ANALYST CHARACTERISTICS AND EARNINGS FORECAST ERRORS

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Abstract

In this article, we investigate the association between analysts' earnings forecast errors and analyst characteristics. These characteristics include working experience, company experience, brokerage house size, and boldness in making recommendations. We use t-tests and time-series regressions to examine the relationship. Our results reveal that analysts' years of experience is the most important factor. The more experience analysts have, the more accurate their forecasts tend to be, which is consistent with the learning-by-doing theory. For the brokerage house size, analysts from larger brokerage houses are more likely to provide accurate forecasts. For boldness, when an analyst's recommendation is far away from mean recommendation, the earnings forecast tends to be less accurate. Company-specific experience has no robust relation with forecast errors. We conclude that experience of analysts, brokerage size, and analysts' recommendation dispersion are correlated with forecast accuracy.

Keywords: analyst; characteristics; forecast errors

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1: Introduction

Stock analysts are significantly indispensable participators in nowadays capital markets. “The recommendations and forecasts issued by sell-side analysts play a significant role in the operations of the markets (Kothari 2001, Michaely and Womack 2005, Frankel, Kothari and Weber 2006)”. It’s true for several reasons. Firstly, most of financial models are based on analysts’ earnings forecast data. Reliable earnings forecast data drives the movements of equity prices and therefore has influence on the operation of society and promotes the development of economy. Secondly, researches commonly used by regulators and academics are often based on financial analysis and forecast from stock analysts. In order to provide more accurate research results to the public, regulators and academics are better to follow more reliable analysts who show superior forecasting abilities in the past.

It is widely accepted that analysts differ in their forecasting abilities. Sinha, Brown, and Das (1997) find indications that some analysts consistently outperform the rest. There are many factors having influence on the forecast accuracy of an analyst. Given the irreplaceable effect of financial analysts’ forecast, it is worthwhile to study what factors are associated with their forecast accuracy and how they related to the forecast accuracy. People relying largely on analysts’ forecasting data are interested in learning about what contributes to the difference in forecast accuracy as well. As a result, they will know whose forecasting data they should follow up in the future to make better investment decisions.

The findings in prior research of determinants of forecast accuracy are mixed. In O'Brien (1985), he found no evidence that some brokerage firms consistently produced more accurate earnings forecasts. O'Brien (1987) also indicated no evidence of consistent differential ability.

O'Brien (1990) examined a sample of forecasts for firms in nine different two-digit SIC industries over the period 1975 to 1981. He studied the forecast accuracy of individual analysts in nine industries by estimating and comparing average accuracy across individuals and industries. Firstly, he estimated a fixed effects regression model to test whether analysts are heterogeneous in forecast accuracy. Secondly, he rank order analysts in quartiles each year and compare the observed distribution of analysts' average ranks with the distribution expected if all analysts were alike and each year were an independent observation. “In both parametric and nonparametric tests, individual analysts fail to exhibit consistent differences in forecasting ability.”

Scott E. Stickel (1992) finds that Institutional Investor All-American research team provide more accurate reports than Non All-Americans’ forecasts, mainly due to All-Americans supply forecasts more often than other analysts and stock return immediately follow their forecast trend. “Stocks returns immediately following large upward forecast revisions suggest that All-Americans impact prices more than other analysts. However, there is virtually no difference in returns following large downward revisions. Nevertheless, the collective results suggest a positive relation between reputation and performance, and, assuming that All-Americans are better paid, pay and performance.”

John Jacob (1997) used time-series approach to discuss about whether security analysts improve their performance with experience. Results indicate that abnormal returns at earnings announcement dates are positively associated with the mean forecast errors of experienced analysts but not with the mean forecast errors of inexperienced analysts. The authors interpret these results to imply that the market's expectation of earnings is more strongly influenced by the forecasts of experienced analysts.

Sinha, Brown and Das (1997) identify systematic differences in forecast accuracy among a larger body of analysts. In studying sell-side security analysts, Michael B. Mikhail, Beverly R. Walther and Richard H. Willis (1997) measured firm- specific experience and concluded that analysts' forecast error will decrease with the increase of firm-specific experience, as suggested by learning-by-doing model.

