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Earnings Forecast and Stock Recommendation by Security Analysts

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by

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This dissertation consists of 3 chapters.

Chapter 1: Last Minute Earning Forecast Revision

Chapter 2: Security Analysts' Double Down Behavior in Stock Recommendation

Chapter 3: Cost of Speaking in Two Different Tongues

Chapter 1: I study financial analysts who revise their earnings forecasts just a few days before firms' earnings announcement. Analysts who apply this strategy are more accurate in their earnings forecasts, and they are more likely to move to a larger brokerage firm. All-star analysts are more likely to take this last minute revision strategy than non-all-star analysts. All-star analysts using the strategy are likely to maintain their all-star status and get a better career path, while non-all-star analysts are less likely to get promotion when they apply this strategy.

Chapter 2: When a stock experiences a significant loss after a favorable recommendation from an analyst, the analyst can either continue to issue a favorable recommendation or reverse the course. I define the behavior of continuing favorable coverage as the analyst's doubling down behavior.I find analysts who double down are likely to get demoted and less

likely to become an all-American analyst in the next year. Analyst makes biased recommendation in the double down behavior because of overconfidence instead of defending the firm. Stocks recommended by doubling down analysts have worse performance than stocks recommended by other analysts. Investors perform worse if they follow the buy recommendations of doubling down analysts.

Chapter 3: Malmendier and Shanthikumar (2014) find that some analysts prefer to issue relatively higher stock recommendation ratings and relatively lower earnings forecast on the same firm at the same time. They describe this behavior as speaking in two different tongues. Following Malmendier and Shanthikumar (2014)'s definition of the two-tongue strategy, I explore the external influence of this strategy on financial analysts. I show that when analysts take the two-tongue strategy, they are suffering a cost by sacrificing their accuracy on their target firms. The more frequent an analyst takes the two-tongue strategy in the previous year, the less likely this analyst would be promoted to a top 10 brokerage house and be nominated as an All-American analyst in the current year. Moreover, investors respond more positively to the higher stock recommendation ratings but ignore the lower earnings forecast on the firms where analysts apply the two-tongue strategy by showing no significant negative reaction.

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Contents

List of Tables

Chapter 1

Last Minute Earning Forecast Revision

1.1 Introduction

Financial analysts function as important players in the security market. They collect firm information on business entities in order to write reports and communiques about them. Frequently they issue earnings forecast and recommendations on given securities published for the benefit and use of the clients for their firm. Of course, there are buy-side analysts and sell-side analysts. Whether buy-side or sell-side, they seek to achieve better career path through quality and quantity of their work. Most importantly, a financial analyst attempts to attract the attention of investors thereby building-up a reputation over time. The existing literature includes many examples of research on the reputations of analysts and on the attention investors pay to them. To establish a better career path, these analysts need to attract investors' attention and build their reputation. Analyst reputation affects analysts' career outcomes (Hong and Kubik (2003b), Leone and Wu (2007)) and their ability to generate trading commissions (Jackson (2005)). Clement and Tse (2003) touch upon the notion of limited investor attention to analyst forecasts by showing that investors over-rely on easily observable summary proxies of forecast accuracy when responding to analyst forecast revisions, for example, broker size than on other predictors of forecast accuracy. Athanasakou and Simpson (2014) find that investor does pay attention to what the analysts say and they pay attention to the salient features of analyst forecasts. These papers talk about the analysts' reputation building and investor attention on financial analysts separately.

Security analysts establish and then augment their reputation by timing the release of their earnings forecast when investor attention is high, for example, when the public announcement of a firm's earnings is just around the corner in time. In this way, analysts are more likely to attract the focus of investors on their output thereby making themselves familiar to investors. Essentially this study combines two aspects of security analysts into a unifying whole: one, analyst reputation building and two, the attention paying of investors to analysts and their work. In particular, I study analysts who revise their earnings forecasts just a few days before firms' earnings announcement. In addition, this study show the different impact of last minute earning forecast revision made by all-star (viz., high reputation) analysts in comparison to those made by non-star (viz., moderate high and low reputation) analysts.

Drake et al. (2012) find investors tend to increase their attention two weeks prior to the firms' earnings announcement by studying from Google search data. Investors' attention reaches the highest level in the last week before the firm's earnings announcement. Forecasts made by analysts during this time are more likely to grab the attention of investors. Accordingly, I define a last minute earning forecast as one that is made within seven calendar days period immediately prior to the public earnings announcement of the firm in question. Subsequent to this, this paper investigates specific analyst characteristics which possibly can influence the probability (or likelihood) of making a last minute earning revision. A key finding of this study is high reputation analysts are more likely to make last minute revision.

Also, this behavior persists into the future: analysts making last minute revisions are more likely to do so again in the next fiscal quarter.

To test whether or not making a last minute earnings revision has a strategic goal of the analysts attracting the attention of investors, I check the accuracy of these analysts' forecasts. If an analyst desires to attract attention, a forecast issued within the the last seven calendar days may be able to catch the investor eyeballs. However, an inaccurate forecast also would attract investor attention and presumably would be detrimental to the reputation of the analyst. Indeed, and perhaps unsurprisingly, last minute revision forecasts are more accurate than those forecast made outside the seven calendar days period preceding a firm's public earnings announcement. To control for the general trend of these late forecasts, I also measure the accuracy using relative forecast error, and I find the same result. It indicates that these last minute earnings forecasts are indeed more accurate and analysts could use this higher accuracy to grab the investor attention.

If analysts apply this last minute earnings revision strategy to build their reputation, then the effect will be reflected in their career paths. I check the impact of last minute earnings revision on the analysts' career path. To ensure that our result is robust, I apply five different measurements to measure an analyst's promotion and demotion in their careers. I find that the last minute earning revision is helpful for analyst in their career path. Analysts with such behavior in the previous year are more likely to be promoted and less likely to be demoted in the next year.

If the last minute earning revision is beneficial to an analyst, then why do only a small number of analysts adopt this strategy? Why do not all analysts adopt this last minute earning revision strategy? Derived from the previous results that all-star analysts are more likely to take the last-minute earning revision, I check the difference between star-analysts and non star-analysts applying last minute earnings forecast revision. An important finding of this paper is that the all-star analysts are much more likely to adopt the last-minute earnings revision strategy than the non-star analysts. This difference is also reflected in their career paths. All-star analysts who applied the last minute earnings forecast revision strategy in the previous year are more likely to be promoted and less likely to be demoted. On the other hand, for the non-star-analysts, they are less likely to be promoted to a top-ten brokerage firm and less likely to be nominated as an all-star analyst if they take the same strategy. The opportunity cost is obvious. Last minute earnings forecast revision only works for the analysts who already have good reputation. The different influence of the last-minute earning revision strategy on analysts' career path between the all-star analysts and non-star analysts show that this strategy is employed by analysts to maintain their reputation.

One possible issue in this research is endogeneity. Guttman (2010) uses a theoretical model to show that high learning ability analysts tend to issue their forecasts later. If those analysts who take the last minute earnings forecast revision strategy are high quality analysts to begin with, it is quite possible that the better career path is not the result from the strategy but from the high quality of these analysts. To solve this problem, I adopt a method in Wooldridge (2002) to solve endogeneity problem. After controlling for the endogeneity, the results stay robust for the two strict promotion career measurements.

This research makes contributions to the existing research on the two fronts: First, I combine the analyst reputation and investor attention literature together to show high reputation analyst strategic behavior to issue last-minute earning revision to maintain their reputation, and this strategy is only helpful for the high reputation analyst career path. Second, this paper is complementary to the literature about the timing of analysts' forecasts by exploring a very special time window, namely one to five calendar days before earnings announcement. I find that the revisions made during this period of time are more accurate. Our work provide empirical evidence to prove the theory of Guttman (2010) that analysts with high learning ability tend to issue their forecasts later.

The rest of this paper is organized as follows. Section 2 is the literature review. Section

3 presents the data and summarizes all the relevant variables I will use in the rest of paper. Section 4 presents empirical results and the interpretation of these results. Section 5 shows the Robustness Test of the previous results. Section 6 concludes the paper.

1.2 Literature Review

The topic of attention has been widely studied by researchers in different research areas. Geer and Kahn (1993) find that politicians take advantage of the headlines to have a sizeable effect on the views of the subjects and use this way to get the attention of their supporters. Almazan et al. (2008) prove that managerial announcements not only convey information to the market but also attract attention to the firm and guide speculators in their investigation efforts. Barber and Odean (2007) show that stocks that experience high abnormal trading volume and stocks with extreme one-day return are more likely to grab investors' attention. Firms, managers, politicians use different strategies to attract the attention of investors, shareholders and supporters. For the same reason, grabbing investors' attention is also critical for analysts because the attention of investors could help analysts to build or maintain a good reputation. Analyst's reputation could affect their career development (Hong and Kubik (2003b), Leone and Wu (2007)) and their trading commissions(Jackson (2005)). Having a good reputation is extremely helpful for an analyst in his or her career path. But the question for the analysts who want to build or maintain their reputation is how to attract the attention from the investors.

The previous literature on the investors' side shows that investors do look for signals to qualify an analyst. Hirshleifer and Teoh (2003) argue that investor has limited attention. Stickel (1992),Park and Stice (2000), Gleason and Lee (2003) show evidence exists that investors look for more elaborate signals for the expected accuracy of the forecast, such as past forecasting ability, analyst reputation and brokerage firm affiliation. (Hirshleifer and Teoh, 2003) said investors focus on subsets of publicly available information that are more salient and easier to extract. (Clement and Tse, 2003) touch upon the notion of limited investor attention to analyst forecasts by showing that investors over-rely on easily observable summary proxies of forecast accuracy when responding to analyst forecast revisions, for example, broker size than on other predictors of forecast accuracy. Athanasakou and Simpson (2014) find iInvestor does pay attention to what the analysts said and they pay attention to the salient features of analyst forecasts. Then if analysts want to grab the investor's or manager's attention, their method could not be too complex or sophisticated because of investors limited attention. Taking all conditions from the investor side into consideration, if analysts want to use a simple signal to grab investor attention, they need find a good time to send the signal. Now the question for an analyst is what is the good time? Drake et al. (2012) find investors show an increase in their attention two weeks prior to the firms earnings announcement. Ivković and Jegadeesh (2004) show that earning forecast revisions are more informative in the week before earnings announcements than the week after the earnings announcements.

1.3 Data

I get the actual firm earnings and analyst forecast data from the I/B/E/S Detail History files from 1994 to 2012. The sample is started from 1994 because forecasts may be inaccurate due to the reason of batch delivery before 1994 in I/B/E/S. I focus on quarterly forecast and I include all US firms with CRSP data. Then my main sample includes all the public firms in the three main exchange, NYSE, AMEX and Nasdaq. For each firm-analyst, I use the last forecasts issued by the analyst before firm's public earning announcement but following the same firm's previous public earning announcement. I take the last earnings forecast by analysts because I want to see the most recent forecast by analysts in my analysis.

Analyst's employment information is also obtained from the I/B/E/S database by reviewing the brokerage firm for analysts. Accounting data comes from Compustat annual data and stock return data is from CRSP daily data.

1.4 Empirical Results

1.4.1 Define last minute earning revision

If an analyst attempts to attract the attention from investors, one of the simplest methods is to pick up a good time to issue his or her forecast when investors' interest and attention is high. Drake et al. (2012) show that investors have an increase in their attention two weeks prior to the firms' earnings announcement by applying Google search.

The last minute earning forecast revision period covers one to seven calendar days before a firm's earnings announcement because this special period would draw a lot of investors' attention according to Drake et al. (2012). Another reason for the immediately preceding 7 calendar days period is that the "timing signal" is salient and may easily be recognized by the investors. According to the previous studies, investors over-rely on easily observable summary proxies of forecast accuracy than on other predictors (Clement and Tse, 2003). In addition to that, Athanasakou and Simpson (2014) find that investors do pay attention to what the analysts said and they pay attention to salient features of analyst forecasts. Taking all possible conditions into consideration, I define the last minute earning forecast revision to be a strategy that issues earning forecast within the 1-7 calendar days before firm's earnings announcement.

To define the last minute earning forecast revision in a detailed way, I apply the following method:

The $LME_{i,j,t}$ (Last Minute Earning Forecast Revision) is an indicator variable that equals to 1 if the forecast issued by an analyst satisfies the following conditions: 1) If an EPS forecast is issued by an analyst 1 to 7 days before the firms earnings announcement. 2) The EPS forecast must be the only one forecast of the target firm in that day. In other words, if there are two EPS forecasts on a same firm issued by two different analysts, even if they are within the 7 days before the firms earnings announcement, I will not count them to last minute earning forecast revision. The reason why these forecasts are excluded is because I want to exclude the forecasts generated by the firm event, if there is an event for the firm within 1-7 calendar days before the firms earnings announcement, then there will be more than one analysts revise their forecasts about the firm. These kinds of forecasts may be generated by the firms events that attract analysts attention to revise their forecasts but not generated directly from analysts.

1.4.2 Define control variables

To get meaningful and accurate rankings, I delete firms covered by fewer than 2 analysts. All the control variables are ranked with a similar method as those used in previous papers.I use the method of Hilary and Hsu (2013) to build the control variable of accuracy, boldness, gap,firm experience and breadth.

$$Accuracy_{i,j,t} = 1 - (rank_{i,j,t})/(number\, of\, analysts\, following\, firm\, j - 1) \tag{1.1}$$

First, I calculate the forecast error for analyst in on firm j, then I take the absolute value of this forecast error. Second, I rank all analysts covering firm j in quarter q based on the absolute forecast error. In the last, I calculate the mean of the ranking scores and get the ranking variable.

Boldness is the absolute value of the difference between the forecast by analyst i and the street consensus following Ke and Yu (2006). The street consensus is defined as the average of all the other analysts forecasts for firm j within the past 90 days to the point of the forecast by analyst i for firm j at time t. Gap is defined as the total number of calendar days between the analyst forecast date and the firm public announcement date following Clement and Tse (2003). Firm-Experience is defined following Hong and Kubik (2003a), which is the log of the number of quarters the analyst has covered the firm. Experience is the log of the number of years the analyst has in the I/B/E/S following. Breadth is defined following Hong and Kubik (2003b), which is the number of firms that the analyst gives forecast in a fiscal given year. Since I measure accuracy by rankings and to keep the consistency, I also apply ranking variables for Boldness, Gap, Firm-Experience, Experience, and Breadth.

1.4.3 Description of the summary statistics

Table 1 provides the summary statistics for my main variables. In panel A, I provide the quarter-analyst-firm summary statistics for the variables in the regression of Table 4. It includes 179411 quarter-analyst observations. Except for the variable LME (Last Minute Earning Forecast Revision), all the other control variables are defined following the previous literature. The details are in the Section 3. Panel B provides the summary statistics for the quarter-analyst variables, all the variables in Panel B are defined the same way as Panel A except that they are calculated as the average across all the firms by the same analyst each quarter. Panel C shows the summary statistics for year-analyst results, the variables are calculated across all the firms covered by the same analyst each year. I have 1245894 quarter-firm-analyst observations and 49787 firm-year observations. I would name the last minute earning forecast revision to be "LME" strategy in the rest of this paper.

1.4.4 Analysts characteristics that could affect the analyst last minute earning forecast revision strategy

To have a good understanding of what kinds of analysts are more likely to apply the last minute earning forecast revision strategy, I first explore the analysts characteristics that could affect analysts LME strategy.

To test the analyst characteristics that may influence the analysts' LME strategy, I apply the following Logistic Regression Model:

$$\begin{aligned} LME_{i,j,t} =& Allstar_{i,t} + LME_{i,j,t-1} + Accuracy_{i,j,t-1} + Boldness_{i,j,t} + Firm - Experience_{i,j,t} + \\ & Firm\_Experience^2_{i,j,t} + LogFollow_{i,j,t} + Breadth_{i,j,t} + \epsilon_{i,j,t} \end{aligned} \tag{1.2}$$

Table 2 presents the logistic regression results with quarter fixed effect for the analyst characteristics that may influence the probability for an analyst to have an Last Minute Earning Forecast Revision behavior. The dependent variable is a dummy variable. The coefficient of Allstar is 0.235 with a significant z-statistic of 8.15. The coefficients of LME in the previous quarter, accuracy in the previous quarter, boldness, LnFollow are all positive and significant. These positive and significant coefficients indicate that all-star analysts, analysts with higher boldness and analysts who are more accuracte are more likely to have an Last Minute Earning Forecast Revision behavior. Considering the risk of an instant verification (investors will know the accuracy of analysts forecasts several days later) for the forecasts made by the analyst, more accuracy give analysts who apply last minute earning forecast revision strategy more advantage and make them more confident to play this "LME" game. For the firms followed by more analysts, analysts are also more likely to apply the Last Minute Earning Forecast Revision strategy. If an analyst did have an Last Minute

Earning Forecast Revision behavior in the previous quarter, then he or she would be more likely to be Last Minute Earning Forecast Revision than the analysts who do not have such a behavior in the previous quarter. On the other hand, the coefficient of Firm-Experience is -0.148 with a significant z-statistic of -2.56 and the coefficient of Breadth is -0.224 with a significant z-statistic of -15.79. These results show that analysts who are more experienced and analysts who cover more firms than the other analysts would be less likely to have the Last Minute Earning Forecast Revision strategy.

