LEADERS AND FOLLOWERS AMONG SECURITY ANALYSTS

By
Li Wang, M.A

A Project

Submitted to the School of Graduate Studies

in Partial Fulfillment of the Requirements

for the Degree

Master of Science

McMaster University

MASTER OF SCIENCE (2006) MCMASTER UNIVERSITY

(Statistics) Hamilton, Ontario, Canada

TITLE: Leaders and Followers among Security Analysts

AUTHOR: Li Wang

M.A. (Nanjing University, China)

SUPERVISOR: Dr. Mike Veall

Dr. K.Kanagaretnam

NUMBER OF PAGES: iii, 66

ACKNOWLEDGEMENTS

I would like to take this opportunity to express my sincere appreciation to Dr. Veall and Dr. Kanagaretnam, my supervisors, for their guidance, encouragement and patience trough this project work.

I would like to thank Prof. Viveros-Aguilera and Prof. Macdonald for their valuable suggestions.

I would like to thank all the Professors at McMaster University who have ever taught me.

Finally, I would like to thank my parents, my husband, Dr. Kai Wu, and our lovely son, Jerry, for their love, support and understanding.

Abstract

We developed and tested procedures to rank the performance of security analysts according to the timeliness of their earning forecasts. We compared leaders and followers among analysts on various performance attributes, such as accuracy, boldness, experience, brokerage size and so on. We also use discriminant analysis and logistic regression model to examine what attributes have an effect on the classification. Further, we examined whether the timeliness of forecasts is related to their impact on stock prices. We found that the lead analysts identified by the measure of forecast timeliness have a greater impact on stock price than follower analysts. Our initial sample includes all firms on the Institutional Brokers Estimate System (I/B/E/S) database and security return data on the daily CRSP file for the years 1994 through 2003.

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1. Introduction

1.1 Background

There are lots of analysts on Wall Street. Most brokerage firms employ a number of analysts with expertise in tracking certain industries and following selected firms within those industries. These analysts produce research reports that are used to "sell" an idea to individuals and institutional clients. Individual investors gain access to these reports mainly by having accounts with the brokerage firm. For example, to get free research from Merrill Lynch, you need to have an account with a Merrill Lynch broker. Sometimes the reports can be purchased through a third party such as Multex.com. Institutional clients (i.e. mutual fund managers) get research from the brokerage's institutional brokers. An analyst estimates for a company's future quarterly or annual earnings. Analysts use forecasting models, management guidance, and fundamental information on the company in order to derive an estimate. A good sell-side research report contains a detailed analysis of a company's competitive advantages and provides information on management's expertise and how the company's operating and stock valuation compares to a peer group and its industry. The typical report also contains an earnings model and clearly states the assumptions that are used to create the forecast.

Analysts are ranked annually by Institutional Investor (II) magazine and The Wall Street Journal (WSJ). Institutional Investor (II) magazine ranks the analysts by surveying directors and CIOs of major money management institutions, key investors, analysts at top institutions and portfolio managers. The analysts are ranked for picking stocks, writing reports, estimating earnings, acquiring knowledge of the industry, being responsive to clients' requests, and initiating timely calls to investors. Investors and the media apparently believe that there are well-defined quality differentials between Wall Street research analysts, i.e. that some analyst's research is superior to others.

In this paper, we will focus on analyst's earning estimates. Prior research has documented that information asymmetry between managers and investors is negatively associated with the number of analysts following a firm (Brennan and Subrahmanyam, 1995, and Easley, O'Hara, and Paperman, 1998). When a large number of analysts release forecasts for a single firm, a question arise regarding that what's the marginal informativeness of the forecast released by the n^{th} follower analyst? Therefore, we classify analysts as leaders and followers based on the relative timeliness of their earnings forecasts. We then compare leaders and followers among analysts on various performance attributes linked to analyst compensation, such as price impact, accuracy, boldness and so on. We will build a logistic regression model and discriminant analysis to examine what attributes have an effect on the classification and to see what roles leaders and followers among analysts play in the capital market. Further, we will examine whether timeliness of forecasts is related to their impact on stock price.

1.2 Data, Variable Definitions

Our initial sample includes all firms on the Institutional Brokers Estimate System (I/B/E/S) database for the years 1995 through 2003. I/B/E/S provides powerful insight into the depth of the I/B/E/S quality database of historical estimates. The I/B/E/S database contains analyst estimates of various measures of U.S. and International company financial performance. There are three primary sections to the IBES database: Detail History, Summary History and Recommendations. The Detail History file contains individual analyst estimates by company, date, fiscal period and measure, which is used in our sample. The Daily Detailed Earning Estimate History is setup in a relational database format. It is comprised of 10 data files, Detail File, Identifier File, Adjustments File, Excluded Estimates File, Broker Translations, S/I/C Codes, Stopped Estimate File, Exchange Rate File, Report Currency File and Actuals File. The identifying variable key for most of the files is the I/B/E/S Ticker. The I/B/E/S ticker is a unique identifier assigned to each security that is consistent throughout the I/B/E/S history. In our sample, we mainly use Detail File and Actual File. Detail File contains analyst by analyst estimates for as many as five fiscal year periods and four quarterly forecasts as well as long term growth estimates for each security followed. In our sample, we just pick up one fiscal year forecast estimates. The output of Detail File in I/B/E/S datasets is showed in Table 1-1.

Detail File Output:

Table 1-1: Output of Detail File in I/B/E/S Dataset

ticker	broker	analyst	indicator	endate	year	value	estdate
AA3R	01593	072907	1	200309	2003	0.11	20030102
ADBE	00016	056285	1	200311	2003	1.06	20030103
ADBE	01989	071276	1	200311	2003	0.95	20030103
ADTN	00220	009867	1	200212	2002	0.41	20030103
ADTN	00192	013967	1	200212	2002	0.42	20030103
ADTN	00464	057927	1	200212	2002	0.42	20030103
ADTN	00158	081516	1	200212	2002	0.425	20030103
ADVS	00251	010496	1	200212	2002	0	20030103
ADVS	00094	010694	1	200212	2002	0.02	20030103
ADVS	00282	019966	1	200212	2002	0.02	20030103
ADVS	00260	049331	1	200212	2002	0	20030103

Actual File is a list of actual reported earnings and the date on which they were received by I/B/E/S. Table 1-2 gives us the output of the Actual File.

Actual File Output:

Table 1-2: Output of Actual File in I/B/E/S Dataset

Ticker	Measure	Periodicity	End	Value	Report
AA3R	EPS	QTR	0009	0.04	011009
AA3R	EPS	ANN	0009	0.04	011009
AA3R	EPS	QTR	0012	0	011009
AA3R	EPS	QTR	0103	0.04	011009

We provide a brief description of the variables in Detail File and Actual File.

Variable Definitions:

Analyst Name: Individual analysts name

Analyst Code: A numerical code matched to each contributing analyst

Broker Code: A numerical code matched to each contributing broker

Estimate Date (YYMMDD): Date that an estimate was entered into the I/B/E/S database

Forecast Period End Date (YYMM): Forecast period end date (in year/month format) of observed estimates

Measure: Data type indicator (i.e. EPS, CPS, DPS etc.)

I/B/E/S Ticker: Unique identifier supplied by I/B/E/S. This variable should be used to link data across files and time periods as it will not change and will remain unique.

Reported Period End Date: Year and month corresponding to the close of a company's Business period

Value: Estimate value

Forecast Period Indicator: Each fiscal period (FY1, FY2, Q1, etc.) is given a numerical value.

This allows company comparison regardless of FY end. FY year end can be cross referenced through the Forecast period end date.

The sample for tests of price impact of forecasts includes firms with security return data on the daily CRSP (The Center for Research In Security Prices) file. CRSP US Stock Databases cover common stock issues listed on the New York Stock Exchange, the American Stock Exchange and the NASDAQ Stock Market. The files provide complete historical descriptive information and market data including comprehensive distribution information, high, low and closing prices, trading volumes, shares outstanding, and total returns.

1.3 Sampling

We examine earnings forecasts for firms in technology industry. Technology industry has more rapid technological change than the other industries, such as the retail industry and the restaurant industry. This industry faces an intense competition among firms to innovate. The analysts following the industries have the opportunity to create significant value for investors, who are interested in the investment but unable to accurately measure relative investment value.

Our sample comprises all analysts with current fiscal-year (FY1) earnings estimates for domestic U.S common stocks from July 1994 to Dec. 2003 on the Daily Detail Earnings Estimate History File. We track each analyst's most recent outstanding forecasts as of six months before the end of the stock's fiscal year. Our choice of forecast horizon is based on the idea that six months before the fiscal year-end, there is sufficient uncertainty about future earnings to generate dispersion across analysts. If we take one year forecast horizon, our sample may include lots of inactive forecasts. The reason we don't take one quarter forecast horizon is that forecasts tend to converge and analysts seem more homogeneous as the end of the fiscal year approaches. We retain an analyst for a firm only if he/ she issues at least 3 earnings forecast for the firm during sample period. We also exclude the firms that are followed by less than 3 analysts.

Table 1-3: Sample Size

Year	Forecasts	Firms	Analysts	Brokerage
1994	2619	241	580	152
1995	2963	293	633	154
1996	3907	380	820	175
1997	4371	437	952	197
1998	3970	430	1039	211
1999	3281	384	1012	198
2000	3402	431	1129	179
2001	3140	365	1061	140
2002	2545	316	962	159
2003	2549	304	942	192
Total	32,747	3,581	9,130	1,757

Table 1-3 reports, for each year over the sample period, the size of the sample used in our analysis. We tabulate the number of eligible: the number of analysts issuing estimates, the number of firms covered, and the number of brokerage firms affiliated with the analysts, are reported for each calendar year over the sample period. In overall sample there are 32,747 forecasts issued by 9,130 analysts employed by 1,757 brokerage firms covering 3,581 stocks.

1.4 Method

We identify leaders and followers according to the measure of timeliness and forecast accuracy. Each of these performance measures is used to classify leader analysts during an estimation period from the Jan. 1 to Dec.31 for each fiscal year. Given the lead analysts identified by timeliness of earning forecasts release, we test our hypothesis concerning analysts' performance using a whole sample from Jan 1, 1994 through Dec. 31, 2003. Logistic regression was used to examine the timeline leaders and follower in relation to various performances attributes, such as accuracy, boldness, brokerage size, and experience. Further regressions with cumulative excess returns as the dependent variable were conducted with forecast surprise for leaders and followers as independent variables, which is to characterize that the leader and follower have different impact on the stock price.

The analysis consists of three stages. Chapters 2 gives descriptive and univariate analyses for security earnings estimation data. In the univariate analysis, an F test for classifying the leaders and followers is introduced and we use a T-test and Mann-Whitney test for examining the difference in means of performance measures for leaders versus followers. Chapter 3 presents topics related to logistic regression model and discriminant analysis, interpretation of the models, and assessing the fit of the models of security data. Chapter 4 discusses the regression model for the different impact on the stock price between leaders and followers. Finally, I conclude with a summary of findings, implications, strengths and limitations of the study in Chapter 5.

All the analyses were conducted using SAS statistical software.

Chapter

2. Hypothesis Development and Research

2.1 Timeliness

Lead analysts have superior access to information or a differential ability to process that information. Therefore, lead analysts can prepare and release earning forecasts before competing analysts. As a leader, he/she should be a first mover. Herd behaviors in financial market will accentuate the tendency of clustering of forecasts following the forecast of the first mover. (Truman, 1994). Thus, we can use timeliness of the analysts' forecast revision as a proxy. Our classification of leaders and followers is based on the LFR (leader-follower ratio) used by Cooper et al. (2001).

There are some assumptions when we calculate LFR (leader-follower ratio).

