or equity pipeline & registrations) with the bank within the 10 years before the collapse. Relationship definitions are organized by rows within 2X2 cells of each model type & relationship level pair.
- I use 2 relationship horizons: 10 years and 5 years. Relationship horizons are organized by column within 2X2 cells of each model type & relationship level pair.

The marginal effect of being a Lehman's client is statistically insignificant at significance level 10% over all settings. The marginal effect is economically significant (around -2%) when firms have equity deals with Lehman, and no equity deals with other big banks. The numbers of observations in this setting are 47 for 10 years horizon and 35 for 5 years horizon, which are small.

Appendix Table 1: Definitions of Variables

Variables	Definitions
FirmAge	Logarithm of age Formula: $ln(Number\ of\ days\ since\ the\ appreance\ on\ CRSP)$ Data source: CRSP
CAR7	Seven-day cumulative abnormal returns from Fama-French-Carhart four-factor model *CAR(-5;+1)* Data source: CRSP, Kenneth R. French's website
DistressDummy	Distress dummy variable Formula: *equals 1 if ZSCORE<1.8 and equals 0 otherwise* Data source: Compustat, CRSP
IndustryAbnormalReturn	Average of the *CAR7* of firms those are neither clients of Lehman nor other top ten banks in industries. I use 2-digit SIC code for the industry classification. Formula: $Average_{firms\ in\ the\ industry}(CAR7)$ Data source: CRSP, Kenneth R. French's website
LehmanClient	Lehman's clients dummy, Formula: *equals 1 if the firm is a former equity underwriting client of Lehman and equals 0 otherwise* Data source: Thomson Reuters
MarketToBook	Logarithm of market-to-book ratio of firms' assets Formula:$ln((csho * \ prcc\_f + lt)/at)$ Data source: Compustat
MarketValue	Logarithm of market value Formula: $\ln(csho * \ prcc\_f + lt)$. Data source: Compustat
NetLeverage	Net leverage Formula: $(dltt + dlc - che)/(prc * shrout)$ Data source: Compustat
ZScore	Altman's Z-Score Formula: $3.3 * ebit + revt + 1.4 * (ni - dvt) + 1.2 * (act - lct))/at + 0.6 * (csho * \ prcc\_f - lt)/(lt)$ Data source: Compustat

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