1.4.5 Analyst accuracy in last minute earning forecast revision

Analysts who take the last minute earning forecast revision would take more risk because they are tolerating the risk of losing the chance to revise their earning forecast revision due to the time limitation before firm's earnings announcement date. Their forecasts would be verified soon several days later after they issue their "LME" forecasts. As a result, they may just do this by issuing a gambling forecast or they are confidently to do this and use this as a strategy to prove their high quality and build their high reputation. In order to explore on their accuracy in last minute earning forecast revision, I check the accuracy for these "LME" analysts from a firm_quarter_analyst level and a quarter_analyst level.

I use the following empirical model to test the accuracy of the "LME" strategy:

$$\begin{aligned} Accuracy_{i,j,t} =& LME_{i,j,t} + Accuracyi,j,t-1 + Boldness_{i,j,t} + Firm - Experience_{i,j,t} + \\ & LogFollow_{i,j,t} + Breadth_{i,j,t} + Gap_{i,j,t} + \epsilon_{i,j,t} \end{aligned} \tag{1.3}$$

$$\begin{aligned} Accuracy_{i,t} =& LME_{i,j,t} + Accuracyi,t-1 + Boldness_{i,t} + Firm - Experience_{i,t} + \\ & LogFollow_{i,t} + Breadth_{i,t} + Gap_{i,t} + \epsilon_{i,t} \end{aligned} \tag{1.4}$$

The Column 1 of Table 3 and Column 1 of Table 4 present the results. The coefficient of LME is positive with a result of 0.0129 and 0.0192, respectively. They are both significant with a t-value of 8.43 and 5.63, respectively. This proves that the analysts who apply the last minute earning forecast revision do have a higher accuracy than analysts who do not apply this strategy. The high accuracy in a firm_quarter_analyst level and a quarter_analyst level prove that analysts who take last minute earning forecast revision are using this as a strategy to increase their accuracy instead of giving a random forecast like a gamble before the firm's earnings announcement date.

Although I find a higher accuracy for analysts who apply last minute earning forecast revision, there is a potential problem inside in the model I apply. The analysts who revise their forecasts within the 1-5 calendar days before earnings announcement will have more available information than the analysts who revise their forecasts earlier, so the higher accuracy may be generated by timing. To solve this problem, I apply the method of Kim et al. (2011) to build a measurement called the relative forecast error, which could solve the timing problem. After I build this relative forecast error measurement, I apply the similar method to give a rank number of all analyst's relative forecast error covering firm j in time t.

$$RFE_{i,j,t} = FE_{i,j,t} - CFE_{i,j,t}$$

$$FE_{i,j,t} = 100 * abs[(analyst\_forecast_{i,j,t} - quarterly\_earnings_{j,t})/quarterly\_earnings_{j,t}]$$

$$CFE_{i,j,t} = 100 * abs[(consensus\_forecast_{i,j,t}) - quarterly\_earnings_{j,t}/quarterly\_earnings_{j,t}]$$

$$RA_{i,j,t} = 1 - (RFE\_rank_{i,j,t})/(number\,of\,analysts\,following\,firm\,j - 1) \tag{1.5}$$

$$\begin{aligned} RA_{i,j,t} =& LME_{i,j,t} + Accuracyi, j, t-1 + Boldness_{i,j,t} + Firm - Experience_{i,j,t} + \\ & LogFollow_{i,j,t} + Breadth_{i,j,t} + Gap_{i,j,t} + \epsilon_{i,j,t} \end{aligned} \tag{1.6}$$

$$\begin{aligned} RA_{i,t} =& LME_{i,j,t} + Accuracyi, t-1 + Boldness_{i,t} + Firm - Experience_{i,t} + \\ & LogFollow_{i,t} + Breadth_{i,t} + Gap_{i,t} + \epsilon_{i,t} \end{aligned} \tag{1.7}$$

The consensus is defined as the average of all the other analyst forecasts for firm j within the past 90 days to the point of earning forecast by analyst i for firm j at time t. A negative(positive) value of RFE indicates that the analysts revised forecast is more(less) accurate than the consensus forecast. The column 2 of Table 3 and Column 2 of Table 4 reports the results for the RA. The coefficients of LME are negative with a result of -0.0183 and -0.00774, respectively. They are both significant with a t-value of -2.31 and -2.07, respectively. The results indicate that "LME" strategy give analysts a lower relative forecast error and analysts with last minute revision strategy have a lower relative forecast error than analyst who do not have. Combining the results of Table 3 and Table 4, I find that analysts are taking the "LME" strategy as a strategy because they have a higher accuracy during the 1-5 calendar days before earnings announcement. Considering the results from Table 2 that analysts with a higher accuracy in the previous quarter are more likely to apply last minute revision strategy in the next quarter, the high accuracy during the specific period before firm's earnings announcement is a salient and simple signal by analysts to attract investor's eyeballs.

1.4.6 Investor attention to the forecast by last minute earning forecast revision analysts

To test whether there is higher attention paid to the analysts who revise their earning forecast 1-7 calendar days before the firm's earnings announcement. I calculate 2-day abnormal size-adjusted return, $CAR_{i,j,0-1}$ for analyst's earning forecast revision. The forecasts made 1 day before firm's earnings announcement date are deleted from my sample because their 2-day abnormal return would include the CAR for firm's earnings announcement date, which would contaminate the CAR generated by analysts. I use the model by Hugon and Muslu (2010).

$$\begin{aligned} CAR_{i,j,t} = &\alpha_{j,t} + Two - Tongue_{i,j,t} * Rev_{i,j,t} + Two - Tongue_{i,j,t} + Rev_{i,j,t} \\ &+ AbsRev_{i,j,t} + LogSize j, t-1 + BM_{j,t-1} + Loss_{j,t} + \\ &Brokersize_{i,t-1} + Frequency_{i,t-1} + Breadth_{i,t-1} + \\ &Firm - Experience_{i,j,t} + LogSize j, t-1 * Rev_{i,j,t} + \\ &BM_{j,t-1} * Rev_{i,j,t} + Loss_{j,t} * Rev_{i,j,t} + Brokersize_{i,t-1} * Rev_{i,j,t} + \\ &Frequency_{i,t-1} * Rev_{i,j,t} + Breadth_{i,t-1} * Rev_{i,j,t} + \\ &Firm - Experience_{i,j,t} * Rev_{i,j,t} + \epsilon_{i,j,t} \end{aligned} \tag{1.8}$$

The results of Table 5 show that the coefficient of the interaction variable of LME and Revision is 0.147 with a significant t-value of 3.58. The market reaction is higher when analyst issues their forecast within a LME timing period (1-7 calendar days before firm's earnings announcement). Market is going to react more positively when the analyst's forecast is higher than consensus and more negatively when the analyst's forecast is lower than the consensus. This confirms my previous argument that analyst is issuing their forecasts 1-7 calendar days before firm's earnings announcement date, the investors would pay higher attention than other times.

1.4.7 Check the career path of these last minute earning forecast analysts

If an analyst uses the last minute revision strategy to attract investors' eyeballs, this strategy should be a strategy that would influence their career path. One potential reason for analysts to play this instantaneously verified last minute revision game may be these analysts are eager to build or main their good reputation. Good reputation would be extremely helpful for analysts' future career path. Table 5 reports the results for the influence of "LME" on analysts career path. I use 5 different measurements to measure the career path of an analyst. Stayup is a variable I take from Kini et al. (2009), when an analyst is promoted to a brokerage house that is larger in the number of analysts of that firm or stay in the same firm, the analyst is defined to have a status of stayup. Demotion is another variable from Ke and Yu (2006), when an analyst is demoted from a brokerage house that has more than 25 analysts to brokerage house that has less than 25 analysts, the analyst is defined to be demotion. Exittop is a variable to measure analysts career path from Hilary and Hsu (2013), when an analyst is demoted from a top 10 brokerage house to a non-top 10 brokerage house, the analyst is defined to be Exittop. Movetop is defined to be equal to 1 when an analyst is promoted from a non top 10 brokerage house to a top 10 brokerage house or stay in the top 10 brokerage house. All-star analyst is defined to be equal to 1 when an analyst is named as All-American analyst by the magazine Institutional Investor. In the 5 measurements, Movetop and Allstar measurement are the well accepted and efficient to measure the promotion for an analysts career path. The Stayup, Demo and Exittop is also used by previous literature, but moving to a smaller brokerage house or staying in the same brokerage house could not clearly picture the career demotion or promotion of an analyst. I use all these 5 measurements in order to see the influence of investor attention on the analysts career path from different views. The empirical model I use to measure the career path of an analyst is as follows:

$$\begin{aligned} Stayup_{i,t} =& LME_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + Breadth_{i,t-1} + Logfollow_{i,t-1} \\ &+ Experience_{i,t-1} + \epsilon_{i,t-1} \end{aligned} \tag{1.9}$$

$$\begin{aligned} Demo_{i,t} =& LME_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + Breadth_{i,t-1} + Logfollow_{i,t-1} \\ &+ Experience_{i,t-1} + \epsilon_{i,t-1} \end{aligned} \tag{1.10}$$

$$\begin{aligned} Exittop_{i,t} =& LME_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + Breadth_{i,t-1} + Logfollow_{i,t-1} \\ &+ Experience_{i,t-1} + \epsilon_{i,t-1} \end{aligned} \tag{1.11}$$

$$\begin{aligned} Movetop_{i,t} =& LME_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + Breadth_{i,t-1} + Logfollow_{i,t-1} \\ &+ Experience_{i,t-1} + \epsilon_{i,t-1} \end{aligned} \tag{1.12}$$

$$
\begin{aligned}
Allstar_{i,t} = & LME_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + Breadth_{i,t-1} + Logfollow_{i,t-1} \\
& + Experience_{i,t-1} + \epsilon_{i,t-1}
\end{aligned}
\tag{1.13}
$$

The coefficient of last minute revision is 0.269, 0.128 and 0.229 in column 1, column 4 and column 5 in Table 5, respectively. The z-statistics of the coefficient is 6.5, 5.88 and 6.43, respectively. The results indicate that the last minute revision is helpful for analysts to get promoted to a larger brokerage firm, a top 10 brokerage firm and all-American analyst. The sign of the coefficient of last minute revision is -0.373 and -0.29 respectively in column 2 and column 3. These results prove the last minute revision strategy is protecting analysts from being demoted to a smaller brokerage firm and exit the top 10 brokerage firm. The last minute revision strategy is proved to be helpful for analysts in their career path.

1.4.8 Different Influence between Star and Non-Star

The results insight me that the last minute revision could help analysts to get promoted and keep them away from being demoted in their career path. However, the results also bring another question, if doing this last minute revision game is really helpful for analysts, then why I do not see every analyst come and join this game? The last minute earning forecast revision only takes a small portion of all analyst forecasts. One possible explanation may be even if it is a good time that investor attention is centered on the firm, but in that 1-7 days period, the street consensus on the firm is almost settled down. How can an analyst convince the investors that their forecasts are more valuable than the street consensus? In other words, what kinds of analysts' words are really trustful and influential during this period of time when it is only a few days to the firm public earnings announcements. Fang and Yasuda (2013) research may be helpful to answer this question, they find that the all star analyst opinions worth more than the non-star analysts. Table 7 reports the results in total number of the last minute revision strategy for analysts in their whole career. The average number of last minute revision strategy for non-star analyst is about 6.6, while the average number for all-star analyst is about 16.7, the difference in the number of last minute revision strategy between star and non-star analyst is both statistical significant with a t-value of -27.3 and economic significant with a difference of 10. Linking the results from Table 2 that all star analysts are more likely to play this last minute revision game than non all-star analysts, the answer to the small portion LME is clear, existing reputation of an analyst could have different influence on analysts' career. To explore the different influence of last minute revision strategy on all-star analyst and non-star analyst, I do the following tests. The empirical model to check the career path difference between the non-star analyst and all-star analyst is as follows:

$$\begin{aligned} Stayup_{i,t} = & LME - Allstar_{i,t-1} + LME - Non - Allstar_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + \\ & Breadth_{i,t-1} + Logfollow_{i,t-1} + Experience_{i,t-1} + \epsilon_{i,t-1} \end{aligned} \tag{1.14}$$

$$\begin{aligned} Demo_{i,t} = & LME - Allstar_{i,t-1} + LME - Non - Allstar_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + \\ & Breadth_{i,t-1} + Logfollow_{i,t-1} + Experience_{i,t-1} + \epsilon_{i,t-1} \end{aligned} \tag{1.15}$$

$$Exittop_{i,t} = LME - Allstar_{i,t-1} + LME - Non - Allstar_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + Breadth_{i,t-1} + Logfollow_{i,t-1} + Experience_{i,t-1} + \epsilon_{i,t-1} \tag{1.16}$$

$$Movetop_{i,t} = LME - Allstar_{i,t-1} + LME - Non - Allstar_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + Breadth_{i,t-1} + Logfollow_{i,t-1} + Experience_{i,t-1} + \epsilon_{i,t-1} \tag{1.17}$$

$$Allstar_{i,t} = LME - Allstar_{i,t-1} + LME - Non - Allstar_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + Breadth_{i,t-1} + Logfollow_{i,t-1} + Experience_{i,t-1} + \epsilon_{i,t-1} \tag{1.18}$$

LME-Allstar is defined to be equal to 1 if an analyst is an all-star analyst and he or she has at least 1 last minute revision in the previous year, 0 otherwise. LME-Non-Allstar is defined to be equal to 1 if an analyst is an non all-star analyst and he or she has at least 1 last minute revision in the previous year, 0 otherwise.

Table 7 shows the results of the different influence of "LME" strategy on star-analysts and non-star analysts. The coefficient of LME-Non-Allstar Column 4 and Column 5 is -0.131 and -1.253 respectively. The z-statistics of the two coefficients are -5.05 and -23.71 respectively. While the coefficient of LME-Allstar is 1.88 and 3.346 respectively. The t-value of the two coefficients are 39.8 and 54.97, respectively. The results prove that the all-star analysts who have the last minute revision behavior are more likely to be moved or stayed in a top 10 brokerage house and they are also more likely to be nominated as an all-star analyst in the next year. Compared with the all-star analysts, the non-star analyst who have the last minute revision behavior in the previous year are less likely to be promoted or stayed in a top 10 brokerage house and less likely to become an all-star analyst in the next year. The results are telling a clear story what is happening in this last minute revision game. All-star analyst could really grab the investors' attention and get the benefit of playing this game. While for the non-star analysts, playing this risky last minute revision game would actually hurt them. The cost of playing this game explains why there are not a lot of analysts trying to play this last minute revision game even if the last minute revision strategy seems to be beneficial for them in their career path. After all, all-star analysts are a small group of people in each industry. The results also explain the huge difference in the number of last minute revision strategy between the star-analyst and non-star-analyst. Combing the results from Table 2, Table 6 and Table 7, I get the conclusion that the last minute revision strategy is a strategy applied by analysts to maintain their existing reputation.