- The times until the following analysts release revised forecasts have independent exponential distribution (Lawless, 1982) conditional on the release of a forecast revision by leader analysts, with expected release-time of next forecast revision, θ_1, i.e.,

$$\frac{1}{\theta_1} e^{-t/\theta_1}$$

- Similarly, conditional on the release of a forecast revision by follower analysts, the times until the release of revised forecast by other analysts have independent exponential distribution, with expected released-time of next forecast revision, θ_0, i.e.,

$$\frac{1}{\theta_0} e^{-t/\theta_0}$$

- We expected arrival times during the pre- and post-forecast periods can be estimated for each of the forecast revisions in our sample using the cumulative length of time required to generate the *N* forecast revisions preceding and following that forecast revision.

We identify lead analysts by comparing the expected release times of forecasts by other analysts during the periods preceding and following each analyst's forecast revisions. We estimate these expected release times for each analyst by using the cumulative days required to generate the *N* forecasts proceeding and following each forecast by that analyst. We use t_{i0}^{0} denote the number of days by which forecast *i* precedes each forecast by a selected analyst and t_{i1}^{1} denote the number of days by which forecast *i* follows each forecast by a selected analyst. Then we define the lead-time for a forecast revision by analyst *j* as the cumulative number of days by which the forecast is preceded by the *N* previous forecast revisions,

$$T_{0j} = \sum_{i=1}^{N} t_{i0} .$$

The follow-time is defined as the cumulative number of days required to generate the N forecast revisions,

$$T_{1j} = \sum_{i=1}^{N} t_{i1} \,.$$

Under these assumptions, we can estimate the expected arrival times θ_0 and θ_1 of the pre- and post- release periods by using maximum likelihood estimates. Let $\hat{\theta}_0$ and $\hat{\theta}_1$ denote estimates of the expected arrival times during the pre- and post-release periods. We can easily obtain the maximum likelihood estimates of $\hat{\theta}_0$ and $\hat{\theta}_1$ as T_{0j} / N and T_{1j} / N respectively. Obviously, $2T_{0j} / \theta_{0j}$ and $2T_{1j} / \theta_{1j}$ is distributed as χ^2_{2N}, then the ratio LFR is distributed as $F_{(2N,2N)}$, i.e,

$$LFR = \frac{2T_{0j} / \theta_0}{2T_{1j} / \theta_1} \sim \quad F_{(2N,2N)} \,.$$

Lawless (1982) proved that the *LFR* statistic is equal to $\hat{\theta}_0 / \hat{\theta}_1$ under the null hypothesis that θ_0 and θ_1 are same. Since the pre- and post-revision periods contain the same number of forecast revisions, the LFR statistic can be expressed as

$$LFR = \frac{T_{0j}}{T_{1j}} .$$

We can determine whether an analyst is a leader or a follower using the test statistic LFR $= T_{0j} / T_{1j}$. The Leader Follower Ratio (LFR) represents the ratio of the cumulative number of the analyst days by which an analyst's forecasts follow the N previous forecasts to the cumulative number of analyst days required to generate the next *N* forecasts. Whenever the cumulative analyst days prior to an analysts' forecast revision is large relative to the cumulative analyst days used to generate the next *N* forecasts, we can reject the null hypothesis that the analyst is a follower. Therefore, a lead analyst has an LFR statistic greater than one. This hypothesis is formally stated as:

Hypothesis 1: Testing the forecast arrival times for leaders in pre-release periods are greater than those in post-release periods.

We remove all forecasts issued within five days of an earnings announcement for each firm and fiscal year. When more than one forecast revision is released on a given day, we exclude each of these forecasts from the computations of the cumulative lead- and follow-times for the respective analysts. In order to avoid that an analyst's classification is attributable to a single lucky forecast, our sample only included the analysts who made at least five forecasts for firms. We also exclude any additional forecasts made by that analyst in the pre- and post-release period. We choose the technology industry as an example to classify the timeliness of leaders and followers. Unlike Cooper et al (2001), we calculate the leader-follower ratio for each analyst level rather than industry level. In this project, for each remaining forecast, we find the five preceding forecasts and the five subsequent forecasts that are issued by other analysts.

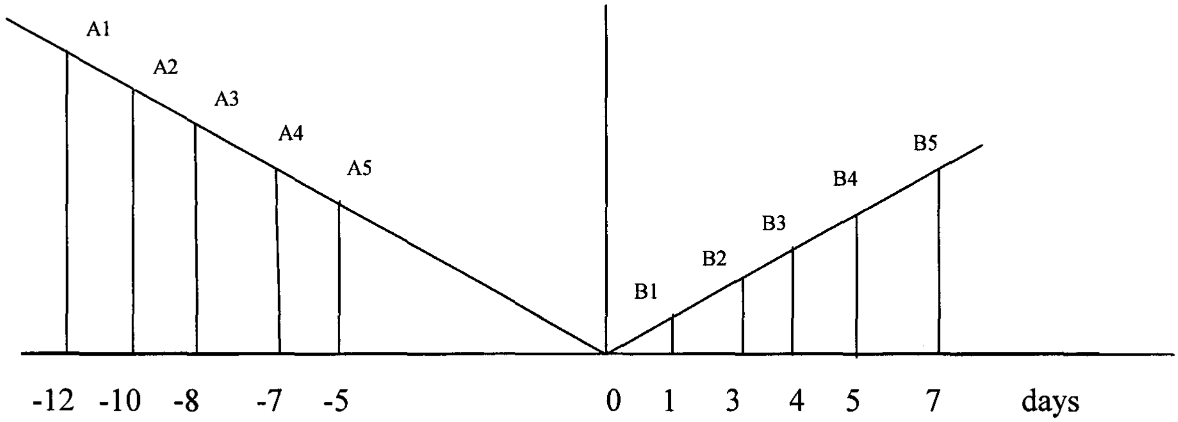

Figure 2-1: Forecast revision dates surrounding the forecast revision of a lead analyst

Figure 2-1 illustrates the computation of the LFR ratio. Each timeline depicts the release of a forecast revision by analyst *j* at date 0 along with the release of forecast revisions by other analysts during the time periods preceding and subsequent to the release date. The earning forecasts by analysts A1, A2, A3, A4 and A5 precede the selected analyst's earning forecast 12 day, 10 days, 8 days, 7 days and 5 days respectively, with a cumulative total of 52 analyst days. However, the subsequent forecasts issued by analysts B1, B2, B3, B4, and B5 quickly response to the selected analyst's forecast with 1 day, 3 days, 4 days, 5 days and 7 days. The cumulative days are 20 days. The results suggest that analyst *j*'s forecast revision contains new information. Moreover, since the forecast revision by analysts B1, B2, B3, B4, and B5 follow analyst *j*'s forecast revision almost immediately; their forecasts are likely to depend on the information contained in the forecast by analyst *j*. The LFR ratio is 52/20=2.6, which suggests that analyst *j* is a lead analyst.

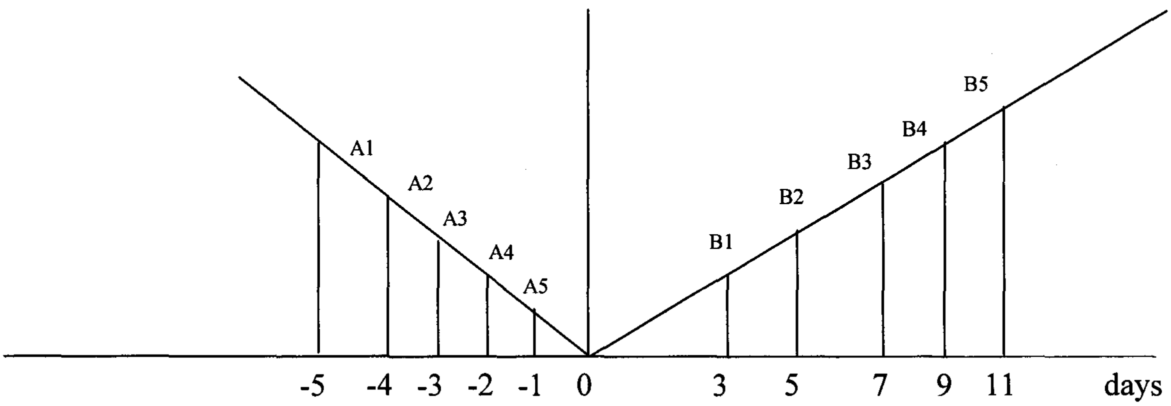

Figure 2-2: Forecast revision dates surrounding the forecast revision of a follower

Contrast to the Figure 2-1, the pattern of forecast release dates for a follower analyst is illustrated in Figure 2-2. We can see that the five forecast revisions precede analyst's forecast with a cumulative total of 3 days, whereas the forecasts follow the forecast of analyst *j* by a cumulative total of 10 days. The LFR ratio is 0.3333. The relatively long period of inactivity following the release of analyst *j*'s forecast revision suggests that other analysts do not believe that the new information revealed by analyst *j*'s forecast revision is sufficient to justify updating their own forecasts.

In our project, for each firm and fiscal year, we identify the leaders and followers based on the relative LFR. But, it results that there is no leader for some firms and too many leaders for other firms. Thus, we identify the leaders by combining the 10% significance level of LFR and the quartile of the number of analysts following the same stocks (Brown, 2001). Table 2-1 shows the quartile of the number of analysts in our sample. We identify one leader (with the highest LFR) for firms with analyst-following ranging from two to five, two leaders for analyst-following ranging from six to eight, three leaders for analyst-following ranging from nine to twelve, and so on. The maximum number of analysts identified as leaders for a firm is 6 (set arbitrarily). By this way, on average, 13.68% of analysts are classified as leaders for each firm over our sample period. 28.10% of analysts are leaders for each firm in a given year. The number and the percentage of leaders and followers in each year are reported in Table 2-2. On average, 31.73% of analysts are ranked as leaders for at least one firm they worked for in a given year. Table 2-3 presents the detail percentage for each given year. We also found that 10.87% of leaders are classified as leaders in the subsequent year. But, only 4.60% of analysts are leaders during three consecutive years. The detail results are in the Table 2-4. We also can see the empirical distribution of the leader- follower ratios for Technology industry in Figure2-3, in which the leader-follower ratios start with a bin at 0 and end with a bin at 15. The sample statistics are with an average LFR of 1.2957, a standard deviation of 1.096 and skewness of 3.234.

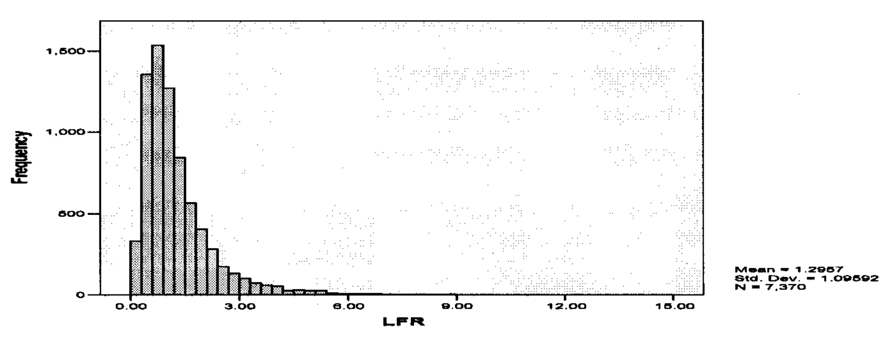

Figure 2-3: Histogram of firm-Specific leader-follower ratio

Table 2-1: Quartile of the number of analysts who follows the same stocks

Quantile	25%	50%	75%	100%
Estimate	5	8	12	27

Table 2-2: Result of classification for each firm in a given year

	Analyst Classification		
Year	**Overall**	**Leader**	**Follower**
1994	695	198 (28.49%)	497 (71.51%)
1995	742	212 (28.57%)	530 (71.43%)
1996	957	266 (27.80%)	691 (72.20%)
1997	1024	286 (27.93%)	738 (72.17%)
1998	947	261 (27.56%)	686 (72.44%)
1999	698	203 (29.58%)	495 (70.42%)
2000	635	177 (27.87%)	458 (72.13%)
2001	643	179 (27.84%)	464 (72.16%)
2002	532	147 (27.63%)	385 (72.37%)
2003	497	142 (28.57%)	355 (71.43%)
Total	7370	2071 (28.10%)	5299 (71.90%)

M-H chi-square test for trend of classification is 0.8129 (P = 0.994). There is no significant linear trend in proportions over year.