Michael B. Clement and Senyo Y. Tse (2005) classifies earning forecast as herding or bold and find that bold forecasts are more accurate than herding forecasts. Herding forecasts are more strongly related to earnings forecast errors. Salvador Hutira (2016) finds that forecast accuracy has been steadily decreasing over the sample period and that forecast dispersion has been steadily increasing. Lily H. Fang and Ayako Yasuda (2007) study the effect of reputation on the values of analysts' stock recommendations and find differences between tech sector and non-tech sector analysts.

Gus De Franco and Yibin Zhou (2009) compare the performance of sell-side equity analysts with and without a Chartered Financial Analyst (CFA) designation and provide evidence consistent with "credentialism". They found evidence that charter holders improve along the dimension of timeliness after they receive their CFA charter.

This result provided support for a human-capital explanation in which charter holders improve their productivity during the CFA program.

In this article, we use analysts' forecasts for end of fiscal year during the period 1993-2016. We collect our raw data from I/B/E/S and CRSP database and implement a cleaning procedure to explore the association between analysts' characteristics and earnings forecast errors. The characteristics of analysts include forecast experience, firm-specific experience, brokerage size and individual's recommendation difference from the mean. We observe statistics of these variables and group them by size and nature to investigate a positive or negative relationship with the forecast accuracy. T-test results for the first and last group further help us to realize if error has obvious difference with change of variables. In order to see if these four variables have different extent of influence on the analyst's forecast accuracy, we also run regression of earnings forecast errors on the analyst's characteristics. Our finding shows that experience, firm-specific experience and brokerage size have positive relationship with the analyst's forecast accuracy, while boldness is negatively correlated with the analyst's forecast accuracy. Our results also reveal that analysts' years of experience is the most important factor among these four characteristics.

We contribute to the literature by using data analysis to explore the association between analysts' characteristics and their forecast accuracy and prove several theories like learning-by-doing theory. The result suggests that an analyst's characteristics may be useful to predict the accuracy of the analyst. Based on our finding, people can simply distinguish whose forecast data should they use when making decisions in the future according to different analysts' characteristics. This will also help to make financial models and publicly used researches more accurate.

2: Data and Empirical Procedure

2.1 Data source and cleaning procedure

We obtain 774,417 analyst recommendations from the I/B/E/S database for 17,948 US-based companies with the date range from January 1993 to July 2017. These recommendations are provided by 18,262 individual analysts. Specifically, our sample contains official ticker for each company, estimator ID, analyst name, IBES recommendation code (where 1 means strong buy and 5 means strong sell), estimator masked code, analyst masked code and announcement date of recommendation. In addition, we collect estimated and actual EPS according to same company tickers with a forecast period indicator equals one (FY1) from the I/B/E/S database. This file, which is based on 21,069 individual analysts, also contains forecast period end date and actual announcement date. In order to normalize our error variable, we collect 1,815,541 monthly stock prices with corresponding date for each company from CRSP as well.

We hypothesize that the estimation accuracy for earnings is the indicator of analysts' forecasting ability (Hall and Tacon 2010). For boldness, since recommendation has five levels, we hypothesize that a forecast is bold if its absolute difference from the mean recommendation is larger than two.

We implement a screening process to clean our raw data. Firstly, if an analyst has more than one forecast record for the same company in the same month, we only keep the latest EPS forecast before the actual announcement date to calculate the analyst's accuracy of the end of fiscal year EPS. In addition, for analysts who make several recommendations within a month, we only keep the latest recommendation as well. If we use recommendation made before, analysis is not efficient.

Moreover, we drop EPS when the time difference between the actual announcement date and announce date of estimated EPS is less than one day to avoid analysts using non-public material information. It's unusual that the analyst reports estimated EPS today and by chance actual EPS will be released tomorrow. There may be some connection between these two. To avoid misusing bias, we do not think these estimated EPS are valid. We keep the minimum time difference and drop observations that are given by analysts on the same date.