1.5 Robustness test to solve the endogeneity

A possible concern in my results for the career path of analyst may be that there is an endogeneity problem among the analysts who apply the "LME" strategy. As I have showed, it is the all-star analysts who are more likely to play this game. Guttman (2011) also proves that analysts who are more likely to issue later forecasts revision are analysts with high learning abilities. It is quite possible that it is the high quality of the analysts instead of their "LME" strategy are helping these analysts to get promoted and nominated to be all-American analysts. To solve this potential problem, I apply a method by Wooldrige, which is from his book of Econometrics. First, I need to create an instrumental variable which is closely related to the variable of last minute revision and not correlated with the variables I apply to measure the analyst career path. One instrumental variable that could be applied is called Imitate. This variable is a binary variable which is equal to 0 if the LME from an analysts is not the first one for the same firm. If an last minute revision behavior is not the first within the 1-7 calendar days for a firm, then the analysts who revise their forecasts are defined to imitate the first analyst in taking the strategy. This variable is very closely related with my last minute revision variable, but totally independent from the promotion or demotion variable. I apply this instrumental variable to do the two-stage regression endogeneity checking procedure to test if there is endogeneity problem in my regression model. In the first stage regression, I use the last minute revision as the dependent variable and regress it on my instrumental variable and the other control variables. The following is the first-step regression model:

Step 1:

$$\begin{aligned} LME_{i,t-1} =& Induce_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + Breadth_{i,t-1} + \\ & Logfollow_{i,t-1} + Experience_{i,t-1} + epsilon_{i,t-1} \end{aligned} \tag{1.19}$$

I get the residuals from the above regression model and then input the residual into the regression model in step2 as following:

Step 2:

$$\begin{aligned} Stayup_{i,t} =& LME_{i,t-1} + Residuals_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + \\ & Breadth_{i,t-1} + Logfollow_{i,t-1} + Experience_{i,t-1} + \epsilon_{i,t-1} \end{aligned} \tag{1.20}$$

$$\begin{aligned} Demo_{i,t} =& LME_{i,t-1} + Residuals_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + \\ & Breadth_{i,t-1} + Logfollow_{i,t-1} + Experience_{i,t-1} + \epsilon_{i,t-1} \end{aligned} \tag{1.21}$$

$$\begin{aligned} Exittop_{i,t} =& LME_{i,t-1} + Residuals_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + \\ & Breadth_{i,t-1} + Logfollow_{i,t-1} + Experience_{i,t-1} + \epsilon_{i,t-1} \end{aligned} \tag{1.22}$$

$$\begin{aligned} Movetop_{i,t} =& LME_{i,t-1} + Residuals_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + \\ & Breadth_{i,t-1} + Logfollow_{i,t-1} + Experience_{i,t-1} + \epsilon_{i,t-1} \end{aligned} \tag{1.23}$$

$$\begin{aligned} Allstar_{i,t} =& LME_{i,t-1} + Residuals_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + \\ & Breadth_{i,t-1} + Logfollow_{i,t-1} + Experience_{i,t-1} + \epsilon_{i,t-1} \end{aligned} \tag{1.24}$$

Table 9 shows the results of robustness tests. The coefficients of the LME in column 4 and column 5 are 0.516 and 0.723, respectively. Both of these coefficient remain significant with a z-statistics of 7.16 and 6.35, respectively. The results of the logistic regression results in the Table 9 show that for the last two measurements of an analysts career path, the movetop and the all-star, there is no endogeneity issue. While for the stayup, demo and exittop, there is some endogeneity issue because the coefficient of LME are not significant in the Column 1, Column 2 and Column 3. This results are not surprising, the three measurements of Stayup, Demo and Exittop are relatively weak measurements compared with the Movetop and Allstar. The empirical results from Table 9 solve the concern of endogeneity and prove the last minute revision strategy is a good strategy to maintain an analyst's reputation, which would be helpful for his or her career path.

1.6 Conclusion

This paper explores the last minute earning forecast revision strategy applied by security analysts to attract the attention of investors within the seven day period immediately preceding firm's earnings announcement. Those analysts applying the LME strategy have a higher accuracy in forecasting a firm earnings. Moreover, compared with the non-star analysts, the all-star analysts are more likely to adopt the last minute earning forecast revision strategy. By comparing the different influence on analyst career paths of the "LME" strategy between all-star analysts and non-star analysts, the conclusion is reached that the all-star analysts may use the last minute revision strategy to maintain their good reputation and thus help them to get on a better career path by making themselves more likely to get promoted to a top 10 brokerage house and more likely to be continuously nominated as an all-American analyst. However, when non-star analysts adopt the last minute revision strategy, it is hurtful to them. The results are robust after control for the endogeneity problem.

The results in this paper are insightful for the study of security analyst behavior and strategy. The strategy taken by security analysts to catch the investors eyeballs are also intuitive for the study in investor attention behavior. Investor limited attention make investors overly rely on the salient features of financial analyst reports. While the "last minute earning forecast revision" strategy by security analysts could make analysts to be salient by standing out in the last seven calendar days before a firm earnings announcement, when investor attention are highly centered around the firm. I show the truth that catching investor attention could maintain the analyst reputation and help them to get a better career, but this only works for the all-star analysts. The results could also help investors to identify the voice within the last 7 calendar days when they are looking are all the possible information of the earnings announcement firm. The forecast made within this period is noteworthy because of its high accuracy, especially relative to previous analyst reports.

1.7 Tables

Table 1.1: Summary Statistics. This table presents the summary statistics of the whole sample in my analysis. Panel A presents the descriptive statistics for analyst forecasts in a firm-quarter-analyst level.This table presents the summary statistics of the whole sample in my analysis. The sample consists of all the analyst EPS forecasts in I/B/E/S from 1994 to 2012. The stock return is from CRSP daily data. Panle A presents the descriptive statistics for analyst forecasts in a firm-quarter-analyst level. Panel B shows the descriptive statistics for earnings forecast in a analyst-quarter level. Panel C gives the summary statistics in a analyst-year level.

Panel A

	count	mean	sd	min	p50	max
Accuracy	179411	0.497	0.173	0	0.500	1
RFE	179411	-0.00302	0.626	-118.0	-0.000712	69.10
$Accuracy_{i,t-1}$	179411	0.500	0.176	0	0.500	1
Boldness	179411	0.503	0.165	0	0.500	1
Breadth	179411	0.527	0.279	0.0546	0.538	1
LnFollow	179411	2.251	0.546	0.693	2.303	4.190
Firm-Experience	179411	0.467	0.239	0	0.483	1
Gap	179411	0.496	0.206	0	0.500	1
Observations	179411					

Panel B

	count	mean	sd	min	p50	max
LME	1245894	0.0379	0.191	0	0	1
Accuracy	1245894	0.500	0.315	0	0.500	1
RFE	1245894	-0.00605	1.607	-777.9	0	483.7
$Accuracy_{i,j,t-1}$	1245894	0.503	0.314	0	0.500	1
Boldness	1245894	0.500	0.310	0	0.500	1
LnFollow	1245894	2.252	0.704	0.693	2.303	4.190
Breadth	1245894	0.504	0.330	0	0.500	1
Firm_Experience	1245894	0.501	0.308	0	0.500	1
Gap	1245894	0.506	0.316	0	0.501	1
Observations	1245894					

Panel C

	count	mean	sd	min	p50	max
Stayup	49787	0.941	0.237	0	1	1
Demo	49787	0.0240	0.153	0	0	1
Exittop	49787	0.0179	0.133	0	0	1
Allstar	49787	0.0961	0.295	0	0	1
Imitate	49787	0.0908	0.245	0	0	1
AG	49787	0.520	0.500	0	1	1
Accuracy	49787	0.499	0.136	0	0.502	1
Boldness	49787	0.505	0.129	0	0.500	1
Breadth	49787	0.504	0.277	0.001	0.562	1
Follow	49787	2.495	0.558	0	2.565	4.060
Experience	49787	1.249	0.852	0	1.386	2.944
Observations	49787					

Table 1.2: Logistic Regression. This table shows the results of the analysts' characteristics that may influence the analysts' probability of taking the last minute earning forecast revision strategy.$Allstar_{i,t}$ is a dummy variable that equals to be 1 if analyst i is nominated by the magazine Institutional Investor to be an All-American analyst in his or her industry in year t. $Accuracy_{i,j,t}$ is the standardized earnings forecast ranking of analyst i relative to other analysts follow firm j in quarter t. $LME_{i,j,t}$is also a dummy variable if analyst applies the last minute earning forecast revision strategy for firm j in quarter t. $Boldness_{i,j,t}$ is the ranking result of the difference of quarterly earnings forecast by analyst i relative to the consensus for the firm j in quarter t. $Firm - Experience_{i,j,t}$ is the total number of quarters analyst i follows firm j until t. $LnFollow_{i,j,t}$ is the log total number of analysts following firm j in quarter t. $Gap_{i,j,t}$ is the difference on calendar days between the public announcement date for firm j and the last earning forecast date of analyst i in quarter t. $Breadth_{i,t}$ is the number of firms analyst i covered in quarter t.

	(1) $LME_{i,j,t}$
dummy	
$Allstar_{i,t}$	0.235***
	(8.15)
$LME_{i,j,t-1}$	1.019***
	(67.87)
$Accuracy_{i,j,t-1}$	0.108***
	(7.44)
$Boldness_{i,j,t}$	0.253***
	(17.23)
$Firm - Experience_{i,j,t}$	-0.148**
	(-2.56)
$Experience^2_{i,j,t}$	0.0303
	(0.56)
$LnFollow_{i,j,t}$	0.0361***
	(5.13)
$Breadth_{i,t}$	-0.224***
	(-15.73)
Quarter FE	Yes
N	1245894

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.3: OLS Regression. This table presents the results of analyst's accuracy for the last minute earning forecast revision strategy in a firm-quarter-analyst level. $Accuracy_{i,j,t}$ is the standardized earnings forecast ranking of analyst i relative to other analysts follow firm j in quarter t. $RA_{i,j,t}$ is defined in Section 4. $LME_{i,j,t}$is also a dummy variable if analyst applies the last minute earning forecast revision strategy for firm j in quarter t. $Boldness_{i,j,t}$ is the ranking result of the difference of analyst quarterly earnings forecast by analyst i relative to the consensus for the firm j in quarter t. $Firm - Experience_{i,j,t}$ is the total number of quarters analyst i follows firm j until t. $LnFollow_{i,j,t}$ is the log total number of analysts following firm j in quarter t. $Gap_{i,j,t}$ is the difference on calendar days between the public announcement date for firm j and the last earning forecast date of analyst i in quarter t. $Breadth_{i,t}$ is the number of firms analyst i covered in quarter t.

	(1)	(2)
	$Accuracy_{i,j,t}$	$RA_{i,j,t}$
$LME_{i,j,t}$	0.0129***	0.00892***
	(8.43)	(5.57)
$Accuracy_{i,j,t}$	0.0582***	0.0591***
	(65.55)	(63.70)
$Boldness_{i,j,t}$	-0.122***	-0.128***
	(-135.06)	(-135.85)
$Firm - Experience_{i,j,t}$	0.00956***	0.00795***
	(10.38)	(8.26)
$LnFollow_{i,j,t}$	-0.000651	-0.000150
	(-1.64)	(-0.36)
$Breadth_{i,t}$	0.00207**	0.0000523
	(2.41)	(0.06)
$Gap_{i,j,t}$	-0.0938***	-0.0378***
	(-101.12)	(38.96)
N	1245786	1245786

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.4: OLS Regression. This table presents the results of analyst's accuracy for the last minute earning forecast revision strategy in a quarter-analyst level. $Accuracy_{i,t}$ is the average of standardized earnings forecast ranking of analyst i relative to other analysts follow firm j in quarter t. $RA_{i,t}$ is average of $RA_{i,j,t}$ across all firms in quarter t for analyst i. $LME_{i,t}$ is the average of of $LME_{i,j,t}$ across all firms in quarter t for analyst i.$Boldness_{i,t}$ is the average $Boldness_{i,j,t}$ for analyst i across all firms in quarter t. $Firm-Experience_{i,t}$ is the average of $Firm-Experience_{i,j,t}$ across all firms for analyst i in quarter t. $LnFollow_{i,t}$ is the average of $LnFollow_{i,j,t}$ across all firms for analyst i in quarter t. $Gap_{i,t}$ is the average of $Gap_{i,j,t}$ across all firms for analyst i in quarter t. $Breadth_{i,t}$ is the number of firms analyst i covered in quarter t.

	(1) $Accuracy_{i,t}$	(2) $RA_{i,t}$
$LME_{i,t}$	0.0192***	0.0119***
	(5.63)	(3.28)
$Accuracy_{i,t-1}$	0.0830***	0.0785***
	(36.55)	(32.69)
$Boldness_{i,t}$	-0.140***	-0.153***
	(-57.26)	(-58.84)
$Firm-Experience_{i,t}$	0.00894***	0.00407**
	(5.09)	(2.19)
$LnFollow_{i,t}$	0.000937	0.00140*
	(1.25)	(1.78)
$Breadth_{i,t}$	0.0184***	0.0121***
	(12.09)	(7.50)
$Gap_{i,t}$	-0.109***	-0.0218***
	(-52.29)	(9.82)
N	179340	178443

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.5: OLS Regression. This table presents the results for the market reaction to analysts' earnings forecast when they apply the "LME" strategy. $Rev_{i,j,t}$ is earnings forecast revision of analyst i, calculated as forecast by analyst i at year t for firm j minus the mean consensus forecast for firm j scaled by the most recent preceding monthly stock price. $AbsRev_{i,j,t}$ is the absolute value of earnings forecast revision by analyst i. $Loss_{i,j,t}$ is dummy variable equal to 1 if a firm has negative earnings in quarter t, otherwise 0. $Size_{j,t-1}$ is defined as the market capitalization at the beginning of year t. $BM_{j,t-1}$ is book to market ratio, calculated as Compustat annual item CEQ divided by firm size at the end of year t-1. $Firm - Experience_{i,j,t}$ is a the number of years analyst i has covered firm j until year t. $BrokerSize_{i,t}$ is defined as the log of the number of analysts hired by the brokerage firm of analyst i at the end of year t-1. $Freq_{i,t}$ is the total number of earnings forecasts made by analyst i in year t. $Breadth_{i,t}$ is the number of firms analyst i covered in year t.

	(1) $CAR_{i,j,t}$	(2) $CAR_{i,j,t}$
$LME_{i,j,t} * Rev_{i,j,t}$		0.147^{***} (3.58)
$LME_{i,j,t}$		0.00241^{***} (5.93)
$Rev_{i,j,t}$	0.222^{***} (5.04)	0.203^{***} (4.56)
$AbsRev_{i,j,t}$	0.116^{***} (13.23)	0.116^{***} (13.21)
$LogSize_{j,t-1}$	-0.0000297 (-0.59)	-0.0000418 (-0.83)
$BM_{j,t-1}$	0.000758^{***} (3.56)	0.000743^{***} (3.49)
$Loss_{j,t}$	-0.0132^{***} (-54.20)	-0.0132^{***} (-54.19)
$LogBrokersize_{i,t-1}$	-0.0000324 (-0.44)	-0.0000276 (-0.37)
$Freq_{i,t-1}$	0.000113 (1.01)	0.000106 (0.94)
$Breadth_{i,t}$	0.0000200 (1.57)	0.0000203 (1.59)
$Firm - Experience_{i,j,t}$	0.000269^{*} (1.70)	0.000287^{*} (1.82)
$LogSize_{j,t-1} * Rev_{i,j,t}$	0.0186^{***} (3.21)	0.0164^{***} (2.81)
$BM_{j,t-1} * Rev_{i,j,t}$	-0.0249^{***} (-5.31)	-0.0245^{***} (-5.21)
$Loss_{j,t} * Rev_{i,j,t}$	-0.150^{***} (-11.13)	-0.154^{***} (-11.35)
$LogBrokersize_{i,t-1} * Rev_{i,j,t}$	0.0151^{***} (2.61)	0.0170^{***} (2.91)
$Freq_{i,t-1} * Rev_{i,j,t}$	-0.0615^{***} (-5.26)	-0.0592^{***} (-5.06)
$Breadth_{i,t} * Rev_{i,j,t}$	-0.00230^{***} (-3.38)	-0.00244^{***} (-3.58)
$Firm - Experience_{i,j,t} * Rev_{i,j,t}$	0.114^{***} (11.69)	0.115^{***} (11.76)
N	779237	779237

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

Table 1.6: Logistic Regression. This table reports the influence of last minute earning forecast revision strategy on analysts' career path. $Stayup_{i,t}$ is a dummy variable that is equal to 1 if analyst i is promoted to a larger brokerage house or stay in the same brokerage house in year t. $Demo_{i,t}$ is a dummy variable that is equal to 1 if analyst i is demoted from a brokerage house that has more than 25 analysts to a smaller brokerage house that has less than 25 analysts in year t. $Exittop_{i,t}$ is a dummy variable that is equal to 1 if analyst i leaves a top 10 brokerage house in year t. $Movetop_{i,t}$ is a dummy variable that is equal to 1 if analyst i moves from a non top 10 brokerage house into a top 10 brokerage house in year t. $Allstar_{i,t}$ is a dummy variable that is equal to 1 if analyst i is nominated to be an All-American analyst by the magazine Institutional Investor in year t. $Accuracy_{i,t}$ is average of $Accuracy_{i,j,t}$ across all firms in year t for analyst i. $LME_{i,t}$ is the average of of $LME_{i,j,t}$ across all firms in year t for analyst i. $Boldness_{i,t}$ is the average $Boldness_{i,j,t}$ for analyst i across all firms in year t. $Firm\_Experience_{i,t}$ is the average of $Firm-Experience_{i,j,t}$ across all firms for analyst i in year t. $LnFollow_{i,t}$ is the average of $LnFollow_{i,j,t}$ across all firms for analyst i in year t. $Breadth_{i,t}$ is the number of firms analyst i covered in year t.