Table 2-3: leaders for at least one firm out of firms they cover in a given year

At least one firm leader	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
Technology %	43.01	41.56	45.74	39.41	37.07	38.77	34.80	34.60	34.19	35.33

Table 2-4: Time series leaders for each firm in a giver year

Firm Leader	1 years	2 years	3 years	4 years
Technology %	31.73	10.87	4.60	2.55

2.1 Measure of forecast accuracy

The forecast accuracy is an important measure of an analyst's quality. We use the percentage forecast error to measure each analyst's forecast accuracy (Butler, 1997). The percentage forecast error for analyst *i*'s forecast of earnings per share of firm *j* at date *t* is

$$PFE_{ijt} = (FE_{ijt} - AE_j) / |AE_j|$$

Where FE_{ijt} is the earnings forecast made by analyst *i* for firm *j* at date *t*, and AE_j is the actual earnings of firm *j* that are forecasted by the analyst. As we know, a good analyst must provide accurate earnings forecast on a timely basis. But, lead analysts may sacrifice accuracy for timeliness since they have the desire to generate high trading volume to maximize compensation. Some follower analysts can update their forecast after evaluating leader's information. Therefore, the forecasts of follower analysts may be more accurate than those of leaders. Thus, we test whether the earning forecasts of followers are more accurate than those of leaders.

We also define forecast bias as the signed forecast error, which is calculated as actual earnings minus the forecast. Since forecast accuracy and forecast bias are not directly comparable across firms and across fiscal years due to variation in the level and predictability of earnings, we standardize the ranks to scores according to the methodology in Hong et al. (2000) The absolute errors are ordered from highest to lowest, and the percentile ranking is used as a score. Suppose stock i at date t is followed by N_{it} analysts with outstanding forecasts of earnings per shares for the current fiscal year. If analyst $j's$ rank on absolute forecast error for the stock at that date is $R_{ijt} = 1,\ldots,N_{it}$, the analyst's score is

$$\rho_{ijt} = \frac{R_{ijt} - 1}{N_{ijt} - 1}.$$

We track each analyst's most recent outstanding forecasts as of six months before the end of the stock's fiscal year end, since the forecast horizon has sufficient uncertainty about future earnings to generate dispersion across analysts. The final result is that every result is assigned an indicator of forecast accuracy that lies between zero (the least accurate forecaster) and one (the most accurate forecaster). Similarly, for forecast bias, more optimistic forecasts receive higher scores. (Das, 2001)

Hypothesis 2: The earning forecasts of followers are more accurate than those of leaders over the estimation year and the subsequent year.

Table 2-5: Relative forecast accuracy of leaders and followers

Panel A : Half-year ahead earnings forecast errors and forecast bias:					
	Overall	**Leader**	**follower**	**T test**	**M-W test**
forecast accuracy:					
N	7,155	1998	5157		
Mean	0.493	0.486	0.512	-3.12***	-3.627***
Median	0.500	0.511	0.500		
Bias:					
Mean	0.494	0.490	0.494	0.52	-1.335
Median	0.500	0.500	0.500		

Panel B: One- Quarter ahead of earnings forecast errors and forecast bias					
	Overall	**Leader**	**follower**	**T test**	**M-W test**
forecast accuracy:					
N	3,992	1239	2753		
Mean	0.474	0.470	0.476	0.65	-2.567
Median	0.500	0.500	0.500		
% Bias:					
Mean	0.485	0.471	0.491	1.87*	-1.235
Median	0.500	0.500	0.500		

* Significant level at 0.1
** Significant level at 0.05
*** Significant level at 0.01

Table 2-5 reports the means and median of forecast errors and forecast bias of leaders and followers over the sample period. Panel A shows that the mean forecast accuracy score for half year ahead earnings forecasts for leaders are lower than that for followers. We use the T-test and nonparametric Mann-Whitney methods to test the difference in mean of forecast accuracy scores between leaders and followers at significant at 1% level. However, results in Panel B show that the differences in the mean and median forecast accuracy score for one-quarter ahead forecasts are not significant by using both T test and nonparametric Mann-Whitney methods. The result in Panel A is consistent with our hypothesis that the leaders will sacrifice accuracy to be the first mover in order to enlarge the trading volume. The result in Panel B indicates that the analysts earning forecasts are tend to be homogeneous as the end of the fiscal year approaches. Cooper et al. (2000) found that the leaders have higher positive bias in there forecasts than followers for both one-quarter and half-year ahead forecasts. But, in our sample, the difference in forecast bias between leaders and followers is not significant.

2.3 Boldness

We expect that lead analyst's earning forecast provide more information to investors when their earnings forecasts differ significantly from the consensus of the other analysts. The incremental information content for analysts' forecasts can be estimated by boldness or forecast surprise. Empirical studies (Stickel, 1990, and Leone and Wu, 2002) define the boldness as the absolute value of the difference between a particular forecast and the outstanding consensus forecast, which is the mean of all outstanding forecasts issued prior to the forecast being evaluated. In order to mitigate the effects of stale forecasts on the consensus, we eliminate all forecasts that have been outstanding for longer than 100 days as of six months prior to the fiscal year end. Similar to forecast accuracy and forecast bias, within each firm and fiscal year, boldness is converted to scores from 0 to 1 with the large deviation receiving higher scores. Our measure of consensus is based on the forecasts issued previously which is different from that in Hong et al. (2000) Here, the null hypothesis we want to test is whether the boldness of leader's earning forecasts are larger than that of followers.

Hypothesis 3: A higher percentage of forecasts of leaders derivate from the consensus forecast compared to those of follower analysis.

Table 2-6: Boldness of leaders and followers

Absolute Consensus Surprise	Overall	Leader	Follow	T-test	M-W test
N	7149	2021	5128		
Mean	0.4954	0.5225	0.4847	-5.44***	-5.758***
Median	0.5000	0.5294	0.4808		

The result in Table 2-6 suggests that the leaders are bolder than the followers. The mean of boldness for leaders is 0.5225 compared to 0.4847 for followers and the difference in boldness score between leaders and followers is significant at 1% level by using T-test and Mann-Whitney method. Boldness can be regard as a proxy for herding behavior among analysts. Herding is defined as ignoring their private information and mimicking the behavior of their predecessors. Later, we will calculate the forecast surprise at there benchmarks to examine whether the leaders have more impact on stock market. The definition of forecast surprise is similar to the boldness.

2.4 Forecast Frequency

For each firm and fiscal year with at least three analysts following, all forecasts issued more than 180 days prior to the fiscal year end. Relative forecast frequency for an analyst is defined as the number of forecasts issued by that analyst minus the average number of forecasts issued by all other analysts for the same analyst and each year. Leaders always are the first mover. It doesn't mean the leaders release more earning forecasts than followers. We also use T-test and Mann-Whitney procedure to test the null hypothesis.

Hypothesis 4: Leaders release earnings forecasts more frequently than the followers.

Table 2-7: Relative forecast frequency of leaders and followers

Frequency	Overall	Leader	Follower	T-test	M-W test
N	7312	2068	5244		
Mean	1.131	1.119	1.136	1.03**	-9.55*
Median	0.882	0.879	0.882		

The result from Table 2-7 indicates that the relative forecast frequency for leaders is significantly lower than for followers. This result is opposite to what we expect that the leaders are more active than followers. Lead analysts spend time to get the new information and release valuable forecast, but, follow analysts usually response quickly with the other's earning forecasts and release more forecasts.

2.5 Other characteristics of leaders and followers

We also test the difference in other characteristics of leaders and followers, such as the stock coverage, working experience and the size of the brokerage firm that the analysts are employed. We examine whether the lead analysts work in large brokerage, have more experience, and cover few stocks.

Stock coverage is defined as the number of stocks that an analyst issues earnings forecasts for in a given year. Table 2-8 examines the extent of coverage of firms by analysts. There are two perspectives. Panel A reports the distribution of firm in terms of how many analysts follow a stock, Panel B considers how many firms an analyst covers.

Brokerage size is referred to the number of analysts in brokerage firm that the analyst is employed. We examine whether the leaders are likely to be employed by a large brokerage house.

Experience is related to the expertise level and specialization. More experienced and more specialized analysts presumably should be able to produce more accurate forecast. It is measured by overall business experience (the number of years the analyst appears on the I/B/E/S data) and the number of years' experience forecasting the particular firm. For each analyst, we calculate two measures of experience. Business experience is the number of years between the analyst's first estimate records on the file to the same analyst's last recorded estimate. Firm experience is the number of years from the analyst's first estimate for a given firm and the same analyst's last estimate for the same firm. Table 2-9 reports the distribution of analysts by experience.

Statistics in Table 2-8 are reported for calendar year 2001 on the distribution of firms with respect to the number of analysts with outstanding forecasts and the distribution of analysts with respect to the number of stocks covered. In Panel A, 29.19 percent of the firms covered on the I/B/E/S database are followed by two or one analysts. The median of the firms is covered by 5 analysts. In Panel B, we can see most of analysts cover multiple stocks within the technology industry. The median of the stock coverage is roughly 3. 16.38 percent of the analysts cover more than 10 stocks and 29.40 percent of analysts just concentrate on a single stock.

Table 2-9 reports the distribution of experience level of analysts. Panel A is the overall business experience which is defined as the length of time the analyst appear on the I/B/E/S file. We can see that more than 25 percent of analysts have more than 8 years business experience. On the other hand about 17 percent of analysts just come into this field. The median year of the business experience is 5. Panel B shows an analyst's experience covering a given firm. The specified firm experience is obviously shorter than the business year. More than 60% of analysts only have worked two or a few years for a given firm. Closer to 10% percent of analysts have more than five years firm experience.

We also use T-test to test the difference in means of variables and use nonparametric Mann-Whitney method to examine whether leaders are likely to be employed by a larger brokerage house, have more experience, and follow fewer stocks.

Table 2-8: The distribution of analysts with respect to the number of stocks covered and the distribution of firms with respect to the number of analysts with outstanding forecasts

Panel A: firms by analyst coverage			**Panel B: analysts by firm coverage**		
Firm Coverage	Percent of analyst	Cumulative percent	Analyst Coverage	Percent of firms	Cumulative percent
1	29.40	29.40	1	19.43	19.43
2	14.87	44.27	2	9.77	29.19
3	8.59	52.86	3	8.07	37.26
4	6.28	59.15	4	9.02	46.28
5	5.18	64.32	5	6.79	53.08
6	4.52	68.84	6	6.48	59.55
7	4.97	73.82	7	5.10	64.65
8	3.92	77.74	8	3.61	68.26
9	3.22	80.95	9	3.50	71.76
10	2.66	83.62	10	3.93	75.69
11-15	10.7	94.32	11-15	11.33	87.02
16-20	4.07	98.39	16-20	5.95	92.97
21-25	1.3	99.69	21-25	3.39	96.36
26-30	0.25	99.94	26-30	1.70	98.06
>30	0.06	100.0	>30	1.94	100.0

Table 2-9: Distribution of working experience of analysts

Panel A: Business experience			**Panel B: Firm experience**		
Business Experience	Percent of analysts	Cumulative percent	Firm Experience	Percent of analysts	Cumulative percent
1	17.37	17.37	1	35.64	35.64
2	14.28	31.65	2	28.40	64.04
3	10.52	42.18	3	14.59	78.62
4	9.37	51.54	4	8.17	86.79
5	7.23	58.78	5	4.62	91.40
6	7.18	65.95	6	2.57	93.98
7	7.46	73.42	7	1.87	95.85
8	4.94	78.36	8	1.17	97.02
9	3.73	82.09	9	0.74	97.76
10	3.27	85.36	10	0.59	98.35
11	2.75	88.11	11	0.45	97.02
12	2.01	90.12	12	0.28	97.76
13	1.65	91.77	13	0.21	98.35
14	1.39	93.15	14	0.16	98.80
>15	6.85	100.0	>15	1.20	100.0

Results in Table 2-10 show that the mean of the brokerage firm size for leaders is larger than that for followers. The result is same as the one obtained by Womack. (1996) The analysts employed in large brokerage firms have more privilege to get the information. We also found that the leaders work a fewer stocks than followers. The means of firm specific experience and business for leaders are significantly higher than those for followers and the difference in experience between leaders and followers is significant by using both T-test and non-parametric Mann-Whitney test.