Lastly, due to data limitation in CRSP we only have stock price before 2017. As a result, data after December 2016 from another source will not be considered to maintain consistency.

2.2 Data measures

To measure whether there is relation between analysts' characteristics and earnings forecast errors, we classify four characteristics from our sample and define the forecast error and then do t-tests and time-series regressions to examine the relationship. Four characteristics are working experience, company experience, brokerage size and boldness of analysts. Experience is the number of years since the analyst appears in I/B/E/S recommendation file. Company experience is the number of years since the analyst provided his/her first recommendation for the given company. Both of longer working experience and longer firm-specific experience means the analyst is more experienced. Brokerage size is the number of analysts providing recommendation for the given company in a given year. Lager brokerage size means the brokerage house owns great scale and has more analysts working for it. Boldness is the absolute difference between the analyst's recommendation and the average recommendation of all other analysts covering the same company. Boldness equals one if the absolute difference is larger than 2, otherwise zero. As mentioned before, one means the analyst's forecast is bold. These characteristics are unique for everyone, so people can clearly identify individual analyst.

Earnings forecast error is calculated as the absolute value of the difference between actual EPS and estimated EPS divided by the absolute value of share price. Obviously, smaller error means more accurate estimated EPS. We exclude extreme values of the error variable at the 1 percentile and the 99 percentiles to pursue more accurate results.

3: Empirical Results

In order to measure the association between absolute forecast errors and the four variables, we first sort each variable and divide them into groups. Within each variable, we do t-test for the first and last group to explore if they have significant difference. After that, we run regression containing all the variables as independent variables, keep absolute forecast error as dependent variable and get further results.

3.1 Data distribution and t-test results

In this part, we would like to study the data distribution and t-test results of the four variables we use. From the results we could find the characteristics of variables and their relationship with absolute forecast error.

In Table 1, we first give detailed explanation of the variables. Then we provide the Descriptive Statistics for four variables which includes mean, standard deviation, 25th percentile, median and 75th percentile to get a basic knowledge of variables.

Next, we sort each variable and divide them into several groups at the yearly level. For Experience and Brokerage Size, we divide the sample data into four groups respectively from the shortest to longest. For company experience, we divide sample data into three groups because most of the data is 0. For Bold, we divide the sample data into two groups based on the meaning of Bold.

From Table 2 Panel A, we can see that, the mean of the group decreases from group 1 to 4, indicating that the group with longer experience has less mean absolute forecast error. The t-test result shows that the expected difference of group 1 and group 4 is significantly different from zero, which means that experience of the analysts is correlated with the absolute forecast error. The analysts with longer experience will be more likely have a lower absolute forecast error, which is consistent with learn-by-doing theory.

From Table 2 Panel B, we study the difference among 3 groups based on company-specific experience. Descriptive statistics shows that mean absolute forecast error of each group decreases. The significant t-test result shows that the expected difference from group 1 to group 3 is significant different from zero, indicating that company-specific experience is correlated with analysts' absolute forecast error.

From Table 2 Panel C, we study the variable brokerage size. Group 1 has smallest brokerage size and group 4 has largest brokerage size. A large brokerage house has advantage for analysts forecasting ability as it has more data sources and professional colleagues helping analysts to get a more accurate forecasting result. And the result confirms this point of view. The mean of absolute forecasting error for groups decreases as the increase of brokerage size. The t-test result is significant at the 1% level, indicating that brokerage size does affect absolute forecast error.

Table 2 Panel D provides information concerning boldness. In the first group, the difference between analysts' recommendation and the mean of all the recommendation results for a firm in the same month of a year is less than 2. In the second group, the difference is more than 2. The result shows that the analysts with more consistency with all the consensus recommendation has a relatively smaller error. The t statistic is significant at the 1% level, showing that analysts' who provide bold estimates are actually less accurate.

3.2 Regression analysis

Given the fact that results of distribution and t-test reveal experience, company experience and brokerage size seem to have positive relationship with forecast accuracy. Boldness seems to have negative relationship with forecast error. In order to further test the association, we would like to see if the four variables have different extent of influence in the forecast accuracy.