	(1) $Stayup_{i,t}$	(2) $Demo_{i,t}$	(3) $Exittop_{i,t}$	(4) $Movetop_{i,t}$	(5) $Allstar_{i,t}$
main					
$LME_{i,t-1}$	0.269***	-0.373***	-0.290***	0.128***	0.229***
	(6.50)	(-5.84)	(-3.93)	(5.88)	(6.43)
$Accuracy_{i,t-1}$	0.544***	-0.662***	-0.933***	0.485***	1.699***
	(3.92)	(-3.02)	(-3.71)	(6.16)	(8.85)
$Boldness_{i,t-1}$	-0.165	0.128	-0.0578	-0.123	0.0863
	(-1.13)	(0.56)	(-0.22)	(-1.51)	(0.44)
$Breadth_{i,t-1}$	0.282***	-0.144	-0.323**	-0.0815*	1.770***
	(3.35)	(-1.12)	(-2.17)	(-1.81)	(22.21)
$LnFollow_{i,t-1}$	-0.129***	0.279***	0.365***	0.435***	1.205***
	(-3.59)	(4.94)	(5.55)	(21.90)	(29.15)
$Experience_{i,t-1}$	-0.148***	0.113***	0.140***	0.0305**	1.320***
	(-5.21)	(2.62)	(2.74)	(1.99)	(35.10)
Year FE	Yes	Yes	Yes	Yes	Yes
N	49755	49755	49755	49755	49755

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.7: Difference in number of last minute earning forecast revision between Star and Non-Star Analysts. This table reports the difference in the number of last minute earning forecast revision strategy between Star analysts and Non-Star analysts, the number is the total number of last minute earning forecast revision in an analyst's whole career path. I count the number of the last minute earning forecast revision strategy from the time when an analyst is recorded in I/B/E/S until the analyst is disappeared in I/B/E/S.

Star VS Non_star in the number of LME				
Group	Obs	Mean	sd	T-Value
Non-Star	7300	6.618356	9.165202	
Star	1085	16.67834	20.67765	
Total	8385	7.920095	11.8243	
Difference		-10.05998		t = -27.2831

Table 1.8: Logistic Regression This table reports the different influence of last minute earning forecast revision strategy on analysts' career path between star-analyst and non-star analyst. $Stayup_{i,t}$ is a dummy variable that is equal to 1 if analyst i is promoted to a larger brokerage house or stay in the same brokerage house in year t. $Demo_{i,t}$ is a dummy variable that is equal to 1 if analyst i is demoted from a brokerage house that has more than 25 analysts to a smaller brokerage house that has less than 25 analysts in year t. $Exittop_{i,t}$ is a dummy variable that is equal to 1 if analyst i leaves a top 10 brokerage house in year t. $Movetop_{i,t}$ is a dummy variable that is equal to 1 if analyst i moves from a non top 10 brokerage house into a top 10 brokerage house in year t. $Allstar_{i,t}$ is a dummy variable that is equal to 1 if analyst i is nominated to be an All-American analyst by the magazine Institutional Investor in year t. $Accuracy_{i,t}$ is average of $Accuracy_{i,j,t}$ across all firms in year t for analyst i. $LME_{i,t}$ is the average of of $LME_{i,j,t}$ across all firms in year t for analyst i. . $Boldness_{i,t}$ is the average $Boldness_{i,j,t}$ for analyst i across all firms in year t. $Firm-Experience_{i,t}$ is the average of $Firm-Experience_{i,j,t}$ across all firms for analyst i in year t. $LnFollow_{i,t}$ is the average of $LnFollow_{i,j,t}$ across all firms for analyst i in year t. $Breadth_{i,t}$ is the number of firms analyst i covered in year t.

	(1) $Stayup_{i,t}$	(2) $Demotion_{i,t}$	(3) $Exittop_{i,t}$	(4) $Movetop_{i,t}$	(5) $Allstar_{i,t}$
main					
$Non-Star-LME_{i,t-1}$	0.160***	-0.182**	-0.284***	-0.131***	-1.253***
	(3.13)	(-2.23)	(-3.02)	(-5.03)	(-23.71)
$Star-LME_{i,t-1}$	0.294***	-0.523***	-0.0682	1.880***	3.346***
	(2.94)	(-3.00)	(-0.42)	(39.80)	(54.97)
$Accuracy_{i,t-1}$	0.797***	-0.872**	-1.619***	0.473***	1.373***
	(3.54)	(-2.34)	(-3.96)	(4.04)	(5.40)
$Boldness_{i,t-1}$	0.242	-0.220	-0.708*	-0.148	-0.0259
	(1.05)	(-0.58)	(-1.71)	(-1.23)	(-0.10)
$Breadth_{i,t-1}$	0.136	-0.00829	-0.114	-0.144***	1.431***
	(1.32)	(-0.05)	(-0.61)	(-2.73)	(13.95)
$Lnfollow_{i,t-1}$	-0.251***	0.474***	0.535***	0.426***	1.123***
	(-5.14)	(5.84)	(5.83)	(16.99)	(20.37)
$Experience_{i,t-1}$	-0.00202	-0.0334	-0.0983	-0.0826***	0.892***
	(-0.04)	(-0.46)	(-1.18)	(-3.61)	(17.85)
Year FE	Yes	Yes	Yes	Yes	Yes
N	49787	49787	49787	49787	49787

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.9: Robustness Test-Step 1. This table shows the robustness test results for Step 1. $Imitate_{i,t}$ is the instrumental variable I apply in Step 1, it is defined in detail in Section 6. $Accuracy_{i,t}$ is average of $Accuracy_{i,j,t}$ across all firms in year t for analyst i. $LME_{i,t}$ is the average of of $LME_{i,j,t}$ across all firms in year t for analyst i. . $Boldness_{i,t}$ is the average $Boldness_{i,j,t}$ for analyst i across all firms in year t. $Firm - Experience_{i,t}$ is the average of $Firm - Experience_{i,j,t}$ across all firms for analyst i in year t. $LnFollow_{i,t}$ is the average of $LnFollow_{i,j,t}$ across all firms for analyst i in year t. $Breadth_{i,t}$ is the number of firms analyst i covered in year t.

	(1) $LME_{i,t-1}$
$Imitate_{i,t-1}$	0.556***
	(67.02)
$Accuracy_{i,t-1}$	0.196***
	(13.12)
$Boldness_{i,t-1}$	0.0813***
	(5.16)
$Breadth_{i,t-1}$	0.570***
	(69.02)
$Follow_{i,t-1}$	-0.0338***
	(-9.05)
$Experience_{i,t-1}$	0.0143***
	(5.31)
N	49787

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.10: Robustness Test-Step 2. This table shows the robustness test results for Step 2. $Residual_{i,t}$ is the residuals I get from the Step 1 in Table 8. $Stayup_{i,t}$ is a dummy variable that is equal to 1 if analyst i is promoted to a larger brokerage house or stay in the same brokerage house in year t. $Demo_{i,t}$ is a dummy variable that is equal to 1 if analyst i is demoted from a brokerage house that has more than 25 analysts to a smaller brokerage house that has less than 25 analysts in year t. $Exittop_{i,t}$ is a dummy variable that is equal to 1 if analyst i leaves a top 10 brokerage house in year t. $Movetop_{i,t}$ is a dummy variable that is equal to 1 if analyst i moves from a non top 10 brokerage house into a top 10 brokerage house in year t. $Allstar_{i,t}$ is a dummy variable that is equal to 1 if analyst i is nominated to be an All-American analyst by the magazine Institutional Investor in year t. $Accuracy_{i,t}$ is average of $Accuracy_{i,j,t}$ across all firms in year t for analyst i. $LME_{i,t}$ is the average of of $LME_{i,j,t}$ across all firms in year t for analyst i. . $Boldness_{i,t}$ is the average $Boldness_{i,j,t}$ for analyst i across all firms in year t. $Firm - Experience_{i,t}$ is the average of $Firm - Experience_{i,j,t}$ across all firms for analyst i in year t. $LnFollow_{i,t}$ is the average of $LnFollow_{i,j,t}$ across all firms for analyst i in year t. $Breadth_{i,t}$ is the number of firms analyst i covered in year t.

	(1)	(2)	(3)	(4)	(5)
	$Stayup_{i,t}$	$Demo_{i,t}$	$Exittop_{i,t}$	$Movetop_{i,t}$	$Allstar_{i,t}$
main					
$LME_{i,t-1}$	0.190	-0.149	0.194	0.516***	0.723***
	(1.28)	(-0.67)	(0.80)	(7.16)	(6.35)
$Residual_{i,t-1}$	0.0856	-0.245	-0.533*	-0.424***	-0.533***
	(0.55)	(-1.04)	(-2.08)	(-5.64)	(-4.55)
$Accuracy_{i,t-1}$	0.562***	-0.713**	-1.044***	0.396***	1.575***
	(3.94)	(-3.18)	(-4.05)	(4.94)	(8.12)
$Boldness_{i,t-1}$	-0.158	0.108	-0.103	-0.159	0.0388
	(-1.08)	(0.47)	(-0.40)	(-1.93)	(0.20)
$Breadth_{i,t-1}$	0.332**	-0.289	-0.637**	-0.332***	1.455***
	(2.68)	(-1.52)	(-3.00)	(-5.24)	(13.81)
$Follow_{i,t-1}$	-0.130***	0.281***	0.368***	0.435***	1.204***
	(-3.60)	(4.97)	(5.61)	(21.92)	(29.11)
$Experience_{i,t-1}$	-0.149***	0.114**	0.142**	0.0323*	1.336***
	(-5.21)	(2.63)	(2.77)	(2.11)	(35.22)
Year FE	Yes	Yes	Yes	Yes	Yes
N	49787	49787	49787	49787	49787

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chapter 2

Security Analysts' Double Down Behavior in Stock Recommendation

2.1 Introduction

Financial analysts play an important role in today's financial market. Analysts produce two important output for investors, earnings forecasts and stock recommendations. For investors, it is important to understand why analysts make certain forecasts and recommendations. Meanwhile, financial analysts have public research outputs, and these outputs can be measured easily by the investor community and researchers in general. Hence I can study financial analysts to gauge how individuals' behavioral biases can impact the career outcome.

In this paper, I study analysts' doubling down behavior. In investing, "doubling down" refers to someone increases the investment position after initial loss on the position. For example, hedge fund managers normally buy stocks when they believe these stocks are undervalued. If, after the purchase, the stocks experience a significant in price, how would these managers react? One response is to double down, buying more of the same stocks at the current (lower) prices. Rhinesmith (2014) find out that the managers who double down stocks on positions that have run against them tend to outperform the other managers. He presents empirical evidence and shows that managers who invest more in the ”dropped down” (stock price are experiencing a significant drop) stocks perform better than the managers who sell the dropped down stocks after controlling for the other effects.

If a stock that an analyst previously believes to be a good stock (recommended buy or strong buy) is experiencing a significant drop in the stock price, the analyst may downgrade the stock or drop the coverage of the stock altogether. On the other hand, the analyst can reiterate the same favorable recommendation of the stock or even upgrade the stock. This is the double down behavior I consider in this paper. There are two possible reasons for analyst to upgrade or maintain the position for a dropped down stock. One possible reason may be that the analyst is trying to defend the firm by establishing a good relationship with the firm's management. The better relationship with the management may enable the analyst to produce more accurate earnings forecasts, or to help winning investment banking business. The other possible reason for the upgrade is that the analyst believes the dropped down stock is still undervalued even after the stock has experienced a significant drop in the stock price. That is, the analyst is still confident in his or her previous judgment about the stock and insists to maintain or even upgrade his or her previous position about the stock. In this paper, I attempt to answer the following questions: Do analysts double down? How do investors react to the double type type recommendation? Are these recommendations useful to investors? What motivates analysts to double down?

I find that some analysts double down. To explore the reasons for security analysts' double down behavior. I first test the forecast accuracy for the security analyst in the next year after their double down behavior in the current year. I do not find any evidence on the effect of analyst's double down behavior on the analysts' forecast accuracy. This result indicates that when an analyst recommends a dropped down stock, he or she does not gain an advantage in forecast accuracy. To find out whether the analysts' double down recommendations are good or bad investment advice, I check the short-run abnormal return and the long-run abnormal return of these stocks after these recommendations. I find stocks with “double down” recommendations have a significant negative abnormal return compared with the other stocks with positive recommendations. This results present evidence that the "double down" recommendations may be suboptimal advices from the analysts.

To further explore the double down behavior, I design a logistic regression to figure out what kinds of analysts are more likely to have the double down behavior and what kinds of analysts are less likely to have the double down behavior. I find All-American analysts are less likely to have this "double down" behavior. Analysts who have a "double down" behavior in the previous year are more likely to have a double down behavior in the next year. Analyst forecast accuracy, boldness, horizon do not have significant effect on analyst's double down behavior. I also show that analysts tend to have the double down behavior early in their careers. As their careers progress, they tend to be less likely to have the double down behavior. The double down behavior shows a time-series pattern. Most analysts who used to have double down behavior do not have the second time of behaving the double down behavior. In other words, about three quarters of analysts only have double down behavior once in their whole career path. The double down behavior hurts analysts in their career development. Analysts who have double down behavior in current year are more likely to be demoted to a smaller brokerage firm, less likely to be promoted to a larger brokerage firm and less likely to become an All-American analyst in the next year. This result is consistent with the results that most analysts only have one time of double down behavior in their career path. It also explains why All-American analysts are less likely to have the double down behavior.

Following (Rhinesmith, 2014), I also apply the Fama-French 4 factors model to check whether the analysts who used to have double down behavior underperform those who never have double down behavior. Using the method of /citeFang2013a, I follow the buy recommendation and sell recommendation of the double down analysts and never-double-down analysts. I find that the double down analysts have a lower alpha when they upgrade stocks than non-double down analysts. The double down analysts have a less negative alpha when they downgrade stocks than non-double down analysts. This results indicate the double-down analysts is having a less positive market reaction when they upgrade a stock and a more negative market reaction when they downgrade a stock. The negative impact of the double down behavior to analysts is not only reflected in their career development but also reflected in the market reaction when they upgrade stocks.

This paper contributes to the literature related with analyst recommendation bias in two aspects. First, previous literature on analyst recommendation bias is focus on analyst's external source such as analyst's brokerage affiliation, analyst's relationship with hedge fund and analyst's relationship with firm's management. I point out the analyst recommendation bias is also related with analyst themselves. Security analysts suppose to be more rational than individual investors, but they can not avoid suffering from overconfidence, which makes them make bad moves. Second, taking the risk to double down the stocks in hedge fund industry is helpful for the fund managers to become a star, while the double down behavior is hurting analyst in their career development and lowering the influential power of security analysts. This negative impact to security analyst indicates the risk of taking a overconfident move in the analyst industry may not be a good choice for young analysts. My research could also help investors to identify the potential overly optimistic biased recommendation and avoid following these biased recommendations to make their investment decisions. Before an investor make the decision to long a dropped down stock just get upgraded by security analyst, they should review the analyst's previous position on the same stock to make a conservative move instead of an aggressive long investment.

2.2 Literature Review

Previous research has done a lot of work on analysts' recommendation bias. Hong and Kacperczyk (2010) prove that competition among analysts could lead to optimistic bias recommendation because of the conflict of interests. Loh and Mian (2006) find that analysts who give more accurate earnings forecast could also issue more profitable stock recommendations. Ertimur et al. (2007) presents similar evidence that more accurate analysts make more profitable recommendations even after controlling for their expertise. Firth et al. (2013) show evidence that mutual relationship could bias analyst's recommendation. They find analysts' recommendation on a stock is relatively higher compared with consensus when the stock is held by the mutual fund clients of analysts' brokerage firm. Michaely (1999) hold the same opinion by showing the results that underwriter analysts buy recommendations perform worse than that of the unaffiliated analysts. They also find that market does not recognize this bias inside the affiliated analysts. Jegadeesh et al. (2004) present empirical results that higher consensus recommendation are associated with worse subsequent returns if the high recommended stocks are stocks with low value or low negative momentum returns. Lin and McNichols (1998) argue that recommendations from lead analysts could be optimistic biased by presenting the indicated evidence that investors expect lead analysts are more likely to recommend "Hold" when "Sell" is warranted.

But not all the research agree with the idea that bias recommendations are common during security analysts. Clarke et al. (2006) find the market does not view upgrade recommendation issued by affiliated security analysts as biased since there is no price reversal following the upgrade of these recommendations.

Besides the bias recommendation research, some research also explore the relationship between stock recommendation and market reaction. For example, Sorescu and Subrahmanyam (2006) provide a link between analysts' stock recommendation update and stock market return by showing their empirical results.

All the research are focus on the analyst's external characteristics, such as analyst affiliation or analyst's brokerage house effect. To my best knowledge, there is little research on analyst's internal characteristics' effect on their recommendation bias. Since analysts are still human beings, so human being's emotional characteristics such as overconfidence could have a effect on analyst's behavior. My paper is intended to fill this gap in analysts' recommendation bias area by showing the effect of the "double down" behavior on analyst's recommendation bias.