Table 2-10: Other attributes of leaders and followers

	Overall	Leader	follower	T test	M-W test
Brokerage size					
N	7,370	2127	5243		
Mean	16.94	17.47	16.75	-2.16**	-2.468**
Median	14.00	15.00	14.00		
Stock Coverage					
N	7370	2071	5299		
Mean	4.408	2.393	2.447	1.16*	-1.497*
Median	2.000	2.000	2.000		
Firm-Specific Experience					
N	7,370	2071	5299		
Mean	4.715	4.79	4.68	1.2**	-1.463*
Median	4.000	4.00	4.00		
Business Experience					
N	7,370	2071	5299		
Mean	8.036	8.18	7.98	-1.45*	-1.437*
Median	7.000	7.00	7.00		

Chapter

3. Linear Discriminant Analysis and Logistic Regression Model

3.1 Linear Discriminant Analysis

3.1.1 Introduction

Linear discriminant analysis (LDA), introduced by Fisher (Srivastava, 2003), is one of the first statistical classification methods. It is a statistical technique often used to examine whether two or more mutually exclusive groups can be distinguished from each other based on linear contribute to the separation. Mutually exclusive means that a case can belong to only one group. Suppose we have a response variable y which can be taken values $0,\ldots,c-1$ to assign an object to one of c classes. We also have d explanatory variables or features,

$$X = (x_1,\ldots,x_d),$$

describing each subject. Here, d is the dimensionality of the explanatory variable space. Suppose we have data on the explanatory variables x and the class identities for n cases. We denote that the n vectors of explanatory variables by $x^{(1)},\ldots,x^{(n)}$, so that $x_j^{(i)}$ is the value of explanatory variable j for case ($i = 1,\ldots,n; j = 1,\ldots,d$). Let $y_1,\ldots,y_n$ be the corresponding class identities.

n_k is known to belong to class k. We can compute various summary statistics. Let $\overline{X}^{(k)} = (\overline{x}_1^{(k)},\ldots,\overline{x}_d^{(k)})^T$ be the d dimensional vector of sample means over the n_k cases in class k, i.e., $\overline{x}_j^{(k)} = \frac{1}{n_k}\sum_{i=1}^{n_k} x_j^{(i)}$. Similarly, let $S^{(k)}$ be the $d \times d$ sample covariance

for $X = (x_1,\ldots,x_d)^T$,

which is computed from the cases in class k. Element $j,\ j'$ of $S^{(k)}$ involves explanatory variables j and j' and is given by

$$S_{jj'}^{(k)} = \frac{1}{n_k - 1}\sum_{i=1}^{n_k}(x_j^{(i)} - \overline{x}_j{}^{(k)})(x_{j'}{}^{(i)} - x_{j'}{}^{(k)}) \qquad (j = 1,\ldots,d; j' = 1,\ldots,d).$$

LDA is particularly easy to understand when there are just two classes. With two classes, Fisher's discriminant function (DF) is a single linear combination of the d explanatory variables x. The coefficients of the DF are chosen so that the DF values are separated between the two classes as much as possible. If good separation can be obtained, the DF will likely be a good classifier for new objects with unknown membership.

3.1.2 The Variance between Classes relative to within classes

The DF is a linear combination of $x_1,\ldots,x_d$, $w_1x_1+\ldots+w_dx_d$. The problem is to estimate the d-dimensional vector of coefficients or weights $W = (w_1,\ldots\ldots,w_d)^T$ for best separation of the two classes of objects. Suppose the n_k cases known to be in class k are a random sample from the population of class k objects. Under random sampling, the values of the explanatory variables and hence the DF are random variables. We write the DF as

$$D = w_1 x_1 + \ldots + w_d x_d.$$

This is analogous to multiple regression, but the w's are discriminant coefficients which maximize the distance between the means of the dependent variable. The distribution of $X_1, \ldots, X_d$ and hence D will hopefully be different for the two classes; otherwise, there will be no information in the explanatory variable for classification. We will allow the means of $X_1, \ldots, X_d$ to vary between the two classes. As another assumption, we assume that the population covariance matrix for $X_1, \ldots, X_d$ is the same for both classes. We could write the distribution of $X_1, \ldots, X_d$ conditional on class k as

$$X_1, \ldots, X_d | k \sim (\mu^{(k)}, \sum) \quad (k = 0,\ 1),$$

where $\mu^{(k)}$ is a d dimensional vector of population means for class k, and $\sum$ is the $d \times d$ population covariance matrix. Ultimately we will predict the class membership given explanatory variable information.

Now, let's consider the statistical properties of the D distributions. Since D is a linear combination, we can use results on the means and variances of linear combinations of random variables. Conditional on belonging to class k, the means of the D distribution is

$$E(D|Class\ k) = E(W^T X|Class\ k) = W^T E(X|Class\ k) = W^T \mu^{(k)}.$$

Similarly, the variance of D is

$$Var(D) = Var(W^T X) = W^T \sum W.$$

Since the covariance of $X_1,\ldots,X_d$ are the same across classes, this variance doesn't depend on the class. A good DF is given by a set of weights with good separation between the D means for

the two classes. The difference in means is $W^T\mu^{(0)} - W^T\mu^{(1)}$. The estimate of the difference obviously is

$$W^T\overline{X}^{(0)} - W^T\overline{X}^{(1)} = W^T(\overline{X}^{(0)} - \overline{X}^{(1)}),$$

where $\overline{X}^{(k)}$ is a random vector representing possible values of $\overline{x}^{(k)}$. This estimator has variance

$$(\frac{1}{n_0}+\frac{1}{n_1})W^T\sum W.$$

We can estimate $\sum$ by pooling the two class sample covariance matrices, $S^{(0)}$ and $S^{(1)}$:

$$S = \frac{(n_0-1)S^{(0)} + (n_1-1)S^{(1)}}{n_0+n_1-2}$$

Thus, a t-like ratio for comparing the two D means is

$$t = \frac{W^T(\overline{X}^{(0)} - \overline{X}^{(1)})}{\sqrt{(\frac{1}{n_0}+\frac{1}{n_1})W^TSW}} = \sqrt{\frac{n_0n_1}{n_0+n_1}}\frac{W^T(\overline{X}^{(0)} - \overline{X}^{(1)})}{\sqrt{W^TSW}}$$

We say "t-like" because we have not made an assumption of Gaussian distributions for $X_1,\ldots,X_d$. We choose W to make this t ratio as large as possible in absolute value. Equivalently, and for ease, we will square instead of taking the absolute value. The part of t^2 that depends on W is

$$\frac{[W^T(\overline{X}^{(0)} - \overline{X}^{(1)})]^2}{W^T SW} = \frac{W^T(\overline{X}^{(0)} - \overline{X}^{(1)})(\overline{X}^{(0)} - \overline{X}^{(1)})^T W}{W^T SW}.$$

This is a ratio of two positive definite quadratic forms. The numerator quadratic form involves a measure of the variability between the classes, while the denominator involves the within-class variability. Thus, maximizing the ratio maximizes the ratio of between-class to within-class variation. The optimizing W is

$$W \propto S^{-1}(\overline{X}^{(0)} - \overline{X}^{(1)})$$

Finally, we see that Fisher's DF is given by

$$W^T X = (\overline{X}^{(0)} - \overline{X}^{(1)})^T S^{-1} X.$$

To classify a new case with explanatory variables X, we compute its score

$$w_1 x_1 + \ldots w_d x_d = W^T X,$$

using the optimal weights W. It is classified as Class 0 or Class 1 depending on whether $W^T X$ is close to $W^T \overline{X}^{(0)}$ or $W^T \overline{X}^{(1)}$. (Srivastava, 2003)

3.2 Linear Discriminant Analysis for Securities Analysts Data

How do lead analysts differ from the follower analysts? Forecast accuracy? Boldness? Brokerage firm size? Stock coverage? Analysts experience? Timeliness leaders and followers play different informational roles in capital market. We will examine whether timeliness analysts related to the forecast accuracy and boldness. We also want to know whether the analysts' forecast frequency, stock coverage, brokerage firm size and analysts' experience capture the level of analysts' ability, which is likely to be correlated with the timeliness classification. The following, I will present the detailed description for Linear Discriminant Analysis.

Variable specification:

Dependent variables: dummy variables (0, 1) represent timeliness followers and leaders. Leaders and followers are classified based on the LFR measures for each analyst for each firm during a given year.

Explanatory variables:

Forecast accuracy and forecast bias: Forecast accuracy (ACCUSCORE) and forecast bias (BIASSCORE) are calculated as we showed in chapter 2.

Brokerage size: We use two dummy variables to define a larger brokerage house. The first dummy variable takes the value of one if the brokerage house employs 25 or more analysts in a given year and zero otherwise (LARGEBRKR); the second dummy variable takes the value of one if the brokerage house employs at most 5 and zero otherwise (SMALLBRKR). If an analyst works for several brokerage firms, we just pick up the largest one that the analyst works for.

Stock coverage: We use COVER to represent the number of stocks that an analyst issues earnings forecasts for in a given year.

Relative forecast frequency: We use RFREQ to represent the relative forecast frequency for each firm and fiscal year.

Experience: The analyst's expertise is proxied by experience level, measured by the number of years' experience forecasting the particular firm (BUSYEAR). We classify the experience as three levels. The variable FEXP takes on the value of 3 for business years above 10, 2 for business years from3 to 9, and 1 for business years less than two years. We classify them according to the quartile of the firm experience. 25% of the cases are 2 or less, 50% are between 3 and 9, and 25% are 10 or more.

Following analysts: We use NUMANALYST to represent the number of analysts who are following the same stock.

Forecast boldness: we follow similar procedures as in ACCUSCORE and BIASSCORE. We retained all forecasts issued six months before fiscal year end. Boldness is calculated as the absolute value of the difference between a particular forecast and the outstanding consensus forecast. In our model, the consensus forecast is constructed over the preceding 30 days. Similar to ACCUSCORE and BIASSCORE, boldness is ranked within each firm and fiscal year, and converted to scores from 0 to 1 with the large deviation receiving higher scores. We use variable BDSCORE to represent forecast boldness.

3.2.1 Summary statistics

Table 3-1 reports descriptive statistics for the overall sample of leaders and followers over the period from 1993 to 2003. We construct 7431 analyst-year observations from the I/B/E/S database. 2097 or 28.22% are ranked leaders. The mean for both forecast accuracy (ACCUSCORE), forecast bias (BIASSCORE) and boldness (BDSCORE) are very closer to

0.50 because these variables have been converted to rank scores. The leader-follower ratio (LFR) has a mean of 1.304 for overall, 2.275 for leaders and 0.922 for followers. This variable is right skewed because it can take on large values when an analyst's forecast is preceded by other forecasts by many days. The mean years of experience (BUSYEAR) for analysts in our sample are 4.71 and for leaders are 4.79 and for followers are 4.68. The dummy variable for working experience (EXPR) has a mean of 1.769 in overall sample. The mean of leaders is 1.7927 and the mean of followers is 1.7598. The mean brokerage size of overall sample is 16.94 and for leaders is 17.44 and for followers is 16.74.

In Table A 1 in Appendix we report the pooled within-groups matrix which is obtained by averaging the separate covariate matrices for leaders and followers samples and then computing the correlation matrix from the pooled-covariance matrix. The pooled-covariance is showed in Table A 2 in Appendix. From the correlation matrix, we can see that the predictor variables are remarkably uncorrelated, with the exception of some expected correlations, such as those between forecast accuracy and forecast bias and small brokerage size and larger small brokerage size.