We first run regression using absolute forecast error as dependent variable. The independent variables are the four variables, working experience, company experience, brokerage size and bold-difference of recommendation from the mean.

Table 3 shows the regression results for the observed analysts' absolute estimation error between 1993-2016. Both specification include year indicators. Errors are clustered at the firm level. Regression (1) does not contain firm-fixed effect while regression (2) includes firm indicators.

From the regression results, we see that experience is an important factor, the more experiences analysts have, the more accurate the forecast tends to be. This is true both in the cross-section, and when you control for difference in firms, which means the result also makes sense for a given firm over time. This result is consistent with learning-by-doing theory as one's forecast ability can improve with the cumulative of experience.

The result of brokerage size is significant both in the cross-section and firm-fixed regression, showing that an analyst from larger brokerage house are more possibly to give an accurate forecast. It makes sense as larger brokerage house generally has more extensive resources and more accurate financial models, providing analysts more chance to make accurate forecasts.

Company experience and boldness do not give consistent results. Boldness seems not important for the cross section. After you control for firm fixed-effects, it shows as an important factor.

Finally, company experience, seems to flip signs (between specification (1) and (2)), suggesting that it has no robust relation with forecast error. A reasonable explanation for this result is that for most of the forecast, company experience is zero, making company experience does not make too much sense.

4: Conclusion

We examine the association between analysts' absolute forecast errors and their own characteristics by following steps.

Firstly, we list several characteristics which may have some influence on individual's forecast accuracy based on literature and theories and then split them into groups by size and nature and do t-tests to explore the potential relationship. The difference of mean absolute error between characteristics' groups and t-test results show that working experience, firm-specific experience and brokerage size seem to have positive relationship with the analyst's forecast accuracy, while boldness is negatively correlated with forecast accuracy. For all four variables, the expected difference of absolute forecast error between the first and last group is significantly different from zero at different level, which means that all four characteristics are correlated with the absolute forecast error.

In order to further test the association, we run regression to see if the four variables have different extent of influence on the analysts' forecast accuracy. We use absolute forecast error as dependent variable and four characteristics as independent variables. The results of regression provide us more useful information. Our results reveal that experience is the most important factor. The more experience an analyst has, the more accurate the forecast tends to be, which is consistent with learn-by-doing theory. For brokerage size, analysts from larger brokerage houses are more likely to provide accurate forecasts than analysts from small-scale brokerage houses. For recommendation, when an analyst's recommendation is far away from mean, it tends to be less accurate.

Company-specific experience has no robust relation with forecast error probably due to most of data is zero in our sample.

To conclude, there is association between analysts' earnings forecast errors and their own characteristics. Experience of analysts, brokerage size and analysts' recommendation difference from mean do affect their forecast accuracy, and company-specific experience seems making no sense.

The results of the paper have some practical significance. However, more work can be done to investigate this topic further.

Firstly, our selected variables are limited. Analysts' characteristics not restrict to what we defined here. There are lots of ways to describe a person's characteristics. The same method could be used in the future to investigate more characteristics that may have influence on analysts' forecast accuracy, as long as the variable could be measured properly and there indeed is relationship between the variable and individual forecast accuracy. In this way, we could have a more detailed knowledge about determinants of analysts' forecast accuracy and better predict who may have superior forecast ability and whose forecast data should follow up to make investment decisions.

Secondly, if we test analysts' forecast over a longer time, the result may be more significant. In this paper, we use 1 fiscal year forecast to calculate normalized absolute earnings forecast errors. However, a longer period forecast may better reflect an analyst's forecast ability. It is possible that in a longer period, the characteristics of analysts will have a more significant influence on their forecast errors due to potential existence of forecast ability persistency.

Moreover, we only consider US-based companies in this paper. Results may be different if we expand our sample base because of specific conditions and policies in different countries. A characteristic rather than working experience may have a stronger relation with the analyst's forecast accuracy than other interested variables. In order to investigate this topic further and get more accurate results, we can contain global companies as our sample as well to eliminate geographic bias.