2.3 Data

I get analyst's recommendation data from the I/B/E/S Detail Recommendations file from 1994 to 2014. I start my sample period from 1994 because the I/B/E/S's recommendations file cover the period started from late in 1993. The recommendation rating system in I/B/E/S is from 1(strong buy) to 5 (sell). So all the analysts' recommendation ratings in my sample is from 1 to 5. The upgrade and downgrade of analysts' rating is also based on this rating system. Then my main sample includes all the public firms in the three main exchanges, NYSE, AMEX and Nasdaq. Analyst employment information (analyst brokerage house) is also obtained from the I/B/E/S detail history file by reviewing an analyst brokerage firm. Accounting data comes from Compustat annual data and stock return is from CRSP daily data.

2.4 Empirical Results

2.4.1 Define "Double Down"

The double down strategy is defined in the following way: First, I calculate the difference between the current recommendation and the previous recommendation. If an analyst's previous recommendation is 1 or 2, the analyst's current recommendation on the same stock is 1 or 2 and current recommendation has a higher or equal level than the previous recommendation. Then the current recommendation is named an indicator variable to be "Up" and equal to be 1, otherwise 0. Second, I calculate the cumulative market size-adjusted return from 2 days after the previous recommendation until 2 days before the current new recommendation. This cumulative return is named to be CAR. Third, I also care about the distance between the current recommendation and the previous recommendation. The distance is the number of calendar days between the current recommendation and the previous recommendation.

If Up=1 and CAR<-30% and 0<distance<365, then a recommendation would be defined to be "Loseup" and equal to be 1, which means analyst shows double down behavior by upgrading a stock recommendation even if stock is experiencing a significant drop in stock price, otherwise 0.

If Up=1 and CAR>30% and 0<distance<365, then a recommendation would be defined to be "Winup" and equal to be 1, which means analyst upgrades a stock that is experiencing a significant increase in the stock price, otherwise 0.

The upgrade is to make sure the analyst is upgrading the stock. The limitation on the stock recommendation level for the current and the previous to be 1 or 2 is to guarantee analyst's belief on the stock is "good enough to long". I limit the distance between two recommendations to be less than 365 days because I want to avoid the problems generated by stale recommendations. If the distance between two recommendations is too long, analysts barely care about or even forget about his previous belief about the stock. The limitation about CAR is to make sure the stocks are experiencing a significant increase or decrease in the price during the upgrade period for analyst's recommendation. I also try other measurement about CAR with 25% or 20%, a lower CAR could give me more observations for loseup and winup, but does not change my results significantly.

2.4.2 Define control variables

Define the other control variables: All the control variables are ranked following a similar method as that used in the previous literature to measure accuracy.I use the method of Hilary and Hsu (2013) to build the control variable of accuracy, boldness, gap,firm experience and breadth.

$$Accuracy_{i,j,t} = 1 - (rank_{i,j,t})/(number\,of\,analysts\,following\,firm\,j - 1) \tag{2.1}$$

Boldness is the absolute value of the difference between the forecast by analyst i and the street consensus following Ke and Yu (2006). The street consensus is defined as the average of all the other analysts forecasts for firm j within the past 90 days to the point of the forecast by analyst i for firm j at time t. Gap is defined as the total number of calendar days between the analyst forecast date and the firm public announcement date following Clement and Tse (2003). Firm-Experience is defined following Hong and Kubik (2003a), which is the log of the number of quarters the analyst has covered the firm. Experience is the log of the number of years the analyst has in the I/B/E/S following. Breadth is defined following Hong and Kubik (2003b), which is the number of firms that the analyst gives forecast in a fiscal given year. Since I measure accuracy by rankings and to keep the consistency, I also apply ranking variables for Boldness, Gap, Firm-Experience, Experience, and Breadth.

2.4.3 Description of the Summary Statistics

Table 1 provides the summary statistics for my main variables. My sample includes 15888 analysts. The total number of "Loseup" analysts are 2423 and the amount of the "Loseup" behavior is 4661. I also present the total number of "Winup" analysts, which is 2717. The amount of the "Winup" behavior is 5815. Table 1 also presents the frequency of the "Loseup" behavior. About 56% of the analysts only have one time "Loseup" behavior in their whole career path. The number of analysts who have more than 2 times of "Losup" behavior in their career development only takes 20.76%. This results indicate that most analysts stop having the second "Loseup" behavior after they have the first one.

The return by following the recommendation of "Double Down" analysts

To test the performance of the stocks recommended by the double down analysts, I calculate the long-run return of these stocks. Table 2 presents the results of the 60 days, 90 days and 180 days abnormal return by the double down analysts, winup analysts and the return of general stock upgrade. The 60 days return is calculated from two days after the stock recommendation date until 62 days after the recommendation date. The 90 days and 180 days abnormal return is calculated by the same way. The 60 days, 90 days and 180 days abnormal return of the stock recommended by the double down analyst is -0.019, -0.037 and -0.076, respectively. The 60 days,, 90 days and 180 days abnormal return from the general upgrade is 0.007, 0.009 and 0.012, respectively. We could easily make the judgment that the performance of the stocks recommended by the double down analysts is worse than the general level of upgrade recommendation. To compare with the performance of the double down analysts, I also calculate the abnormal return of the winup analysts. The 60 days, 90 days and 180 days abnormal return of the stocks recommended by the winup analysts is 0.023, 0.030 and 0.049, respectively. The abnormal return from the winup analysts is positive and much higher than that of the double down analysts. The difference between the abnormal return from the double down analysts and winup analysts provide clear evidence that the upgrade recommendation by double down analysts is biased.

To confirm that the lower abnormal return is generated by the double down behavior instead of other analyst or firm characteristics, I use the method of Malmendier and Shanthikumar (2014).

$$\begin{aligned} CAR_{j,t} =& Loseup_{i,j,t} + +Persist_{i,j,t} + LogSize_{j,t-1} + BM_{j,t-1} + Brokersize_{i,t-1}+ \\ & Firm - Experience_{i,j,t} + \epsilon_{i,j,t} \end{aligned} \tag{2.2}$$

$Persist_{i,j,t}$ is defined following Mikhail et al. (2004) as the quintile rank of analysts based on the excess returns by taking a long(short) position in their upward(downard) revisions associated with their revisions for the previous one-year period. $BrokerSize_{i,t}$ is the number of analysts for the brokerage firm of analyst i. $Firm - Experience_{i,j,t}$ is a the number of years analyst i has covered firm j until year t.$Size_{j,t-1}$ is firm size, calculated as the market capitalization at the end of year t-1. $BM_{j,t-1}$ is book to market ratio, calculated as firm's book value divided by firm size at the end of year t-1.

The coefficient of loseup is negative of -0.0133 and -0.0429 with significant t-value of -3.07 and -6.58 in column 2 and column 3, respectively. The result indicates that the double down behavior has a negative influence on the long-run 90 days and 180 days return for the recommended stock by the double down analysts. The results also confirm the conclusion in Table 2 that the stock recommended by the double down analyst is biased.

2.4.4 Does Double Down behavior affect analyst's forecast accuracy?

To explore which possible reason leads the analyst to have the "double down" behavior, I first test whether the double down behavior could affect analyst's forecast accuracy. One method to check the whether analyst is defending the firm is to test analyst's forecast accuracy for the same firm next year when an analyst gets "double down" behavior in the current year. If an analyst is trying to defend the firm to build a good relationship with the firm's management, then this analyst is more likely to get higher forecast accuracy in the next year.

I use the following empirical model to test the accuracy for analysts who have double down behavior in the previous year.:

$$\begin{aligned} Accuracy_{i,j,t} =& Loseup_{i,j,t-1} + Accuracy_{i,j,t-1} + Boldness_{i,j,t} + Firm - Experience_{i,j,t} \\ &+ LogFollow_{i,j,t} + Breadth_{i,j,t} + Gap_{i,j,t} + \epsilon_{i,j,t} \end{aligned} \tag{2.3}$$

$$\begin{aligned} Accuracy_{i,j,t} =& Winup_{i,j,t-1} + Accuracy_{i,j,t-1} + Boldness_{i,j,t} + Firm - Experience_{i,j,t} \\ &+ LogFollow_{i,j,t} + Breadth_{i,j,t} + Gap_{i,j,t} + \epsilon_{i,j,t} \end{aligned} \tag{2.4}$$

The coefficient of Loseup is 0.0103 with a insignificant t-value of 1.30. The insignificant results provide evidence that the double down behavior does not influence analyst's forecast accuracy. This result indicates that when an analyst is upgrading the stock that is experiencing a drop in stock price and he believed to be high level previously, the analyst is not defending the firm. Compared with the Loseup, the coefficient of the Winup is positive of 0.0223 wit a significant t-value of 3.67. The Winup analysts in current year have a higher accuracy in the next year. The results of Table 2 show that the long-run abnormal return for stocks recommended by Winup analysts is much higher then the stocks recommended by Loseup (double down) analysts. The higher accuracy for the stocks recommended by Winup analysts indicates the fact that Winup analysts know their recommended stock better than the Loseup analysts. The higher accuracy and positive abnormal short-run and long-run return clearly show that Winup analysts have a significant advantage over the Loseup analyst, no matter in market reaction or forecast accuracy. Combining the results from Table 2 and Table 4, it is not hard to get a clear conclusion. The double down behavior is a bad move and the upgrade recommendation inside the double down behavior is a overly optimistic bias recommendation by double down analysts. The double down behavior is not a strategy applied by analyst to defend the firm, it's just a biased move by analyst in stock recommendation.

2.4.5 Analysts characteristics that could affect the analysts Double Down Strategy

To have a good understand of what kinds of analysts are more likely to have double down behavior, I explore analyst characteristics that may affect analyst's double down behavior. I apply the following empirical Model:

$$\begin{aligned} Loseup_{i,j,t} =& Allstar_{i,t} + Loseup_{i,j,t-1} + Accuracy_{i,j,t-1} + Boldness_{i,j,t} + Experience_{i,j,t} + \\ & LogFollow_{i,j,t} + Breadth_{i,j,t} + \epsilon_{i,j,t} \end{aligned} \tag{2.5}$$

Table 5 shows the results of what kinds of analyst characteristics could affect analyst's double down behavior. The coefficient of Star is -0.508 with a significant t-value of -7.90. This result indicates that All-American analysts are less likely to have the double down behavior. The coefficient of $Loseup_{i,j,t-1}$ is 0.664 with a significant t-value of 4.4. This proves that an analyst would be more likely to have double down behavior if this analyst used to have one in the previous year. The coefficient of Lnfollow is -0.274 with a significant t-value of -9.57, which means analysts are less likely to have the double down behavior when there are more analysts follow the same firm. The other analyst's forecast characteristic such as forecast accuracy, boldness, firm experience and analyst's breadth have no effect on the double down behavior. The fact that All-American analysts are less likely to have the double down behavior indicate that this is a kind of behavior that are not preferred by the analysts with high reputation and maybe hurtful for analysts.

2.4.6 What is the influence of Double Down behavior on an analyst's career development

It is clear that the double down behavior is not the kind of strategy preferred by All-American analysts and it is also obvious that the analysts who have the double down behavior are actually performing badly in their recommendation update since the recommended stock's long run return is much lower than fthe average of general upgrade. Does the double down behavior hurt an analyst in his or her career development because of the bad move in recommendation update? Table 5 reports the results for the influence of double down behavior on analysts career path. I use 5 different measurements to measure the career path of an analyst. Stayup is a variable we use from Kini et al. (2009), when an analyst is promoted to a brokerage house that is larger in the number of analysts of that firm or stay in the same firm, the analyst is defined to have a status of stayup. Demotion is another variable from Ke and Yu (2006), when an analyst is demoted from a brokerage house that has more than 25 analysts to brokerage house that has less than 25 analysts, the analyst is defined to be demotion. Exittop is a variable to measure analysts career path from Hilary and Hsu (2013), when an analyst is demoted from a top 10 brokerage house to a non-top 10 brokerage house, the analyst is defined to be Exittop. Movetop is defined to be equal to 1 when an analyst is promoted from a non top 10 brokerage house to a top 10 brokerage house or stay in the top 10 brokerage house. All-star analyst is defined to be equal to 1 when an analyst is named as All-American analyst by the magazine Institutional Investor. In the 5 measurements, Allstar measurement is the well accepted and efficient to measure the promotion for an analysts career path. The Stayup, Demo and Exittop is also used by previous literature to measure the analyst's move up and move down in his or her career development. I use all these 5 measurements in order to see the influence of investor attention on the analysts career path from different views. The empirical model we use to measure the career path of an analyst is as follows:

$$\begin{aligned} Stayup_{i,t} =& Loseup_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + Breadth_{i,t-1} + Logfollow_{i,t-1} \\ &+ Experience_{i,t-1} + \epsilon_{i,t-1} \end{aligned} \tag{2.6}$$

$$\begin{aligned} Demo_{i,t} =& Loseup_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + Breadth_{i,t-1} + Logfollow_{i,t-1} \\ &+ Experience_{i,t-1} + \epsilon_{i,t-1} \end{aligned} \tag{2.7}$$

$$
\begin{aligned}
Exittop_{i,t} =& Loseup_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + Breadth_{i,t-1} + Logfollow_{i,t-1} \\
&+ Experience_{i,t-1} + \epsilon_{i,t-1}
\end{aligned} \tag{2.8}
$$

$$
\begin{aligned}
Movetop_{i,t} =& Loseup_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + Breadth_{i,t-1} + Logfollow_{i,t-1} \\
&+ Experience_{i,t-1} + \epsilon_{i,t-1}
\end{aligned} \tag{2.9}
$$

$$
\begin{aligned}
Allstar_{i,t} =& Loseup_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + Breadth_{i,t-1} + Logfollow_{i,t-1} \\
&+ Experience_{i,t-1} + \epsilon_{i,t-1}
\end{aligned} \tag{2.10}
$$

Table 6 presents the results of the logistic regression on the effect of double down on an analyst's career development. The coefficient of loseup is negative with -1.332 and has a significant z-statistics of -3.3 in column 1. This result indicates that analyst with double down behavior in the previous yer is less likely to get promoted to a larger brokerage firm in the following year. The coefficient of losup is positive with 1.734 and a significant t-value of 3.22 in column 2. This result means analyst with double down behavior in the previous year are more likely to get demoted to a smaller brokerage firm with less than 25 analysts hired. The coefficient of loseup is -1.447 in column 5 with a significant z-statistics of -2.37. Analysts with double down behavior in the last year are less likely to be nominated as an All-American analyst in the next year. Combing the all results of Table 6, it is obvious to make the judgment that double down behavior would hurt an analyst in his or her career development.

2.4.7 The performance of double down analysts

I have shown that the double down behavior would hurt an analyst in his career development, but what would happen to these analysts who have double down behavior in the rest of their career path? To find the answer of this question, I apply the method of Fang and Yasuda (2013). I define analysts who have double down behavior in year t-1 to be "Lose" analysts from t until the last year in this analyst's career. That means $Lose_{i,t,t+1,t+2......}$ is an indicator variable that is equal to 1 if an analyst has double down behavior in year t-1. I check the abnormal return from the "Sell" recommendation and the "Buy" recommendation by "Lose" analysts and the other analysts by using the following method:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + m_p UMD_t + \epsilon_{i,t-1} \tag{2.11}$$

where $R_{p,t}$ is portfolio's return on month t; $R_{m,t}$ and $R_{f,t}$ are the market return and risk-free rate on month t, and SMB_t, HML_t and UMD_t are the size, book-to-market, and momentum factor, respectively. Table 7 presents the results for the FF-3 factors regression. The abnormal return from the "Buy" recommendation by the "Lose" analysts and other analysts is 0.0158 and 0.0220, respectively. It is clear that the abnormal return generated by the "Lose" analysts is significantly lower than the other analysts. The lower abnormal return by "Lose" analysts is nor surprising because their previously bad move in stock recommendation upgrade is hurting their future reputation. Investors does not respond the same to their recommendation upgrade compared with the other analysts. When we look at the abnormal return from the "Sell" recommendation between the "Lose" analysts and the other analysts, the abnormal return from "Lose" analysts is -0.0415, which is much higher than the abnormal return from the "Sell" recommendation by the other analysts, -0.0231. The investors respond more significantly to the "Sell" recommendation by the "Lose" analysts than the other analysts. This result is not surprising since the Sell recommendation given by the aggressive analysts ("Lose" analysts) would be taken more seriously by the investors. Combing all results from Table 7, it is obvious that the double down behavior would also hurt an analyst's market influential power in his future career path on his buy recommendation, but gives more power to his sell recommendation.