Table 3-1: Summary Statistics

Variables	Mean			Std. Deviation		
	Overall	Leader	Follower	Overall	Leader	Follower
# of analysts	7431	5334	2097			
BROKERSIZE	16.9384	17.4392	16.7415	12.91701	12.9315	12.90726
LARGEBRKR	.2426	.2521	.2389	.42869	.43435	.42642
SMALLBRKR	.2186	.1987	.2264	.41329	.39911	.41852
BUSYEAR	4.7149	4.7927	4.6842	3.63757	3.65032	3.63245
NUMANAYST	9.2213	9.0156	9.3021	5.37532	5.21575	5.43514
ASSUSCORE	.4933	.5106	.4865	.31474	.27642	.32836
BIASSCORE	.4935	.4903	.4947	.31840	.28242	.33150
RFREQ	1.1311	1.1191	1.1358	.60976	.59796	.61433
BDSCORE	.4963	.5244	.4852	.26582	.26258	.26630
EXPR	1.7691	1.7927	1.7598	.63575	.63604	.63546
LFR	1.3037	2.2749	.9220	1.09928	1.42953	.60327
COVER	2.4079	2.3444	2.4329	1.75314	1.68746	1.77783

3.2.2 Discriminant Function

In order to find a linear combination of values of the variables that best separates the leaders from the followers, we will compute the coefficients of the discriminant function.

The standardized discriminant function coefficients shown in Table 3-4 are the coefficients we get when all predicators variables are standardized to a mean of 0 and a within-groups standard deviation of 1. In Table 3-4, variables such as large brokerage, forecast accuracy, boldness and working experience have the same sign, and the small brokerage, stock coverage, the number of analyst following, forecast frequency and forecast bias have the opposite sign. That means that larger brokerages, more forecast accuracy, larger boldness and many years working experience result in large values for the discriminant score. Milkhail and

Walther (1997) also proved that security Analysts improve their performance with experience. We will see that high scores are associated with leaders and low scores are associated with followers.

Table 3-2: Standardized Canonical Discriminant Function Coefficients

Predictors	Function	
	Coefficient	1
LARGEBRKR	+	.045
SMALLBRKR	-	-.302
COVER	-	-.288
NUMANALYST	-	-.290
RFREQ	-	-.195
ACCUSCORE	+	.426
BIASSCORE	-	-.223
BDSCORE	+	.660
EXPR	+	.353

Table 3-3: Classification Coefficients of Fisher's linear discriminant functions

	Rank	
	Follower	**Leader**
LARGEBRKR	2.751	2.774
SMALLBRKR	1.931	1.771
COVER	.424	.388
EXPR	3.647	3.769
BDSCORE	6.382	6.926
BIASSCORE	3.576	3.420
ACCUSCORE	3.136	3.436
RFREQ	2.870	2.804
NUMANALYST	.267	.255
(Constant)	-10.730	-11.932

Table 3-5 presents each weight of variables for leaders and followers. We easily find that the coefficients of ACCUSCORE, BDSCORE, EXPR and LARGEBRKR for leaders are larger than those for followers. The coefficients of SMALLBRKR, RFREQ, NUMANLAYST, and COVER for leaders are smaller than those for followers.

Table 3-4: Structure Matrix

	Function
	1
BDSCORE	.691
ACCUSCORE	.366
SMALLBRKR	-.319
EXPR	.256
NUMANALYT	-.256
COVER	-.246
RFREQ	-.174
LARGEBRKR	.156
BIASSSCORE	-.069

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions variables are ordered by absolute size of correlation within function.

Table 3-6 is the Structure Matrix that can be used to assess the contribution of a variable to the discriminant score. The variables are sorted based on the absolute values of the correlation coefficients. We can see that the boldness has the highest correlation with the discriminant score and the forecast bias has the smallest correlation coefficient. The results suggest that the contribution of the boldness score is greatest to the discrimination between leaders and followers and the contribution of the forecast bias is smallest to the discrimination between leaders and followers. The order of variables which contribute to the discrimination is BDSCORE, ACCUSCORE, SMALLBRKR, EXPR, NUMANALYST, COVER, RFREQ, LARGEBRKR and BIASSCORE. The result is consistent with the univariate analysis for the forecast boldness and forecast bias.

3.2.3 Testing Equality of Discriminant Function Means

The test of the null hypothesis of equity of discriminant function means is based on the Wilk's lambda, which is the ratio of the within-groups sum of squares to the total sum of squares,

$$\Lambda = \left| \frac{S_{wg}}{S_{bg} + S_{wg}} \right| .$$

The analysis-of–variance table is shown in Table 3-6.

In Table 3-7, we can see that there exist significant differences in the mean of most of variables except for forecast bias, relative forecast frequency and large brokerage size based on the value of Wilks' lambda.

From Table 3-8, we can reject the null hypothesis that leaders and followers have the same average discriminant function score in population, with the F value 71.657, which is significant at 1% level.

Table 3-5: Tests of Equality of Group Means

	Wilks' Lambda	F	df1	Df2	Sig.
LARGEBRKR	1.000	1.743	1	7431	.187
SMALLBRKR	.899	7.290	1	7431	.007
COVER	.939	4.323	1	7431	.038
EXPR	.929	4.706	1	7431	.030
BDSCORE	.895	34.176	1	7431	.000
BIASSCORE	1.000	.346	1	7431	.557
ACCUSCORE	.912	9.586	1	7431	.002
RFREQ	1.000	2.165	1	7431	.141
NUMANALYST	.927	4.693	1	7431	.030

Table 3-6: Discriminant Scores from Function 1 for Analysis

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	71.657	1	71.657	71.657	.000
Within Groups	7431.000	7431	1.000		
Total	7502.657	7432			

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3.3 Logistic Regression Analysis

3.3.1 Introduction

We have a response variable y that indexes an object's class. We also have d explanatory variables or features,

$$X = (X_1, \ldots, X_d)^T,$$

describing each object or case. In logistic regression, we model the probabilities of belonging to various classes given explanatory variable information. With only $c = 2$ classes, all we need to do is model the probability of belonging to Class 1, since the probability of belonging to Class 0 is just the complement. Corresponding to y, there is a binary-valued random Y representing the distribution of the possible values (0 and 1) of y. We say that Y is Bernoulli random variables, which is just a special case of a binomial random variable with one trial.

Thus, we will be modeling the conditional probability

$$p(X) \equiv p(Y = 1 \mid X).$$

Unlike a discriminant function, this probability has direct interpretation and can often be immediately applied to an operational objective. In our research, if $y = 1$ signifies a leader analyst, the probability $p(Y = 1 \mid X)$ leads fairly quickly to a decision on whether or not that the analyst is a leader with explanatory variables x. Note also that we are obtaining the conditional probability we want, without resorting to Bayes rule and prior probabilities. Specifically, a logistic regression model has the form

$$\log\left(\frac{p(x)}{1 - p(x)}\right) = \eta(x).$$

On the left-hand side we have a logistic transformation of the probability $p(x)$. On the right-hand side, $\eta(x)$ is a function describing systematic dependence on the explanatory variables. Often, $\eta(x)$ is a linear predictor, that is

$$\eta(x) = \beta_0 + \beta_1 x_1 + \ldots \beta_d x_{d,}$$

where $\beta_{0,}\beta_{1,}\ldots,\beta_d$ are unknown parameters to be estimated. We can rewrite the logistic model as

$$p(x) \equiv p(Y=1|x) = \frac{\exp[\eta(x)]}{1+\exp[\eta(x)]}$$

Clearly, the complementary probability (of belonging to Class 2) is

$$p(Y=0|X) = \frac{1}{1+\exp[\eta(x)]}.$$

We can summarize the above as

$$p(Y=y|x) = \left(\frac{\exp[\eta(x)]}{1+\exp[\eta(x)]}\right)^y \left(\frac{1}{1+\exp[\eta(x)]}\right)^{1-y} \qquad (y=0,\ 1).$$

In the situation where some of the independent variables are discrete or nominal scale, we need to use a collection of design variables (or dummy variables). In general, if a nominal scaled variable has k possible values, then k-1 design variables will be needed. Suppose that the j^{th} independent variable x_j has k_j levels. The $k_j - 1$ design variables will be denoted as D_{jl} and the coefficients for these design variables will be denoted as β_{jl}, $l = 1,2,\ldots,k_j$ -1. The logit for a model with p variables and the j^{th} variable being discrete is

$$\eta(x) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \sum_{l=1}^{k_j - 1} \beta_{jl} D_{jl} + \cdots + \beta_p x_p$$

(Hosmer & Lemeshow, 2000)

3.3.2 Estimation of coefficients for logistic regression model

Suppose we have n cases. We know their classes, $y_1,\ldots,y_n$, and their explanatory variable vectors, $X^{(1)},\ldots,X^{(n)}$. The random variables $Y_1,\ldots,Y_n$ represent the values of $y_1,\ldots,y_n$ that could have arisen under a statistical model. We model $p(X^{(i)}) \equiv p(Y_i = 1 \mid X^{(i)})$ as

$$p(X^{(i)}) = \frac{\exp[\eta(X^{(i)})]}{1+\exp[\eta(X^{(i)})]} \quad (i = 1,\ldots,n).$$

We further assume that $Y_1,\ldots,Y_n$ are independent. These assumptions completely specify the joint distribution of $Y_1,\ldots,Y_n$. Generally, the unknown parameters in $\eta(X) \to \beta_0,\beta_1,\ldots,\beta_{jl},\ldots,\beta_d$ are estimated via maximum likelihood. From the above formulas and the assumption of independence of $Y_1,\ldots,Y_n$, the likelihood is

$$L(y_1,\ldots,y_n;\beta_0,\beta_1\ldots\beta_{jl},\ldots,\beta_d) = \prod_{i=1}^{n}\left(\frac{\exp[\eta(X^{(i)})]}{1+\exp[\eta(X^{(i)})]}\right)^{y_i}\left(\frac{1}{1+\exp[\eta(X^{(i)})]}\right)^{1-y_i}$$

In principle, what we have to do is maximize this with respect to $\beta_0, \beta_1,\ldots,\beta_{jl},\ldots,\beta_d$. Using software, we can get the solutions of the maximum likelihood equations.

3.3.3 Confidence interval of coefficients for logistic regression model

Statistical inference for one model parameter typically involves either a confidence interval, a hypothesis test, or a confidence interval for the estimated odds ratio. A confidence interval for β_i is:

$$\hat{\beta}_i \pm Z^* se(\hat{\beta}_i),$$

where Z^* is the appropriate multiplier from the standard normal distribution. Confidence intervals whose endpoints do not contain zero indicate a relationship between the predictor X_i and the response after adjusting for any other predictor variables in the model. Confidence bounds containing zero do not show significant evidence of a relationship between the predictor and response. A hypothesis test of $H_0 : \beta_i = \delta$ vs $H_a : \beta_i \neq \delta$ uses the standard normal test statistic,

$$Z = \frac{\hat{\beta}_i - \delta}{se(\hat{\beta}_i)}.$$

when $\delta = 0$, this test statistic and p-value are typically given in all statistical packages, and should correspond to the inference that would be made if a confidence interval was computed. When this test gives a small p-value, it will correspond to a confidence interval for β_i that does not contain zero or δ.

3.3.4 Residual Checking for logistic regression model

There are two main types of residuals: Pearson and Deviance. The Pearson residual is defined as,

$$e_i = \frac{(y_i - \hat{y}_i)}{sd_i},$$

where sd_i is the estimated standard deviation of the response. This residual will be positive when the event $y_i = 1$ occurs but the predicted probability of this event is lower. Likewise, the residual will be negative if the event did not occur, but the probability was higher that it would occur. These residuals can be viewed on roughly a standard normal scale -3 to $+3$. Deviance residuals are used in a similar fashion. Let $l(y;\hat{\beta})$ denote the log likelihood for a fitted model with maximum likelihood estimates $\hat{\beta}$, and let $l_{\max}$ denote the maximum possible log likelihood. The deviance for the fitted model is defined to be

$$D(y;\hat{\beta}) = 2[l_{\max} - l(y;\hat{\beta})].$$

Like the residual sum of squares, small deviances indicate a better fit between the data ad the fitted values. The deviance, $D(y;\hat{\beta})$, is often compared with a χ^2_{n-m} distribution, where n is the number of cases in the data and m is the number of fitted model parameters. In particular, a large value of D doesn't always indicate a poor model. The SAS options **influence** or **iplots** will produce summaries of the deviance or Pearson residuals.