Table 1: Descriptive Statistics

The sample consists of 94,778 observations. Experience is the number of years since the analyst appears in IBES recommendation file. Company experience is the number of years since the analyst provided his/her first recommendation for the given company. Bold is the absolute difference between the analyst's recommendation and the average recommendation of all other analysts covering the same company. Brokerage size is number of analysts providing recommendation for the given company in a given year.

Variables	Mean	Standard Deviation	25^{th} percentile	Median	75^{th} percentile
Experience	5.03	4.81	1.00	4.00	8.00
Company Experience	1.59	2.77	0.00	0.00	2.00
Bold	0.41	0.49	0.00	0.00	1.00
Brokerage Size	60.33	58.11	17.00	39.00	91.00

Table 2: Difference of Mean Absolute Error Between Characteristics' Groups

This table partitions all observations to groups based on the empirical distribution of various analysts' characteristics, where 1 is the lowest level group and 4 (or 3 or 2) is the highest-level group, depending on the type of characteristic. Error is the absolute value of difference between actual EPS and analyst forecast EPS (end of fiscal year) divided by the price. The analyst estimate is the one closest to but prior to announcement day, and the price is the stock price at the end of the month in which the earnings announcement is made. The bottom row provides t-test for difference in error between lowest group (group 1) and highest group. Analysts' characteristics are defined in Table 1. *, **, *** represents significance at the 10%, 5%, 1%, respectively.

Panel A: Experience group

Analyst experience group	Variable	Obs	Mean	Std. Dev.	25th percentile	75th percentile
1	Error	29,898	.0444007	.1962557	.0005965	.0099085
2	Error	24,812	.0433782	.1938751	.0005411	.0089623
3	Error	22,201	.0394922	.1828865	.0005478	.0081063
4	Error	17,867	.0354943	.1717888	.0005785	.00746
t-test difference (1-4)			0.0089065*** (5.02)			

Panel B Company experience group

Company experience	Variable	Obs	Mean	Std. Dev.	25th percentile	75th percentile
1	Error	18,473	.0529444	.2147858	.0007153	.0119298
2	Error	12,682	.0446677	.1989206	.000564	.0088116
3	Error	11,929	.0286854	.1515445	.0005076	.0061251
t-test difference (1-3)			0.0243*** (10.731)			

Panel C: Brokerage size group

Brokerage size	Variable	Obs	Mean	Std. Dev.	25^{th} percentile	75^{th} percentile
1	Error	24,760	.0547661	.2191825	.0007075	.0118343
2	Error	23,806	.0397295	.1853801	.00054	.0078431
3	Error	23,631	.0367254	.1780131	.0005086	.0076397
4	Error	22,581	.0329954	.1619238	.0005367	.0080515
t-test difference (1-4)			.0217707 (12.1961)***			

Panel D: Boldness of analysts

Boldness groups	Variable	Obs	Mean	Std. Dev.	25th percentile	75th percentile
1 (low)	Error	56,350	.0404444	.18466486	.0005333	.0085501
2 (high)	Error	38,428	.0425652	.1903129	.0006222	.0090498
t-test difference (1-2)			-.0021638 * (-1.7326)			

Table 3: Regression Analysis

This table reports regression results for the observed analysts' absolute estimation error between 1993-2016. The independent variables are working experience, company experience, brokerage size and difference of recommendation from the mean. The dependent variable is the absolute forecast error. Both specification include year indicators. Errors are clustered at the firm level. *, **, *** represents significance at the 10%, 5%, 1%, respectively. [AR1]

	(1)	(2)
Constant	.0198262***	.0220772***
	(6.40)	(8.66)
Experience	-.0007518***	-.0005562***
	(-3.46)	(-4.07)
Company experience	-.0014456***	.0012872***
	(-4.71)	(6.18)
Brokerage Size	-.0001295***	-.0000155**
	(-9.86)	(-1.97)
Bold	.0013106	.007887***
	(0.92)	(7.52)
Firm fixed-effect	No	Yes
Adjusted R^2	0.0128	0.5487

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