2.5 Conclusion

My study focus on exploring potential biased recommendation by analysts from their internal characteristics and the influence of these biased recommendation on analysts' career development, forecast accuracy and the potential influence of these biased recommendation on investor's investment decision. I find out that analysts who disagree to lower down his previous high rating recommendation even after the stock is experiencing a significant drop is more likely to get demoted to a smaller brokerage firm, less likely to be promoted to a larger brokerage firm and less likely to become an all star analyst. I define this kind of behavior to be "double down" behavior. Analysts are issuing these biased recommendation because of his overconfidence instead of defending the firm. These biased recommendation would mislead investors if they follow the recommendation because the long-run return of these biased upgrade recommendation are significantly lower then the average. Analysts tend to have this double down behavior in their early years but the frequency of this behavior is getting less and less with the increase of general experience for an analyst.

My results are insightful for the study in financial analysts' behavior and strategy. Analysts should be more careful about upgrading a stock's recommendation when a previous "good" stock is experiencing a significant drop in the stock price. Being overconfidence could hurt an analyst in his career development but being conservative makes no hurt to an analyst. In other words, analysts should try to avoid upgrade a stock when the stock is experiencing a significant drop in the stock price even if he or she is confident about the upgrade.

My research is also meaningful for investors who care about analysts' stock recommendation, especially the upgrade recommendation. Before investors make their decision to follow a upgrade stock recommendation and long the stock, investors should check both the analyst's previous recommendation about the same stock and whether the stock is experiencing a significant drop recently. By paying more attention to the analysts and stock, investors could avoid the potential biased recommendations.

2.6 Tables

Table 2.1: Summary Statistics for double down

Summary Statistics

Variable	Obs
Analysts	15588
Loseup Analysts	2423
Loseup	4661
Winup Analysts	2717
Winup	5815

Loseup

Number of Loseup	Frequency
1	1357
2	563
3	225
4	130
5	56
6	34
7	28
8	10
9	6
10	7
11	4
12	1
13	1
30	1

Winup

Number of Winup	Frequency
1	1440
2	583
3	290
4	146
5	90
6	60
7	35
8	30
9	18
10	10
11	5
12	4
13	1
14	3
19	1
21	1

Table 2.2: Abnormal return for double down in different time window

Loseup					
Variable	Obs	Mean	Std. Dev.	1%	99%
CAR_61	4649	-0.01965	0.302021	-0.66220	0.92492
CAR_91	4649	-0.03734	0.359725	-0.76797	1.16284
CAR_180	4649	-0.07562	0.500323	-0.91796	1.66201
Winup					
Variable	Obs	Mean	Std. Dev.	1%	99%
CAR_61	5802	0.023352	0.258556	-0.53881	0.85961
CAR_91	5802	0.030307	0.339427	-0.63285	1.10491
CAR_180	5802	0.049573	0.530008	-0.80132	1.89934
Upgrade					
Variable	Obs	Mean	Std. Dev.	1%	99%
CAR_61	211750	0.007198	0.191441	-0.46578	0.58602
CAR_91	211782	0.008763	0.240287	-0.55476	0.74717
CAR_180	211867	0.012508	0.363453	-0.72601	1.17471

Table 2.3: OLS Regression. This table presents the results of the influence of double down behavior on the recommended stock's long-run abnormal return.$Loseup_{i,j,t}$ is an indicator variable that is defined in Section 4. $Persist_{i,j,t}$ is the quintile rank of analyst i on firm j based on the excess returns earned from taking a long(short) position in upward(downard) revisions associated with forecast revisions by analyst i for the preceding quarter. $BrokerSize_{i,t}$ is the log number of analysts for the brokerage house of analyst i. $Firm\_Experience_{i,j,t}$ is a the number of years analyst i has covered firm j until year t.$Size_{j,t-1}$ is firm size, calculated as the market capitalization at the end of year t-1. $BM_{j,t-1}$ is book to market ratio, calculated as Compustat annual item CEQ divided by firm size at the end of year t-1.

	(1) CAR_61	(2) CAR_91	(3) CAR_180
$Loseup_{i,j,t}$	-0.00296	-0.0133***	-0.0429***
	(-0.86)	(-3.07)	(-6.58)
$Persist_{i,j,t}$	-0.000444	-0.000413	-0.000705
	(-1.22)	(-0.91)	(-1.03)
$Brokersize_{i,t}$	-0.0000143	-0.00001000	-0.00000286
	(-1.54)	(-0.86)	(-0.16)
$Firm\_Experience_{i,j,t}$	0.00207***	0.00305***	0.00510***
	(12.76)	(15.05)	(16.69)
$Size_{j,t-1}$	0.0000263***	0.0000293**	0.0000311*
	(2.65)	(2.36)	(1.66)
$BM_{j,t-1}$	0.0180***	0.0267***	0.0442***
	(15.31)	(18.14)	(19.92)
N	145223	145230	145234

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.4: OLS Regression. This table presents the results of the different influence on accuracy by "Loseup" analysts and "Winup" analysts. $Accuracy_{i,j,t}$ is the standardized earnings forecast ranking of analyst i relative to other analysts follow firm j in quarter t.$Loseup_{i,j,t}$ and $Winup_{i,j,t}$ are indicator variables defined in Section 4. $Boldness_{i,j,t}$ is the ranking result of the difference of quarterly earnings forecast by analyst i relative to the consensus for the firm j in quarter t. $Experience_{i,j,t}$ is the total number of quarters analyst i exists in I/B/E/S until t. $Follow_{i,j,t}$ is the total number of analysts following firm j in quarter t. $Gap_{i,j,t}$ is the difference on calendar days between the public announcement date for firm j and the last earning forecast date of analyst i in quarter t. $Breadth_{i,j,t}$ is the number of firms analyst i covered in quarter t.

	(1) $Accuracy_{i,j,t}$	(2) $Accuracy_{i,j,t}$
$Loseup_{i,j,t-1}$	0.0103	
	(1.30)	
$Winup_{i,j,t-1}$		0.0223^{***}
		(3.67)
$Accuracy_{i,j,t-1}$	0.0522^{***}	0.0522^{***}
	(34.36)	(34.36)
$Boldness_{i,j,t-1}$	-0.0376^{***}	-0.0376^{***}
	(-25.99)	(-25.98)
$Experience_{i,j,t-1}$	0.0223^{***}	0.0221^{***}
	(11.99)	(11.86)
$LnFollow_{i,j,t-1}$	0.000952	0.000920
	(1.43)	(1.38)
$Breadth_{i,j,t-1}$	0.0325^{***}	0.0325^{***}
	(22.10)	(22.09)
$Gap_{i,j,t-1}$	-0.319^{***}	-0.319^{***}
	(-221.98)	(-221.95)
_cons	0.618^{***}	0.618^{***}
	(230.07)	(230.10)
N	435106	435106

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5: Logistic Regression. This table reports the influence of double down behavior on analysts' career development. $Loseup_{i,j,t}$ is an indicator variable defined in Section 4. $Allstar_{i,j,t}$ is a dummy variable that is equal to 1 if analyst i is nominated to be an All-American analyst by the magazine Institutional Investor in year t. $Accuracy_{i,j,t}$ is the standardized earnings forecast ranking of analyst i relative to other analysts follow firm j in quarter t. $RA_{i,j,t}$ is defined in Section 4. $LME_{i,j,t}$is also a dummy variable if analyst applies the last minute earning forecast revision strategy for firm j in quarter t. $Boldness_{i,j,t}$ is the ranking result of the difference of analyst quarterly earnings forecast by analyst i relative to the consensus for the firm j in quarter t. $Firm-Experience_{i,j,t}$ is the total number of quarters analyst i follows firm j until t. $Follow_{i,j,t}$ is the total number of analysts following firm j in quarter t. $Gap_{i,j,t}$ is the difference on calendar days between the public announcement date for firm j and the last earning forecast date of analyst i in quarter t. $Breadth_{i,t}$ is the number of firms analyst i covered in quarter t.

	(1)
	$Loseup_{i,j,t}$
$Allstar_{i,j,t}$	-0.508***
	(-7.90)
$Loseup_{i,j,t-1}$	0.644***
	(4.40)
$Accuracy_{i,j,t-1}$	-0.0620
	(-0.93)
$Boldness_{i,j,t}$	0.0605
	(0.95)
$Experience_{i,j,t}$	0.126
	(1.50)
$Lnfollow_{i,j,t}$	-0.274***
	(-9.57)
$Breadth_{i,j,t}$	0.0000742
	(0.00)
Year FE	Yes
N	194400

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

Table 2.6: Logistic Regression. This table presents the results of the effects analysts' double down behavior on analyst's career development. $Loseup_{i,t}$ is a dummy variable that is equal to 1 if an analyst has at least one time of double down behavior in the previous year. $Stayup_{i,t}$ is a dummy variable that is equal to 1 if analyst i is promoted to a larger brokerage house or stay in the same brokerage house in year t. $Demo_{i,t}$ is a dummy variable that is equal to 1 if analyst i is demoted from a brokerage house that has more than 25 analysts to a smaller brokerage house that has less than 25 analysts in year t. $Exittop_{i,t}$ is a dummy variable that is equal to 1 if analyst i leaves a top 10 brokerage house in year t. $Movetop_{i,t}$ is a dummy variable that is equal to 1 if analyst i moves from a non top 10 brokerage house into a top10 brokerage house in year t. $Allstar_{i,t}$ is a dummy variable that is equal to 1 if analyst i is nominated to be an All-American analyst by the magazine Institutional Investor in year t. $Accuracy_{i,t}$ is average of $Accuracy_{i,j,t}$ across all firms in year t for analyst i. $Boldness_{i,t}$ is the average $Boldness_{i,j,t}$ for analyst i across all firms in year t. $Firm - Experience_{i,t}$ is the average of $Firm - Experience_{i,j,t}$ across all firms for analyst i in year t. $LnFollow_{i,t}$ is the average of $LnFollow_{i,j,t}$ across all firms for analyst i in year t. $Breadth_{i,t}$ is the number of firms analyst i covered in year t.

	(1)	(2)	(3)	(4)	(5)
	$Stayup_{i,t}$	$Demo_{i,t}$	$Movetop_{i,t}$	$Exittop_{i,t}$	$Allstar_{i,t}$
$Loseup_{i,t-1}$	-1.332***	1.734***	0.589	0.760	-1.447**
	(-3.30)	(3.22)	(0.70)	(0.95)	(-2.37)
$Accuracy_{i,t-1}$	1.750***	-2.099***	-0.855***	-1.895***	1.689***
	(18.20)	(-13.88)	(-5.08)	(-10.93)	(13.56)
$Boldness_{i,t-1}$	0.368***	-0.478***	-0.355**	-0.421**	-0.873***
	(3.75)	(-3.15)	(-2.05)	(-2.41)	(-6.67)
$Breadth_{i,t-1}$	0.548***	-0.646***	-0.216	-0.659***	2.932***
	(7.40)	(-5.58)	(-1.60)	(-4.92)	(37.65)
$Experience_{i,t-1}$	-0.196***	0.284***	-0.239***	0.179***	0.217***
	(-8.17)	(7.62)	(-5.34)	(4.14)	(9.61)
$LnFollow_{i,t-1}$	-0.235***	0.322***	0.180***	0.393***	0.583***
	(-8.06)	(7.01)	(3.49)	(7.34)	(17.76)
N	61041	61041	61041	61041	61041

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7: FF-3 factors Regression. This table presents the monthly alphas of 30-day holding period portfolios that buy stocks at the close of the day before the recommendation date. The buy portfolio include recommendations rated "strong buy" and buy, the sell portfolios include recommendations rated "hold", "underperform" and "sell". Lose is an indicator variable that is equal to 1 when an analyst is defined to be a "Lose" analysts. Others refer to the analysts that are not "lose" analysts. $R_{p,t}$ is portfolio's return on month t; $R_{m,t}$ is market return, $R_{f,t}$ is the risk-free rate on month t, SMB_t, HML_t and UMD_t are the size, book-to-market, and momentum factor, respectively.

	(1)	(2)	(3)	(4)
	Lose,Buy	Lose,Sell	Others,Buy	Others,Sell
Excess Return on the Market	1.174***	1.248***	1.126***	1.087***
	(12.75)	(10.32)	(44.56)	(35.05)
Small-Minus-Big Return	0.880***	0.497**	0.584***	0.466***
	(7.49)	(3.22)	(18.02)	(11.72)
High-Minus-Low Return	-0.0224	-0.112	-0.122***	0.0464
	(-0.18)	(-0.68)	(-3.54)	(1.09)
Momentum Factor	-0.442***	-0.549***	-0.139***	-0.320***
	(-5.88)	(-5.57)	(-6.71)	(-12.57)
Constant	0.0158***	-0.0415***	0.0220***	-0.0231***
	(4.05)	(-8.11)	(16.91)	(-17.65)
Observations	224	224	224	224

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chapter 3

Cost of Speaking in Two Different Tongues

3.1 Introduction

Due to the large demand for financial analyst earnings forecasts and recommendations in recent years, researchers are more and more interested in what affects analysts career development and analysts' forecast accuracy. It is meaningful and interesting to explore an analyst characteristic that reflect both an analyst earnings forecast skill and recommendation skill at the same time. Malmendier and Shanthikumar (2014) explore the motivation for an analyst to speak in two different tongues. They find that some analysts strategically distort their earnings forecasts and recommendations by giving relatively higher recommendation ratings and relatively lower earnings forecast. They argue that it is the affiliation relationship between analysts' brokerage house and their target firms that leads them to speak in two different tongues. Malmendier and Shanthikumar (2014) focus on the internal motivation of the strategy why analysts speak in two different tongues. For example, the brokerage house may push the security analyst to give higher recommendation to their target firms since the brokerage house is the IPO underwriter of the analyst's target firm. The internal motivations for analysts to speak in two different tongues are creative and insightful for researchers to understand analysts' behavior and strategy in earnings forecasts and stock recommendation rating. However, questions regarded with the influence of this two tongue strategy on analyst career path, analyst forecast accuracy and market reaction to analysts' two tongues strategy still remain unsolved.

In this paper, using the method from Malmendier and Shanthikumar (2014) to define the analysts who speak in two different tongues, I explore the answers to these unsolved questions. Does the two tongues strategy help analysts to earn a better career path? Does the two tongues strategy contribute to improving the forecast accuracy for analysts? Does this two tongues strategy help analysts to have more market influential power to move the stock price in their recommendation and their earnings revision?

My research starts with testing the accuracy of the forecasts issued by analysts who apply two tongues strategy. I test the accuracy of the forecasts made by analysts who apply the two tongues strategy from a firm-year-analyst level and a year-analyst level. I find that the analysts who are speaking in two tongues are less accurate in their two tongues target firms than the analysts who do not speak in two tongue. I also explore the accuracy before the Regulation Fair Disclosure and after the Regulation Fair Disclosure. The lower accuracy happens after the Regulation Fair Disclosure but does not happen before Regulation Fair Disclosure. This result reflects the fact that Regulation FD increases the cost for the two-tongue strategy. The lower firm-analyst level accuracy can not be found when I check the accuracy in analyst level in contrast to analyst-firm level. This result provides evidence that the two-tongue strategy is a firm-characteristics driven strategy instead of a self-driven strategy. The Regulation Fair Disclosure does not have any effect on the accuracy for the analysts who apply two tongues strategy in analyst level. Combining all the results in the effect of two tongues strategy on accuracy, I confirm the results found by Malmendier and Shanthikumar (2014), the two tongues strategy is driven by firm characteristics such as pressure from the analysts' brokerage house.

The influence of the two tongues strategy on analyst career development is the next question I explore in my paper. According to Malmendier and Shanthikumar (2014), one of the internal reasons that some analysts apply the two tongues strategy is the analyst affiliation and other proxies for incentive misalignment. Since I have found out that two tongues strategy would lower the analysts forecast accuracy in their target firms. The lower accuracy clearly has a negative impact for the analysts. So, after taking these negative impacts generated by their brokerage house, would these analysts get a better career development from their brokerage house or a worse results? A better career path is an indicator that the brokerage house is compensating for the analyst for his contribution of bluffing the affiliated firm's stock recommendation. On the other hand, a worse career path is simply an indication that these analysts who have to speak in two tongues must suffer from the results of being inconsistency between the earnings forecast and stock recommendations. I use 4 different measurements to measure analyst career path. The results of the logistic regression model show that analysts who take more frequent of the two tongues strategy in the previous year are less likely to be promoted to be All-American analysts and promoted to be a top 10 brokerage firm in the current year. These results indicate that the two tongues strategy is actually hurting analysts in their career development.

Malmendier and Shanthikumar (2014) argue that one of the incentives for analysts to take the two tongues strategic distortion in the forecast side and recommendation side is to use the high recommendation to induce naive investors to purchase stocks, please management and generate corporate finance business. I study the market reaction to the analysts who take the two tongues strategy when they revise their recommendation and find that the market reaction is higher for analysts who take two tongues strategy. On the other side, when I test the market reaction to earnings forecast revision by analysts who take the two tongues strategy, I do not find any different market reaction. The fact that there exists higher market reaction in the recommendation side but not on the earnings forecast side is consistent with the results from Malmendier and Shanthikumar (2014) paper. My results indicate analysts who take the two tongues strategy could hide the pessimistic forecast behind the optimistic recommendation. Analysts who take the two tongues strategy could please the management in this way. The general investors appear to ignore the negative information in earnings forecast and react only to the optimistic information in recommendation.