3.4 Fitting logistic regression model for Securities Analysts Data

3.4.1 Fitting logistic regression model

Coefficient correlation

In Table A 3 in Appendix, we report correlation coefficients for the main variables with Pearson (Spearman) coefficients on the upper (lower) diagonal. Several correlations are worth nothing. ACCU scores BOLD scores are positively correlated supporting the contention that analysts make bold forecasts when they have better information rather than gamble. Analysts at larger brokerage firm (LARGEBRKR) issue more accurate and more bias forecasts but less bold forecasts. The significant positive correlation between the working experiences (EXPR) and small brokerage firm, the number of analysts following, forecast frequency, and bold forecasts implies that analysts with more years experience tend to make bold forecasts and release more forecasts, as well as work in small brokerage firm and pay attention to the stocks more analysts are interested in.

Fitted model

The estimated logistic regression model will be

$$LogP(Y = D) = \alpha + \beta_1 * ACCUSCORE + \beta_2 * BIASSCORE + \beta_3 * BOLDSCORE + \beta_4 * RFREQ$$
$$+ \beta_5 * COVER + \sum_{K=1}^{2} \beta_K * SMALLBRKR + \sum_{K=1}^{2} \beta_K * LARGEBRKR + \beta_8 NUMANALYST + \sum_{k=1}^{3} \beta_k * FEXP$$

The results of a multivariate logistic regression analysis in Table 3-10 show that the probability of being a leader is positively associated with the large brokerage firm to which the analyst belongs, the firm specific working experience, forecast accuracy and forecast boldness, but negatively associated with the number of firms followed by an analyst and the frequency of forecasts for a firm issued by an analyst during a year. The coefficients on BOLDSCORE and ACCUSCORE are positive and significant, suggesting analysts that are bolder or more accuracy are more likely to become a leader. The result from the coefficient ACCUSCORE is not consistent with the univariate analysis in chapter 2, in which the ACCUSCORE of lead analyst is significantly larger than that of follow analyst. When more explanatory variables add in the model, the effect of ACCUSCORE has changed that the lead analysts tend to release more accurate earnings forecast. The coefficient on EXPR is positive and significant at 1% level. Older analysts are more likely to become leaders than younger analysts. The skills required to become leaders are likely to be learned from the career. We can say that the analysts become better over time, rather than that the leader analysts likely come to the job with more talent than other analysts. The results are different from those obtained by Leone, and Wu (2002) that the coefficient on EXPR is negative and significant at 1% level, which indicate that the skills required to become leaders are not likely learned on the job but rather innate talent that these analysts bring to the job.

Interestingly, the coefficients on stock coverage and the number of analysts followed by a firm are negative and significant; indicating the likelihood of being ranked as leaders is decreasing if the analysts work on too many stocks or popular stocks. Stock coverage during a year is significantly higher for leaders relative to followers in the univariate analysis, but the sign switches when other explanatory variables are added in the multivariate analysis. The coefficients on forecast bias and forecast frequency are not significant in the multivariate setting.

The odds ratio estimates for each variable are shown in column 6 in Table 3-10 and 95% Wald confidence Limits for each estimates are shown in column 7 and 8 in Table 3-10. The logistic equation can be written in term of odds as

$$\frac{prob(Leader)}{prob(Follower)} = e^{\beta_0+\beta_1 X_1+...+\beta_p X_p} = e^{\beta_0} e^{\beta_1 X_1} ... e^{\beta_p X_p}$$

If β_i is positive, the odds ratio is less than 1, which means that the odds of the analyst being ranked as a leader are increased. If β_i is negative, the odds ratio is less than 1, which means that the odds are decreased. If β_i is 0, the factor equals 1, and the odds are unchanged.

Table 3-7: Analysis of Maximum Likelihood Estimates

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odd Ratio	95% Wald Confidence Limits	
INTECEPT	-1.2182	0.1291	89.0212	<.0001			
COVER	-0.0372	0.0160	5.4334	0.0198	0.963	0.934	0.994
FREQ	-0.0645	0.0414	2.4272	0.1192	0.938	0.864	1.017
EXPR	0.1227	0.0423	8.4142	0.0037	1.131	1.041	1.228
BOLDNESS	0.5410	0.0983	30.3107	<.0001	1.718	1.417	2.083
NUMANALYST	-0.0119	0.00501	5.6637	0.0173	0.988	0.978	0.998
ACCU	0.3144	0.0995	9.9859	0.0016	1.369	1.127	1.664
BIAS	-0.1303	0.0977	1.7792	0.1822	0.878	0.725	1.063
SBRKR	-0.1653	0.0677	5.9708	0.0145	0.848	0.742	0.968
LBRKR	0.0218	0.0633	0.1188	0.0730	1.022	0.903	1.157

Hosmer and Lemeshow test: χ^2=14.137 on 8 d.f., and P =0.0483

3.4.2 Assessing the Fit of the Models

It is always important to examine the appropriateness of fitted models. Here we will use Hosmer-Lemeshow test.

Hosmer-Lemeshow Test

The null hypothesis for this test is that the model fits the data, and the alternative is that the model does not fit. The test statistic is constructed by first breaking the data set into roughly $g = 10$ groups. The groups are formed by ordering the existing data by the level of their predicted probabilities. So, the data are first ordered from least likely to have the event to most likely

for the event. Then g (often 10) roughly equal sized groups are formed. From each group the observed and expected number of events is computed for each group. The test statistic is

$$\hat{C} = \sum_{k=1}^{g} \frac{(O_k - E_k)^2}{\nu_k},$$

where O_k and E_k are the observed and expected number of events in the k_{th} group, and ν_k is a variance correction factor for the k_{th} group. If the observed number of events differs from what is expected by the model, the statistic $\hat{C}$ will be large and there will be evidence against the null hypothesis. This statistic has an approximate chi-squared distribution with $g-2$ degrees of freedom. This statistic is obtained in SAS with the **lackfit** option in the model statement.

In our logistic regression model, the corresponding p-values of coefficient estimation in Table 3-10 indicate that the logistic regression model seem to fit quite well. However, P-values of the Hosmer and Lemeshow test indicate some lack of fit in the logistic regression model.

Residual Checking

Pearson residual and Deviance residual are useful in identifying observations that are not explained well by the model. Figure 3-1 and Figure 3-2 show the selected residuals plotted against predicated mean response, although we emphasize that such plots are not particularly informative. Here we see two trends of decreasing residuals with slope close to -1. We conclude that the logistic regression model is acceptable even though there is some lack of fit as shown by the Hosmer-Lemeshow test.

Difference in deviance and difference in Pearson Chi-square are diagnostics for detecting ill-fitted observations; in other words, observations that contribute heavily to the disagreement between the data and the predicted values of the fitted model. Figure 3-3 and Figure 3-4 show one step difference in deviance and difference in Pearson Chi-square plotted against expected probability. These two residual plots provide some information for detecting outlier and influential data points. There are some points away from the curves, indicating these observations have the highest influence on the chi-square goodness of fit.