My study contributes to the literature in several ways. First, I test the external cost for the analysts who apply the two tongues strategy. My study is an extension of Malmendier and Shanthikumar (2014), I point out the cost in the analyst career path who takes the two tongues strategy. The negative influence on analyst career path by the two tongues strategy shows that this two tongues game is not a cost free strategy that could be used by analysts to please the management and induce the investors to make more purchase on recommended stocks. The cost is obvious for the analysts, this result is consistent with Malmendier and Shanthikumar (2014) that all star analysts do not prefer to take this strategy.

Second, I present evidence on the market reaction for the two tongues strategy. My empirical results show that the two tongues strategy helps the analyst to be more powerful in affecting stock price when they revise their recommendation ratings but has no additional influence power on analyst earnings forecast revision. Investors respond more positively to the high stock recommendations but ignore the lower earnings forecast on the firm where analysts apply the two-tongue strategy. This result is consistent with the previous study that the small and nave investors always respond to the recommendation revision significantly while the large and sophisticated take limited response to these recommendation revisions, the large investors even take no reaction to the buy recommendations (Malmendier and Shanthikumar (2007)). My results provide evidence to prove the fact that the unsophisticated and naive investors are dominated by the analysts' two-tongue strategy.

Third, my paper confirms the argument by Malmendier and Shanthikumar (2014) that the two tongues strategy is driven by firm characteristics such as pressure from the brokerage house affiliation with the target firm. I show the influence of two tongues strategy on analyst forecast accuracy in a firm-analyst level and analyst level. The lower accuracy in a firm-analyst level but not analyst level reveals the fact that the influence of the two tongues strategy is a firm level.

The rest of this paper is organized as follows. Section 2 is the literature review. Section 3 presents the data and summarizes all the relevant variables I will use in the rest of paper. Section 4 presents empirical results and the interpretation of these results. Section 5 concludes the paper.

3.2 Literature Review

Analysts give both earnings forecast and stock recommendations ratings to provide information for the benefit of their clients who lack the information and ability to conduct such kind of stock analysis by themselves. A large body of literature has examined upward distortion of analyst recommendation. Michaely (1999) give empirical evidence that analysts consciously issue upward distortion recommendations to please the management and induce the investors to purchase the stock. Chen and Matusmoto (2006) also showed that upward distortion recommendation is favorable by the management while the analysts who give relative low rating recommendations are likely to be frozen out by the management. Interestingly, when analysts give earnings forecast, opposite to their behavior when issuing stock recommendations, they are more likely to give a downward distortion of earnings forecast. Analysts are often pressured by the management to lower down their earnings forecasts a few days before the earnings announcement. This lowered down earnings forecast allows the firm to easily meet or even beat the earnings forecast. Richardson (2004) document that analysts issue pessimistic forecasts when it is closed to the firm's annual earnings announcement. Chan et al. (2009) argue that analysts intentionally lower down earnings forecasts so that firms could avoid negative earnings surprises and get of positive earnings surprises. Hugon and Muslu (2010) find a stronger market reaction to earnings forecast revision by more conservative analysts. These papers talk about the distortion of higher recommendation ratings and distortion of lower earnings forecast separately. Malmendier and Shanthikumar (2014) combine the earnings forecast side and recommendation rating side together and they find analysts whose brokerage house is affiliated with their target firms are more likely to give relatively lower earnings forecast and relatively higher stock recommendation ratings. To further explore the effect of the two tongues strategy effect on analysts themselves, I combine the method used by previous literature to extend the study by Malmendier and Shanthikumar (2014).

3.3 Data

I get actual annual earnings and annual analyst forecast data from the I/B/E/S Detailed History files from 1994 to 2012. The analyst recommendation data is from I/B/E/S Detail Recommendation files. To be consistent with the analyst forecast data, the sample period of analyst recommendation data is also from 1994 to 2012. The data is started from 1994 because forecasts before 1994 may be inaccurate due to the reason of batch delivery before 1994. I focus on annual forecast. For each firm-analyst, I use the forecasts issued by the analyst before the earnings announcement but following the previous earnings announcement because I will show the effect of forecast revision of the two-tongue strategy on stock market in my analysis. Analyst employment information is from the I/B/E/S database by reviewing an analysts brokerage house. Accounting data is from Compustat annual data and stock data is from CRSP daily data.

3.4 Empirical Results

3.4.1 Define the Two-Tongue Strategy

I strictly follow the method of Malmendier and Shanthikumar (2014) to define analyst's two tongues strategy. I first measure the optimism as the difference between an earnings forecast and the street consensus and a recommendation and the recommendation consensus. I normalize the difference of the earnings forecast by the stock price of the prior-day. I take the average of 3 month outstanding forecasts to calculate the consensus. Since recommendations do not have a definite window as earning forecast, I use a range of 3 month to form the consensus of recommendation ratings. After I get the optimism for both earnings forecast and recommendation, I use the earnings optimism minus the recommendation optimism.

$$EA\_Optimism_{i,j,t} = (Forecast_{i,j,t} - EA\_Consensus_{j,t})/abs(Price_{j,t-1})$$

$$Rec\_Optimism_{i,j,t} = Recommendation_{i,j,t} - Rec\_Consensus_{j,t}$$

$$Two\_Tongue\_Metric_{i,j,t} = EA\_Optimism_{i,j,t} - Rec\_Optimism_{i,j,t}$$

If the Two_Tongue_Metric is less than 0, then the $Two\_Tongue_{i,j,t}$ is defined to be 1 and this analyst is defined to have two tongues strategy, otherwise 0.

3.4.2 Define control variables

To get meaningful and accurate rankings, I delete firms covered by fewer than 2 analysts. All the control variables are ranked with a similar method as those used in previous papers.I use the method of Hilary and Hsu (2013) to build the control variable of accuracy, boldness, gap,firm experience and breadth.

The accuracy is defined in the following way:

$$Accuracy_{i,j,t} = 1 - (rank_{i,j,t})/(number\,of\,analysts\,following\,firm\,j - 1) \tag{3.1}$$

First, I calculate the forecast error for analyst in on firm j, then I take the absolute value of this forecast error. Second, I rank all analysts covering firm j in quarter q based on the absolute forecast error. In the last, I calculate the mean of the ranking scores and get the ranking variable.

Boldness is the absolute value of the difference between the forecast by analyst i and the street consensus following Ke and Yu (2006). The street consensus is defined as the average of all the other analysts forecasts for firm j within the past 90 days to the point of the forecast by analyst i for firm j at time t. Gap is defined as the total number of calendar days between the analyst forecast date and the firm public announcement date following Clement and Tse (2003). Firm-Experience is defined following Hong and Kubik (2003a), which is the log of the number of quarters the analyst has covered the firm. Experience is the log of the number of years the analyst has in the I/B/E/S following. Breadth is defined following Hong and Kubik (2003b), which is the number of firms that the analyst gives forecast in a fiscal given year. Since I measure accuracy by rankings and to keep the consistency, I also apply ranking variables for Boldness, Gap, Firm-Experience, Experience, and Breadth.

3.4.3 Cost of the Two Tongues Strategy

When analysts apply the two-tongue strategy, they are issuing relatively lower earnings forecast and relatively higher recommendation ratings. Is the relatively lower earnings forecast more closed to actual earnings(more accurate) or more far away from the actual earnings(less accurate)? If analysts are more accurate by applying the two-tongue strategy, then one of the external motivation for analysts to take the two-tongue strategy is the high accuracy. If analysts are less accurate for the firms they take the two-tongue strategy. Analysts are suffering from a cost of playing this two-tongue game.

I use the following empirical model to test the accuracy of the two-tongue strategy from a firm-analyst level:

$$\begin{aligned} Accuracy_{i,j,t} =& Two\_Tongue_{i,j,t} + Accuracy_{i,j,t-1} + Boldness_{i,j,t} + Firm\_Experience_{i,j,t} \\ &+ LogFollow_{i,j,t} + Breadth_{i,j,t} + Gap_{i,j,t} + \epsilon_{i,j,t} \end{aligned} \tag{3.2}$$

The coefficient of the Two_Tongue in the regression model in column 1 of Table 2 is negative of -0.0103 with a significant t-value of -4.07. The results of Table 2 indicate that when analysts are taking the two-tongue strategy on a frim, they are actually becoming less accurate in that target firm. This lower forecast accuracy on the target firm is clearly a cost of applying the two tongues strategy. Column 2 and Column 3 in table 2 shows the effect of the two tongues strategy on accuracy before the Regulation Fair Disclosure and after the Regulation Fair Disclosure. The two tongues strategy does not show any influence on the forecast accuracy before Regulation FD. But the two tongues strategy hurt the analyst forecast accuracy after the Regulation FD. The different results before and after the Regulation FD is because the Regulation FD asks for more fair disclosure for the public firms, the two tongues strategy analysts do not have a competitive information advantage over the other non-two tongues strategy analyst in earnings forecast. So the two tongues analysts show a lower accuracy at this point after the Regulation FD. A challenge to the interpretation of the results in Table 2 is maybe the lower accuracy on the two tongues strategy target firm is because the analysts are having a lower accuracy in a general level than the other analysts. To solve this potential problem, I use the following empirical model to test the accuracy of analysts' two-tongue strategy from analyst level.

$$\begin{aligned} Accuracy_{i,t} =& Two\_Tongue_{i,j,t} + Accuracy_{i,t-1} + Boldness_{i,t} + Firm\_Experience_{i,t} + \\ & LogFollow_{i,t} + Breadth_{i,t} + Gap_{i,t} + \epsilon_{i,t} \end{aligned} \tag{3.3}$$

The results of Table 3 insight me that the two-tongue strategy would not influence the analyst accuracy in an analyst level. The coefficient of the Two_Tongue is 0.00142 with a insignificant t-value of 0.75. This result is robust because the coefficient is of Two_Tongue is also insignificant before the Regulation FD and after the Regulation FD. Combining the results from Table 2 and Table 3, I get the conclusion that when analysts are taking the two-tongue strategy, they will tolerate the cost of losing some accuracy on the firm where they speak in two different tongues. But this two-tongue strategy will not influence their accuracy in an analyst general level. The results in Table 2 and Table 3 indicate that the two-tongue strategy is clearly a firm-driven strategy instead of a general behavioral by security analyst. The result is consistent with Malmendier and Shanthikumar (2014) results that the motivation of the two-tongue strategy is from the affiliation of the brokerage house and the analyst's target firm. The distortion on the earnings forecast side by the analysts who apply the two-tongue strategy is strategic, but the cost for this is losing the accuracy for their distorted firm.

3.4.4 Check the career path of analysts who apply the two-tongue strategy

Malmendier and Shanthikumar (2014) show that when an analyst takes a two-tongue strategy, he is generating more trading for his brokerage house by inducing small and navie investors to buy more. In other words, the two-tongue strategy could generate benefit for the brokerage house. But according to the results I show above, the two-tongue strategy is also hurting analysts by making their forecasts less accurate. Now I continue to explore the next question. If an analyst uses the two-tongue strategy, what is the influence on their career development?

Table 4 reports the results for the influence of attention grabbing on analyst career path. I use 4 different measurements to measure the career path of an analyst. Stayup is a variable we use from Kini et al. (2009), when an analyst is promoted to a brokerage house that is larger in the number of analysts of that firm or stay in the same firm, the analyst is defined to have a status of stayup. Demotion is another variable from Ke and Yu (2006), when an analyst is demoted from a brokerage house that has more than 25 analysts to brokerage house that has less than 25 analysts, the analyst is defined to be demotion. Movetop is defined to be equal to 1 when an analyst is promoted from a non top 10 brokerage house to a top 10 brokerage house or stay in the top 10 brokerage house. All-star analyst is defined to be equal to 1 when an analyst is named as All-American analyst by the magazine Institutional Investor. In the 4 measurements, Movetop and Allstar measurement are the well accepted and efficient to measure the promotion for an analyst career path. The Stayup and Demo is also used by previous literature, but moving to a smaller brokerage house or staying in the same brokerage house could not clearly picture the career demotion or promotion of an analyst. I use all these 4 measurements in order to see the influence of investor attention on the analyst career path from different views. The empirical model we use to measure the career path of an analyst is as follows:

$$
\begin{aligned}
Stayup_{i,t} =& Two\_Tongue_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + Breadth_{i,t-1} + Lnfollow_{i,t-1} \\
&+ Experience_{i,t-1} + \epsilon_{i,t-1}
\end{aligned}
\tag{3.4}
$$

$$
\begin{aligned}
Demo_{i,t} =& Two\_Tongue_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + Breadth_{i,t-1} + Lnfollow_{i,t-1} \\
&+ Experience_{i,t-1} + \epsilon_{i,t-1}
\end{aligned}
\tag{3.5}
$$

$$
\begin{aligned}
Movetop_{i,t} =& Two\_Tongue_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + Breadth_{i,t-1} + Lnfollow_{i,t-1} \\
&+ Experience_{i,t-1} + \epsilon_{i,t-1}
\end{aligned}
\tag{3.6}
$$

$$
\begin{aligned}
Allstar_{i,t} =& Two\_Tongue_{i,t-1} + Accuracy_{i,t-1} + Boldness_{i,t-1} + Breadth_{i,t-1} + Lnfollow_{i,t-1} \\
&+ Experience_{i,t-1} + \epsilon_{i,t-1}
\end{aligned}
\tag{3.7}
$$

Since I have proved that the two tongues strategy is a firm-driven strategy. So applying this strategy should make no contribution to the analysts career development or even hurt the analyst in his or her career development. If taking this strategy is helping the analysts in their career path, then the firm-driven conclusion from my previous results is going to suffer from a potential problem.

The coefficient of Two-Tongue is -0.53 for Column 3 in Table 4 with a significant z-statistic of -22.42 and -0.256 in Column 4 with a significant z-statistic of -6.74. The coefficients of Two-Tongue are insignificant in Column 1 and Column 2 of Table 4. The results of Table 4 show that the more frequent an analyst applies the two-tongue strategy in current year, the less likely that analyst would to be promoted or stayed to the Top 10 brokerage house and less likely to be nominated to be all-star analyst in the next year. The high frequency of applying the two-tongue strategy could clearly hurt an analyst in his or her career development.Since the motivation of the two-tongue strategy is generated from the internal affiliation of analysts' brokerage house and their target firm, not from the analysts' motivation by themselves, this strategy is playing no positive role in helping the two tongues analysts in their career development. This result confirms my previous argument that the analysts' two-tongue strategy is a firm-driven strategy instead of an analyst-driven strategy because if an analysts apply this strategy to all his or her target firms, he or she will get hurt by losing his or her forecast accuracy and getting punishment in his or her career development.

3.4.5 Market reaction for the analysts who apply the two-tongue strategy

Malmendier and Shanthikumar (2007) point out that navie and unsophisticated investors react more positively to analysts' recommendation upgrade. Malmendier and Shanthikumar (2014) also argue that when analysts apply the two-tongue strategy, they are inducing small and naive investors to buy more. But what is the market reaction to the earnings forecast revision and recommendation revision when analysts are taking the two-tongue strategy? This is the question I would focus be on in the following analysis.

To check the market reaction for the analysts who apply the two-tongue strategy, I use the model from Hugon and Muslu (2010) to see the market reaction to analysts' earning forecast revision when they are taking the two-tongue strategy. The details of all the control variables are described in Section 4.2.

$$
\begin{aligned}
CAR_{j,t} =& \alpha_{j,t} + Two - Tongue_{i,j,t} * Rev_{i,j,t} + Two - Tongue_{i,j,t} + Rev_{i,j,t} + AbsRev_{i,j,t} + \\
& LogSize j, t-1 + BM_{j,t-1} + Loss_{j,t} + Brokersize_{i,t-1} + Frequency_{i,t-1} + \\
& Breadth_{i,t-1} + Firm - Experience_{i,j,t} + LogSize j, t-1 * Rev_{i,j,t} + \\
& BM_{j,t-1} * Rev_{i,j,t} + Loss_{j,t} * Rev_{i,j,t} + Brokersize_{i,t-1} * Rev_{i,j,t} + \\
& Frequency_{i,t-1} * Rev_{i,j,t} + Breadth_{i,t-1} * Rev_{i,j,t} + Firm\_Experience_{i,j,t} * Rev_{i,j,t} \\
& + \epsilon_{i,j,t}
\end{aligned}
\tag{3.8}
$$

Following Mikhail et al. (2004), I use the following model to test the market reaction for the recommendations of analysts who apply the two-tongue strategy. The details of all the other control variables are described in Section 4.2.

$$
\begin{aligned}
CAR_{j,t} =& \alpha_{j,t} + Two - Tongue_{i,j,t} * Upgrade_{i,j,t} + Two - Tongue_{i,j,t} + Upgrade_{i,j,t} + \\
& Persist_{i,j,t} + LogSize j, t-1 + BM_{j,t-1} + Brokersize_{i,t-1} + \\
& Firm\_Experience_{i,j,t} + LogSize j, t-1 * Upgrade_{i,j,t} + BM_{j,t-1} * Upgrade_{i,j,t} \\
& + Brokersize_{i,t-1} * Upgrade_{i,j,t} + Firm - Experience_{i,j,t} * Upgrade_{i,j,t} + \epsilon_{i,j,t}
\end{aligned}
\tag{3.9}
$$

The sign of the interaction between the forecast revision and the two-tongue strategy in Table 5 is 0.0363 and with a insignificant t-value of 1.81. That indicates the market reaction to analysts who take two tongues strategy when they are revising their earnings forecasts is not significant. Two tongues strategy means a lower earnings forecast than the consensus, which is easily to generate a negative market reaction, but there is no evidence showing that the market reaction is more negative compared with the earnings revision that is higher than the consensus.