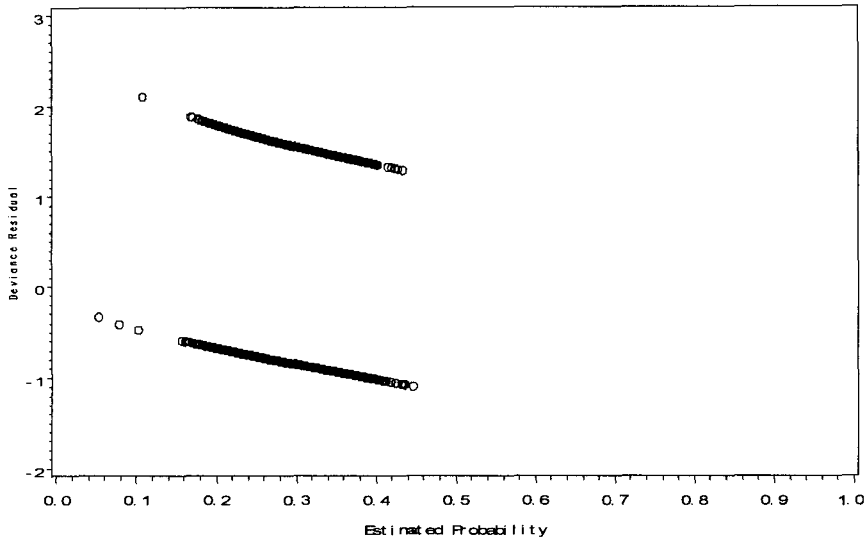

Figure 3-1: Deviance Residual versus Estimated Probability

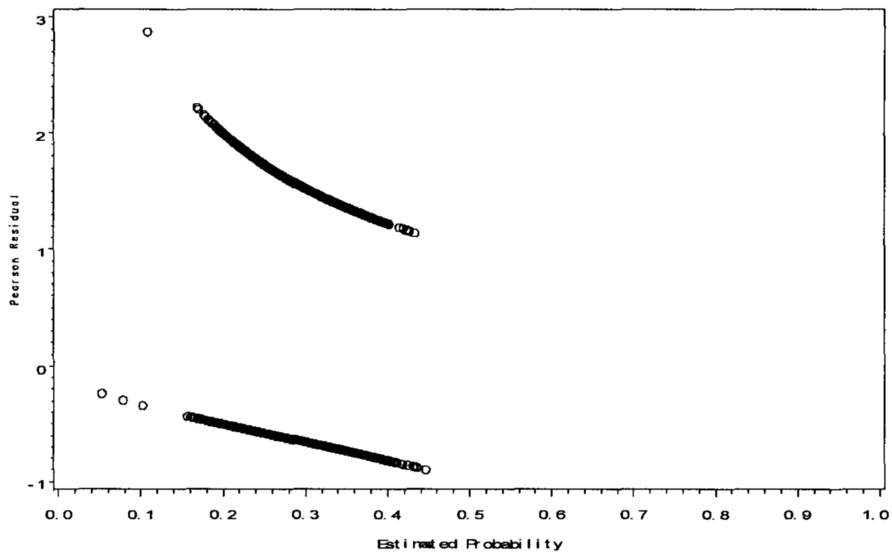

Figure 3-2: Pearson Residual versus Estimated Probability

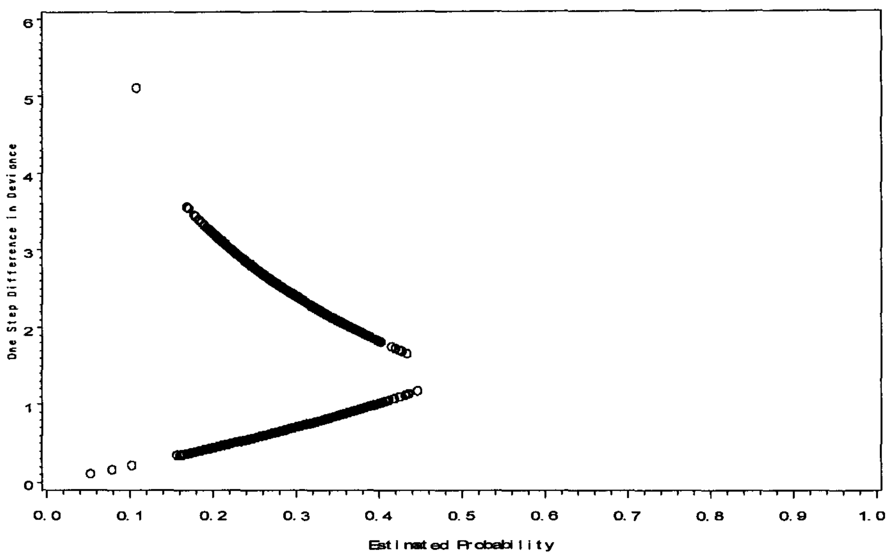

Figure 3-3: Difference in Deviance versus Estimated Probability

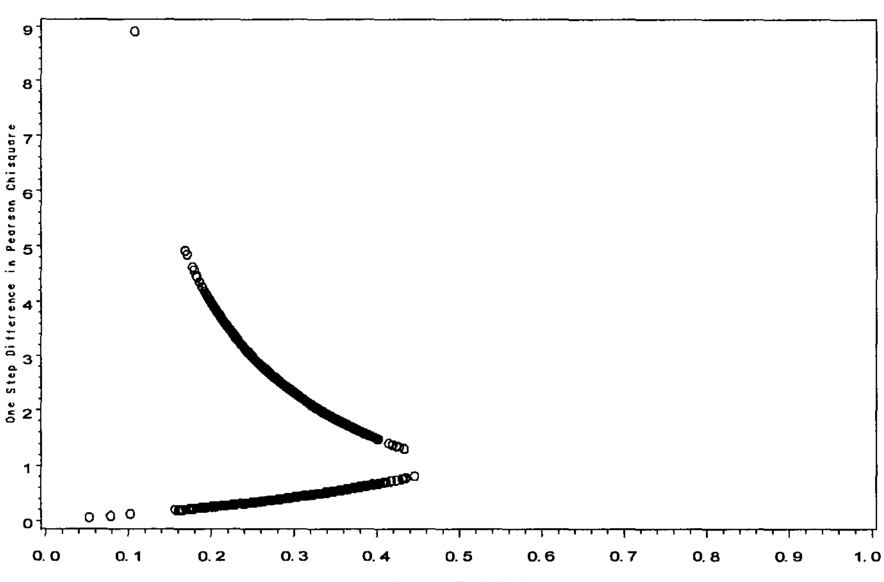

Figure 3-4: Difference in Pearson Chi-square Estimated Probability

Chapter

4. Analyst Timeliness and Stock Price

4.1 Timeliness Analysts and Forecast Surprise

In our research, we use forecast surprise to estimate the incremental information content of each forecast revision. Forecast surprise is measured relative to three benchmarks (Abarbanell, Jeffery and Bushee1997).

(i) Current forecast of an analyst minus the previous forecast issued by the same analyst, i.e. forecast revision.

(ii) Current forecast of an analyst minus the forecast of the predecessor analyst, i.e., predecessor-based surprise.

(iii) Current forecast of an analyst minus the consensus forecast, i.e. consensus-based surprise. The consensus benchmark is similar to the method we use to calculate boldness.

The "forecast surprise" is divided by the absolute value or the standard derivation of the respective benchmark.

The forecast revision for analyst i at date t is given by

$$FS_{it} = \frac{CFE_{it} - PFE_{i(t-1)}}{\left|PFE_{i(t-1)}\right|},$$

Where CFE_{it} the current is forecast of analyst i at date t and $PFE_{i(t-1)}$ is the previous forecast of the same analyst.

The predecessor-based surprise for analyst i at date t is expressed by

$$FS_{it} = \frac{CFE_{it} - FE_{i-1}}{|FE_{i-1}|},$$

where FE_{i-1} is the forecast of the predecessor analyst.

The consensus-based surprise analyst i at date t is given by

$$FS_{it} = \frac{CFE_{it} - CF_t}{\sigma(CF_t)},$$

where CF_t is the consensus forecast on day t, and $\sigma(CF_t)$ is the standard derivation of the consensus forecast for date t. The consensus forecast is constructed using average of the most recent earnings forecasts for those analysts, who have revised forecasts during the last 30 days,

$$CFE_t = \sum_{i=1}^{n} \frac{FE_{i\tau}}{n}$$

where $FE_{i\tau}$ is the forecast revision in 30 days and n denotes the number of analysts who revised their forecasts within 30 days. We use the recent forecast revisions in order to eliminate stale forecast by analysts who not closely follow the stock. The standard derivation of the consensus forecast at day t is

$$\sigma(CFE_t) = \sqrt{\sum_{i=1}^{n} (CFE_{i\tau} - CF_t)^2 / (n-1)} \quad .$$

Our examination of stock price performance is based on the average abnormal excess returns during three non-overlapping time period: a 2-day forecast release period, the 20 days prior to the release period and the 20 trading days subsequent to the release date. Excess return is the difference between actual wealth and expected wealth at the end of the measurement period. Actual Wealth is the future value of all the cash flows received over the measurement period. Expected wealth is the future value of the initial investment. In our research, abnormal returns for each period are calculated as the difference between the buy-and –hold return for relevant common stock and the corresponding return for a value-weighted industry index in I/B/E/S. We can use EVENTUS software to calculate the excess return. EVENTUS software performs event studies that computer abnormal returns for specific corporate actions or events using data directly from the CRSP stock database.

4.2 Hypothesis Tests for Analyst Timeliness and Price Impact

In this chapter, we will examine whether the timeliness of forecasts is related to their impact on stock prices. Leader analysts have superior ability in collecting and processing information that is an incentive to release earnings forecast ahead of competing analysts. We therefore expect timeliness leaders will have a higher impact on the stock price than followers. (Gleason, and Charles, Lee, 2003). Analyst leaders and followers can be regard as complementary market participants. Leaders provide timely information to the market, while followers take time to fine-tune the information and deliver more accurate reports. Thus, we test the hypothesis that timely analysts generate more information forecasts. We will estimate a regression of excess returns on the surprise component of their forecasts of leaders versus followers. The slope coefficients for these regressions measure the market's response to incremental information provided by the analyst. If the coefficients of leaders are greater, we can conclude that the leader's forecast revisions have a greater impact on excess stock returns and the leader provides more information than followers. Further, we will expect forecasts of followers to have a significant price impact on average, we hypothesis that the impact dissipates with successive followers. Thus,

Hypothesis 4: The coefficient of regression of excess return on forecast surprise for leader analysts is greater than the coefficient for follower analysts in short windows.

Since the leader analysts have superior ability to discovery and analysis of new information, the forecast revisions by lead analysts should independent of stock price performance during the pre-revision period. For follower analysts, they may delay their forecasts in order to herd on the leader's forecasts. They don't have advantage in producing valuable information, but are likely to incorporate public information, such as the recent stock price trend, the recent disclosure and the current economic situation. Thus, forecast revision by follower analysts may have strong correlation with the excess return during the pre-revision period. Therefore, the second hypothesis we wan to test is that:

Hypothesis 5: Forecast surprises by leader analysts are not significantly correlated with the stock price performance during the period preceding the forecast revisions (in long windows).

However, forecast surprises by follower analysts are positively correlated with excess return during the pre-revision period.

Investors in capital market pay close attention to the information that security analysts provide. It is interest to examine the speed with which the information contained in analysts' forecast revisions works on stock prices. If security prices quickly adjust to reflect the information in the forecast revisions, there should be no excess returns during the post-revision period. But, if investors react slowly, it may be possible to earn excess profits using trading strategies based on the magnitude of analysts' forecast revisions.

Hypothesis 6: Excess stock returns during the post-release period (in long window) are not significantly related to the surprise component of analysts forecast revision.

4.3 Test of Analyst Timeliness and Contemporaneous Stock Price

To test whether the stock price impact of forecast surprise in analysts' forecasts is lower for follower analysts relative to leaders at the contemporaneous time (H4), we estimate the following pooled regression:

$$EXR_{ijt} = \beta_1 + \beta_2 Leader * FS_{ijt} + \beta_3 Follower * FS_{ijt} + \varepsilon_{ijt},$$

where EXR_{ijt} is the cumulative excess return over the two-day forecast released period by analyst i for firm j, leader and follower are dummy variables (0,1) that classified on the basis of LFR calculated at the firm-level for each year, and FS_{ijt} is the forecast surprise we calculated at three different benchmarks: forecast revision, predecessor-based and consensus-based.

Table 4-1: 2-day Release Period Forecast Surprise Coefficients for Analysts

	Forecast Revision		**Predecessor-based surprise**		**Consensus-based surprise**	
	Coefficient (1)	P-value (2)	Coefficient (3)	P-value (4)	Coefficient (5)	P-value (6)
Intercept	0.0137	<0.0001	0.00038	<0.0001	-0.0046	<0.0001
Leader * FS_{ijt}	0.0345	0.0345	0.135	<0.0001	0.382	<0.0001
Follower * FS_{ijt}	-0.0182	0.0267	0.078	0.012	0.227	0.004
Adj. R^2	0.03		0.056		0.253	
N	7,025		7,350		6,987	

Table 4-1 presents the results of a regression of two-day forecast released period cumulative excess return on various measures of forecast surprise in analysts' (six-month ahead) earnings forecasts which are used to classify timeless leaders and followers for technology industry. The results of contemporaneous regression on percentage forecast revision are reported in columns (1) and (2). We can see that the coefficients estimate on percentage forecast revision for leaders is significantly higher than that of followers. Consistent with the hypothesis 4, the results suggest that the forecast revisions of timely analysts have a higher contemporaneous price impact. The slope coefficients for these regressions are called forecast response coefficients (FRCs). The F-test of the null hypothesis that the FRCs for leaders and followers is equal is rejected at the 5% level. However, the coefficient for followers is negative, suggesting the revision made by followers have negative impact on stock price and the forecasts of followers have no information content incremental to that of leaders.

The results in column (3) and column (4) are the estimation regression coefficients when predecessor-based forecast surprise is independent variable. We obtained the similar results when the forecast revision is independent variable. Leaders and followers both have positive impact on the 2-day release excess returns. As we expected, the coefficient estimate on forecast surprise of leaders is significantly higher than that of followers at the significant 1% level. The results with forecast surprise based on the consensus forecast forecasts, reported in column (5) and column (6). We also found the similar results that the leaders have higher impact on the stock price than followers. But, the regression R^2 is much larger than those in last two regression model when the forecast revision surprise and predecessor-based surprise are independent variables. It indicates that the 30-day consensus forecast is better to reflect market information than the most recent forecast released by a single analyst or the same analyst's previous forecast.

The results are consistent with the hypothesis that the leaders and followers both have a significant positive impact on 2-day release period excess returns and the leaders have higher impact on the stock price than followers.

4.4 Test of Analyst Timeliness and Past Stock Price

We turned to examine the relationship of forecast surprise and excess stock returns during the pre-release period. We think that forecast revisions by leader analysts provide investors with new information, but, follower analysts just simply review existing information to update their forecasts. If the hypothesis is true, forecast surprises by leader analysts should not be significantly correlated with the stock price performance during the period preceding the forecast revisions. However, forecast surprises by follower analysts are positively correlated with excess return during the pre-revision period. The regression model is as follows:

$$EXR_{ijt} = \beta_1 + \beta_2 Leader * FS_{ijt} + \beta_3 Follower * FS_{ijt} + \varepsilon_{ijt}.$$

The appearance of the regression model is same as the last one, but, here EXR_{ijt} is the cumulative excess stock return over the 20 days pre-release period by analyst i for firm j. Therefore, the meaning of the hypothesis test is definitely different. Here, we use the estimated coefficients from this regression to examine whether the information used in updating analysts' forecasts had a significant impact on stock prices during the pre-released period.

Table 4-2: 20-day Pre-Release Period Forecast Surprise Coefficients for analysts

	Forecast Revision		**Predecessor-based surprise**		**Consensus-based surprise**	
	Coefficient (1)	P-value (2)	Coefficient (3)	P-value (4)	Coefficient (5)	P-value (6)
Intercept	0.00034	<0.0001	0.0053	<0.0001	0.0274	<0.0001
Leader * FS_{ijt}	0.0043	0.0023	0.023	0.134	0.0045	0.345
Follower * FS_{ijt}	0.0012	0.0215	0.006	0.234	0.0034	0.0013
Adj. R^2	0.083		0.067		0.087	
N	6,945		6,752		6,894	

Table 4-2 presents the results of a regression of 20-day pre-release period cumulative excess return on various measures of forecast surprise in analysts' (six-month ahead) earnings forecasts which are used to classify timeless leaders and followers for technology industry. The estimated regression coefficients in Table 4-2 indicate that the market put different effect on the new information in an analyst's various forecast surprise. The estimation coefficients of the regression on percentage forecast revision are reported in columns (1) and (2). We can see that the coefficients estimate on percentage forecast revision for leaders is significantly higher than that of followers and they both have significant relationship with pre-released cumulative excess return. The result implies that forecast revisions by lead and follower analysts tend to incorporate information that was available to the market during the pre-release period. Columns (3) and columns (4) show the results of regression 20-day pre-release period cumulative excess return over the forecast surprise relative to the predecessor analyst who follow the same firm. The result is not robust for leaders and followers who are classified based on timeliness of forecast release. Predecessor based forecast surprise made by leaders and followers have not significant impact on 20-day cumulative excess return.

The results for consensus based forecast surprise differ from the results for forecast revision and predecessor based forecast surprise. We found that the 20-day consensus forecast of timeliness leaders are not significantly related to pre-release returns, but, that of follower analysts are positively correlated with pre-release period excess returns. The results are consistent with our null hypothesis 5 that forecast surprises by leader analysts are not significantly correlated with the stock price performance during the period preceding the forecast revisions. Because the lead analysts provide investors with new information, but, the follow analysts just simply follow the public information to update their forecast release. The public information usually reflects the current trends in stock prices. Thus, it is obvious that there is a positive correlation between the consensus forecast surprise and pre-release excess return.

4.5 Test of Analyst Timeliness and Future Price

In this section, we will test hypothesis concerning the relationship between the forecast surprise and excess stock return during the post-release period. We want to know whether the speed with which the investors react to the information contained in analyst's forecast revisions. Hypothesis expected that excess stock returns during the post-release period are not significantly related to the surprise component of analysts forecast revision. The estimated regression model is

$$EXR_{ijt} = \beta_1 + \beta_2 * BNEW_{ijt} + \beta_3 Leader * FS_{ijt} + \beta_4 Follower * FS_{ijt} + \varepsilon_{ijt} .$$

Here, we use a new dummy variable $BNEW_{ijt}$ represent "bad news", which takes value of one if the forecast surprise of leaders is less then zero, otherwise, takes value of zero. Variable EXR_{ijt} is the cumulative excess stock return over the 20-day post-release period by analyst i for firm j.

Table 4-3 shows the results of a regression of 20-day post-release period cumulative excess return on various measures of forecast surprise in analysts' (six-month ahead) earnings forecasts by which the analysts are classified timeless leaders and followers for technology industry. The estimation coefficients of the regression on percentage forecast revision are reported in columns (1) and (2). We can see that the coefficients estimate on percentage forecast revision for leaders is significantly higher than that of followers and they both have significant relationship with pre-released cumulative excess return. We also get the similar results from the coefficients estimation for the regression on predecessor surprise in column (3) and (4), the parameters estimation of regression 20-day post -release period cumulative excess return are reported in columns (3) and columns (4). We can see that there is a positive relation between the post-released excess return and the forecast surprise. Moreover, the coefficient for the forecast surprise by timeliness leaders is statistically significant. The estimated value of coefficient is 0.0045, which implies that an investor who initiates a trade at the beginning of the post-release period can expect to earn an excess return of 45 basis points for each unit of standard deviation by which the lead analyst's revised earning of forecast exceeds the consensus. However, the coefficient for the forecast surprise by followers is not statistically significant and the value of the coefficient is small. We can see that there are some excess stock returns during the post-release period related to the leaders' predecessor-based forecast surprise.

As for the consensus based forecast surprises, which are reported in column (5) and (6), show that the relation between forecast surprises and post-release excess return is not statistically significant for either lead analysts or followers. The results are consistent with hypothesis 6.

We can see the coefficients for variable *BNEW* in three measurement of forecast surprise are not significant. The result indicates that there is no asymmetry relation between forecast surprise and post-release excess returns for analysts classified according to the timeliness of their forecasts.

By regression of 20 days post-release excess returns on consensus forecast surprise, we can conclude that the cumulative post-release excess is independent of the forecast surprise of leaders and followers. Because the investors use follower analysts' earning forecasts to confirm revised forecast by lead analysts and the security prices doesn't quickly adjust to reflect the information in the forecast revisions.

Table 4-3: 20-day Post-Release Period Forecast Surprise Coefficients for Analysts

	Forecast Revision		**Predecessor-based surprise**		**Consensus-based surprise**	
	coefficient	P-value	coefficient	P-value	coefficient	P-value
Intercept	0.0239	<0.0001	0.0012	0.003	-0.145	0.0001
BN_{ijt}	0.0038	0.145	0.0024	0.673	0.0054	0.378
$Leader * FS_{ijt}$	0.0045	0.003	0.0039	0.012	0.0068	0.345
$Follower * FS_{ijt}$	0.0036	0.5633	0.0025	0.874	0.0042	0.789
Adj. R^2	0.0164		0.0056		0.0027	
N	7,233		7,104		6,886	

Chapter

5. Discussion and Conclusion

The Wall Street Journal (WSJ) in its yearly "Best on the Street" survey chooses analysts who excel on the basis of the performance of their recommendations and the accuracy of their earnings estimations. The list is published in June each year. In this paper, we examine whether there are quality differentials among security analysts in terms of the timeliness of their forecasts. We focus on the time of earning forecasts because they are a central function of security analysts. We consider forecast timeliness to be the most intuitive criterion for classifying analysts as leaders and followers.

Once we classify the analysts as leaders and followers, we use T-test and non-parametric Mann-Whitney test to find the difference in means of the analysts' characteristic variables, such as forecast boldness, forecast accuracy, forecast bias, and forecast frequency and so on. Our results suggest that leader analysts tend to be employed by larger brokerage firms and cover fewer stocks than follower analysts. The business working experience and firm-specific working experience for leaders are significantly higher than those of followers. Interestingly, we found that the forecast frequency for leaders is less than that of followers. We also found that the leaders are bolder than the followers. Especially, the followers usually release more accurate forecasts than leaders because leaders have to sacrifice accuracy to be the first movers.

We also use discriminant analysis and multivariate logistic regression to examine whether the performance of analysts can explain the classification. As expected, we found the forecast accuracy and forecast boldness and other performance, such as number of firms followed and brokerage firm size are significantly related to the likelihood of becoming a leader. Leader analysts are also less optimistic. We also find the likelihood of becoming leader is increasing with experience. The average experience for all leader analysts is greater than that for follower analysts. It's obvious that the leader analysts appear to learn the skills required to become leaders in their career.

Finally, we examine whether the timeliness of forecasts related to the stock price impact by regressing excess stock returns on the unexpected or surprise component of the respective forecast revision by lead and follow analysts. Our empirical results indicate that leaders' forecasts have a positive and significant impact on 2-day release-day excess returns, while, follower analysts also have positive and significant price impact. The impact of followers' forecasts on the stock price is however lower than that of leaders' forecasts. The timeliness also indicates that the forecasts by lead analysts reflect the discovery of new information. We found during the pre-released period, the leaders' consensus- based forecast surprise is independent of excess return. But, the followers' consensus- based forecast surprises are positively correlated with the excess stock return during the pre-release period. But, we don't get the same results for forecast revision surprise and predecessor-based forecast surprise.

During the post-released period, we found that the excess stock returns are independent of the consensus-based forecast surprise. We can see that the security prices quickly adjust to reflect the information in forecast surprise. Thus, we can conclude that the lead analysts identified by forecast timeliness have a greater impact on stock price than follower analysts and the performance rankings based on forecast timeliness are informative.

Appendix

Table A 1: Pooled Within-Groups Matrices

	LARGEBRKR	SMALLBRKR	COVER	NUMANALYST	RFREQ	ACCUSCORE	BIASSCORE	BDSCORE	EXPR
LARGEBRKR	1.000	**-.297**	**-.116**	-.050	-.039	.007	.020	-.011	-.073
SMALLBRKR		1.000	-.042	.013	.033	-.008	.011	-.017	.034
COVER			1.000	**.168**	.041	.013	.009	.021	**.210**
NUMANALYST				1.000	**-.102**	.026	.029	.022	**.140**
RFREQ					1.000	-.020	-.002	.002	.060
ACCUSCORE						1.000	**.419**	.052	.010
BIASSCORE							1.000	-.016	-.003
BDSCORE								1.000	.036
EXPR									1.000

a The total covariance matrix has 7432 degrees of freedom.

Table A 2: Covariance Matrices

Rank		largebroker	smallbroker	cover	expr	bdscore	biasscore	accuscore	rfreq	numanalyst
follower	largebroker	.182	-.054	-.091	-.020	-.001	.001	.001	-.009	-.138
	smallbroker		.174	-.031	.009	-.001	.001	-.002	.008	.039
	cover			3.092	.224	.008	.004	.008	.043	1.607
	expr				.400	.007	.001	.002	.029	.513
	bdscore					.071	-.001	.004	.001	.028
	biasscore						.107	.049	.000	.044
	accuscore							.105	-.005	.041
	rfreq								.425	-.330
	numanalyst									29.615
leader	largebroker	.189	-.050	-.074	-.018	-.001	.006	-.001	-.015	-.061
	smallbroker		.157	-.029	.007	-.005	.003	.002	.011	.004
	cover			2.809	.248	.013	.007	.005	.050	1.454
	expr				.401	.005	-.004	.002	.012	.376
	bdscore					.069	-.002	.004	-.002	.038
	biasscore						.079	.019	-.001	.063
	accuscore							.075	-.002	.052
	rfreq								.376	-.409
	numanalyst									26.951
Total	largebroker	.184	-.053	-.086	-.020	-.001	.003	.001	-.011	-.117
	smallbroker		.169	-.030	.009	-.002	.001	-.001	.009	.031
	cover			3.014	.230	.009	.005	.007	.046	1.569
	expr				.401	.006	-.001	.002	.024	.473
	bdscore					.070	-.001	.004	.000	.028
	biasscore						.099	.041	.000	.050
	accuscore							.096	-.004	.043
	rfreq								.411	-.351
	numanalyst									28.880

a The total covariance matrix has 7432 degrees of freedom.

Table A 3: Correlation Coefficient

	largebroker	smallbroker	cover	numanalyst	Rfreq	accuscore	biasscore	bdscore	expr
largebroker	1	-.299(**)	-.119(**)	-.052(**)	-.035(**)	.006	.017	-.007	-.073(**)
		.000	.000	.000	.004	.635	.158	.545	.000
smallbroker	-.299(**)	1	-.040(**)	.013	.032(**)	-.007	.011	-.023	.032(**)
	.000		.001	.271	.007	.571	.339	.053	.007
Cover	-.098(**)	-.071(**)	1	.168(**)	.034(**)	.011	.008	.020	.209(**)
	.000	.000		.000	.004	.341	.500	.091	.000
numanalyst	-.045(**)	.004	.161(**)	1	-.103(**)	.028(*)	.027(*)	.022	.137(**)
	.000	.727	.000		.000	.019	.021	.063	.000
Rfreq	-.023(*)	.017	.027(*)	-.095(**)	1	.018	.003	.000	.049(**)
	.049	.145	.023	.000		.135	.787	.971	.000
accuscore	-.006	.004	.007	.016	.026(*)	1	.433(**)	.052(**)	.010
	.612	.725	.579	.185	.032		.000	.000	.387
biasscore	.010	.024(*)	-.004	.013	-.001	-.020	1	-.012	-.002
	.416	.048	.707	.259	.944	.099		.302	.870
bdscore	-.006	-.025(*)	.016	.020	.007	.076(**)	-.033(**)	1	.034(**)
	.635	.040	.189	.088	.538	.000	.006		.004
Expr	-.072(**)	.032(**)	.195(**)	.111(**)	.038(**)	.006	-.014	.033(**)	1
	.000	.008	.000	.000	.001	.591	.243	.005	

- Pearson coefficients are above the diagonal line and Spearman coefficients are below the line.
- ***significant at 1% level, ** significant level at 5% level, * significant level at 10% level.

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