Compared with the results in Table 5, the sign of the interaction term between upgrade and two-tongue strategy in Table 6 is 0.00883 with a significant t-value of 3.99. The results of Table 6 show that the market reaction is more positive for the analysts who apply the two-tongue strategy when they upgrade their recommendations. Combining the results from Table 5 and Table 6, I get the conclusion that the unsophisticated investor could be dominated by the two-tongue strategy. They react more positively to the recommendation upgrade even if the earnings revision is lower than consensus on the same day. This result is consistent with the results Malmendier and Shanthikumar (2007) that unsophisticated and naive investors care more about stock recommendation. The results in Table 5 and Table 6 also prove the analysts who take the two-tongue strategy could hide the relatively negative earnings revision news behind the positive recommendation ratings. The two tongues strategy could help the analyst's target firm to avoid a negative market reaction even with a earnings forecast lower than the street consensus.

3.5 Conclusion

I find that analysts who apply the two-tongue strategy by issuing relatively lower earnings forecast and relatively higher recommendation ratings are suffering a cost by becoming less accurate on their earnings forecast in the target firms where they apply the two-tongue strategy. In addition, analyst who take more frequent two tongues strategy are more likely to get punishment in their career path by becoming less likely to be promoted to a top 10 brokerage house and less likely to be nominated as an All-American analyst. After exploring the investor reaction to the analysts' earnings revision and recommendation revision, I find investors react more positively to the recommendation upgrade but do not react more negatively to the lower earnings revision. The results prove that the naive and unsophisticated investors are dominated by the analysts' two-tongue strategy.

My results indicate that the two tongues strategy is a firm driven strategy, which confirms the argument by Malmendier and Shanthikumar (2014) that the motivation for analysts to take the two tongues strategy is the affiliation relationship between analysts' brokerage house and their target firms.

My study is an extension of the work by Malmendier and Shanthikumar (2014), I explore the external results of the analysts' two-tongue strategy and find the cost of this strategy. My conclusions are also intuitive for naive and unsophisticated investors, when these investors see a higher stock recommendation relatively to the consensus, they should check whether there is a relatively lower earnings forecast on the same stock issued by the same analyst by that day. Investors should take both the recommendation and earnings forecast into consideration before they decide whether to buy a stock or not.

3.6 Tables

Table 3.1: Summary Statistics. This table presents the summary statistics of the whole sample in my analysis. The sample consists of all the analyst EPS forecasts in I/B/E/S from 1994 to 2012.Panle A presents the descriptive statistics for analyst forecasts in a firm-quarter-analyst level. Panel B shows the descriptive statistics for earnings forecast in a analyst-quarter level. Panel C gives the summary statistics in a analyst-year level.

Panel A

	count	mean	sd	min	p50	max
Accuracy	59083	0.472	0.197	0	0.500	1
Two-Tongue	59083	0.230	0.377	0	0	1
Boldness	59083	0.499	0.162	0	0.494	1
Firm-Experience	59083	0.509	0.202	0	0.514	1
LnFollow	59083	2.644	0.533	1.099	2.708	4.543
Breadth	59083	0.574	0.271	0.0587	0.601	1
Gap	59083	0.540	0.230	0	0.501	1
Observations	59083					

Panel B

	count	mean	sd	min	p50	max
Accuracy	431217	0.500	0.311	0	0.500	1
Two-Tongue	431217	0.0480	0.214	0	0	1
Boldness	431217	0.500	0.316	0	0.500	1
Firm-Experience	431217	0.501	0.287	0	0.500	1
LnFollow	431217	2.580	0.700	1.099	2.639	4.543
Breadth	431217	0.501	0.318	0	0.500	1
Gap	431217	0.498	0.314	0	0.500	1
Observations	431217					

Panel C

	count	mean	sd	min	p50	max
Stayup	59767	0.945	0.227	0	1	1
Demo	59767	0.0218	0.146	0	0	1
Movetop	59767	0.286	0.452	0	0	1
Allstar	59767	0.0804	0.272	0	0	1
Two-Tongue	59767	0.237	0.425	0	0	1
Accuracy	59767	0.513	0.187	0	0.525	1
Boldness	59766	0.514	0.179	0	0.500	1
Breadth	59767	0.552	0.277	0.0600	0.575	1
LnFollow	59767	2.516	0.647	0	2.627	4.543
Experience	59767	1.207	0.842	0	1.099	2.944
Observations	59767					

Table 3.2: OLS Regression. This table presents the results of analyst's accuracy for the attention grabbing strategy in a firm-quarter-analyst level. $Two\_Tongue_{i,j,t}$ is a dummy variable that equals to 1 if it the analyst gives a recommendation and earning forecast satisfy the conditions in section 4. $Accuracy_{i,j,t}$ is the standardized earnings forecast ranking of analyst i relative to other analysts follow firm j in quarter t. $Boldness_{i,j,t}$ is the ranking result of the deviation of analyst of quarterly earnings forecast by analyst i relative to the consensus for the firm j in quarter t. $Firm - Experience_{i,j,t}$ is the total number of quarters analyst i follows firm j until t. $LnFollow_{i,j,t}$ is the log total number of analysts following firm j in quarter t. $Gap_{i,j,t}$ is the difference on calendar days between the public announcement date for firm j and the last earning forecast date of analyst i in quarter t. $Breadth_{i,t}$ is the number of firms analyst i covered in quarter t.

	(1) $Accuracy_{i,j,t}$ Full Sample	(2) $Accuracy_{i,j,t}$ After FD	(3) $Accuracy_{i,j,t}$ Before FD
$Two\_Tongue_{i,j,t}$	-0.0103***	-0.0157***	0.000999
	(-4.07)	(-4.93)	(0.24)
$Accuracy_{i,j,t-1}$	0.0628***	0.0615***	0.0637***
	(41.18)	(31.62)	(25.92)
$Boldness_{i,j,t}$	-0.0367***	-0.0390***	-0.0324***
	(-25.25)	(-21.12)	(-13.75)
$Firm - Experience_{i,j,t}$	0.0228***	0.0229***	0.0234***
	(12.21)	(9.99)	(7.23)
$Lnfollow_{i,j,t}$	0.00106	0.00178**	-0.000282
	(1.59)	(2.04)	(-0.27)
$Breadth_{i,j,t}$	0.0310***	0.0414***	0.0147***
	(20.92)	(21.89)	(6.18)
$Gap_{i,j,t}$	-0.317***	-0.294***	-0.354***
	(-219.67)	(-158.65)	(-153.72)
N	431217	270676	160541

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3: OLS Regression. This table presents the results of analyst's accuracy for the attention grabbing strategy in a quarter-analyst level. $Accuracy_{i,t}$ is average of $Accuracy_{i,j,t}$ across all firms in year t for analyst i. $Boldness_{i,t}$ is the average $Boldness_{i,j,t}$ for analyst i across all firms in quarter t. $Firm - Experience_{i,t}$ is the average of $Firm - Experience_{i,j,t}$ across all firms for analyst i in quarter t. $LnFollow_{i,t}$ is the average of $LnFollow_{i,j,t}$ across all firms for analyst i in quarter t. $Gap_{i,t}$ is the average of $Gap_{i,j,t}$ across all firms for analyst i in quarter t. $Breadth_{i,t}$ is the number of firms analyst i covered in quarter t.

	(1)	(2)	(3)
	$Accuracy_{i,t}$	$Accuracy_{i,t}$	$Accuracy_{i,t}$
	Full Sample	After FD	Before FD
$Two\_Tongue_{i,t}$	0.00072	0.00117	0.00146
	(0.39)	(0.47)	(0.52)
$Accuracy_{i,t-1}$	0.0705***	0.0767***	0.0580***
	(18.34)	(11.43)	(7.68)
$Boldness_{i,t}$	-0.0878***	-0.0985***	-0.0783***
	(-20.80)	(-12.01)	(-7.86)
$Firm - Experience_{i,t}$	0.0185***	0.0271***	0.0115
	(5.42)	(4.84)	(1.58)
$LnFollow_{i,t}$	-0.0081***	-0.00703***	0.0000421
	(-6.21)	(-3.12)	(0.02)
$Breadth_{i,t}$	0.0678***	0.0607***	0.0459***
	(24.74)	(12.45)	(8.01)
$Gap_{i,t}$	-0.4290***	-0.398***	-0.448***
	(-138.68)	(-72.85)	(-65.50)
N	59083	37044	22039

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.4: Logistic Regression. This table reports the influence of attention grabbing strategy on analysts' career path. $Stayup_{i,t}$ is a dummy variable that is equal to 1 if analyst i is promoted to a larger brokerage house or stay in the same brokerage house in year t. $Demo_{i,t}$ is a dummy variable that is equal to 1 if analyst i is demoted from a brokerage house that has more than 25 analysts to a smaller brokerage house that has less than 25 analysts in year t. $Exittop_{i,t}$ is a dummy variable that is equal to 1 if analyst i leaves a top 10 brokerage house in year t. $Movetop_{i,t}$ is a dummy variable that is equal to 1 if analyst i moves from a non top 10 brokerage house into a top 10 brokerage house in year t. $Allstar_{i,t}$ is a dummy variable that is equal to 1 if analyst i is nominated to be an All-American analyst by the magazine Institutional Investor in year t. $Accuracy_{i,t}$ is average of $Accuracy_{i,j,t}$ across all firms in year t for analyst i. $Boldness_{i,t}$ is the average $Boldness_{i,j,t}$ for analyst i across all firms in year t. $Experience_{i,t}$ is the rank of average number of years the analysts have in I/B/E/S. $LnFollow_{i,t}$ is the average of $LnFollow_{i,j,t}$ across all firms for analyst i in year t. $Breadth_{i,t}$ is the number of firms analyst i covered in year t.

	(1) $Stayup_{i,t}$	(2) $Demo_{i,t}$	(3) $Movetop_{i,t}$	(4) $AllStar_{i,t}$
main				
$Two-Tongue_{i,t-1}$	0.0726	-0.110	-0.530***	-0.256***
	(1.63)	(-1.56)	(-22.42)	(-6.74)
$Accuracy_{i,t-1}$	1.694***	-2.064***	0.630***	1.785***
	(17.39)	(-13.56)	(12.88)	(14.37)
$Boldness_{i,t-1}$	0.394***	-0.465***	-0.146***	-0.552***
	(3.96)	(-3.05)	(-2.84)	(-4.20)
$Breadth_{i,t-1}$	0.493***	-0.581***	-0.216***	2.137***
	(6.26)	(-4.75)	(-5.44)	(26.90)
$LnFollow_{i,t-1}$	-0.226***	0.308***	0.0197	0.988***
	(-7.47)	(6.55)	(1.31)	(27.43)
$Experience_{i,t-1}$	-0.187***	0.261***	0.0557***	1.105***
	(-6.93)	(6.30)	(4.01)	(31.60)
Year FE	Yes	Yes	Yes	Yes
N	59766	59766	59766	59766

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.5: OLS Regression. This table reports the market reaction for analysts' recommendation revision whey they apply the two-tongue strategy. $Two{-}Tongue_{i,j,t}$ is a dummy variable that is equal to 1 if analyst i applies two-tongue strategy for firm j in year t. $Upgrade_{i,j,t}$ is a dummy variable that is equal to 1 if analyst i gives a higher recommendation level for firm j on year t. $Persist_{i,j,t}$ is the quintile rank of analysts based on the excess returns earned from taking a long (short) position in their upward (downward) revisions associated with their revisions for the preceding on-year period. $BrokerSize_{i,t}$ is the number of analysts for the brokerage house of analyst i. $Firm - Experience_{i,j,t}$ is a the number of years analyst i has covered firm j until year t.$Size_{j,t-1}$ is firm size, calculated as the market capitalization at the end of year t-1. $BM_{j,t-1}$ is book to market ratio, calculated as Compustat annual data item CEQ divided by firm size at the end of year t-1.

	(1) $CAR_{j,t}$
$Two - Tongue_{i,j,t}$	-0.00747***
	(-4.58)
$Two - Tongue_{i,j,t} * Upgrade_{i,j,t}$	0.00883***
	(3.99)
$Upgrade_{i,j,t}$	0.0568***
	(38.31)
$Persist_{i,j,t-1}$	-0.00169***
	(-6.48)
$Brokersize_{i,t-1}$	-0.00000395
	(-0.54)
$Firm - Experience_{i,j,t}$	0.00135***
	(18.22)
$LogSize_{j,t-1}$	0.0000387***
	(5.07)
$BM_{j,t-1}$	0.0110***
	(13.90)
$Persist_{i,j,t-1} * Upgrade_{i,j,t}$	0.00357***
	(8.39)
$Brokersize_{i,t-1} * Upgrade_{i,j,t}$	0.0000629***
	(4.78)
$Firm - Experience_{i,j,t} * Upgrade_{i,j,t}$	-0.00136***
	(-10.83)
$LogSize_{j,t-1} * Upgrade_{i,j,t}$	-0.0000380***
	(-2.95)
$BM_{j,t-1} * Upgrade_{i,j,t}$	0.00446***
	(3.38)
Constant	-0.0392***
	(-44.50)
Observations	218551

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

Table 3.6: OLS Regression. This table presents the results for the market reaction to analysts' earnings forecast when they apply the two-tongue strategy. $Rev_{i,j,t}$ is earnings forecast revision of analyst i, calculated as forecast by analyst i at year t for firm j minus the mean consensus forecast for firm j scaled by the nearest preceding monthly stock price. $AbsRev_{i,j,t}$ is the absolute value of earnings forecast revision for analyst i. $Loss_{i,j,t}$ is dummy variable equal to 1 if a firm has negative earnings in quarter t, otherwise 0. $Size_{j,t-1}$ is defined as the market capitalization at the beginning of year t. $BM_{j,t-1}$ is book to market ratio, calculated as Compustat annual item CEQ divided by firm size at the end of year t-1. $Firm-Experience_{i,j,t}$ is a the number of years analyst i has covered firm j until year t. $BrokerSize_{i,t}$ is defined as the log of the number of analysts hired by the brokerage firm of analyst i at the end of year t-1. $Freq_{i,t}$ is the total number of earnings forecasts made by analyst i in year t. $Breadth_{i,t}$ is the number of firms analyst i covered in year t.

	(1) $CAR_{j,t}$
$Two-Tongue_{i,j,t} * Rev_{i,j,t}$	0.0363*
	(1.81)
$Two-Tongue_{i,j,t}$	0.00932***
	(13.49)
$Rev_{i,j,t}$	0.0354***
	(3.02)
$AbsRev_{i,j,t}$	-0.0131***
	(-4.83)
$LogSize_{j,t-1}$	-0.0000172
	(-0.35)
$BM_{j,t-1}$	0.00120***
	(5.84)
$Loss_{j,t}$	-0.00878***
	(-33.18)
$LogBrokersize_{i,t-1}$	-0.000114
	(-1.57)
$Freq_{i,t-1}$	0.000702***
	(5.96)
$Breadth_{i,t}$	-0.0000512***
	(-5.10)
$Firm-Experience_{i,j,t}$	0.000803***
	(5.51)
$LogSize_{j,t-1} * Rev_{i,j,t}$	-0.0132***
	(-8.78)
$BM_{j,t-1} * Rev_{i,j,t}$	-0.0146***
	(-10.80)
$Loss_{j,t} * Rev_{i,j,t}$	-0.111***
	(-19.10)
$LogBrokersize_{i,t-1} * Rev_{i,j,t}$	0.0181***
	(10.96)
$Freq_{i,t-1} * Rev_{i,j,t}$	-0.0233***
	(-7.03)
$Breadth_{i,t} * Rev_{i,j,t}$	0.00114***
	(3.14)
$Firm-Experience_{i,j,t} * Rev_{i,j,t}$	0.0545***
	(15.02)
N	1408302

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

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