Analyst Coverage, Unique Linkages with Firms, and Earnings Forecasting Accuracy

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Abstract. We propose a characteristic-model to separate the linkages information between analysts and listed firms from analyst coverage and investigate the impact of analysts' unique linkage with target firms on earnings forecasting accuracy. Regression results indicate that keeping intense interactions with the target firm will maintain easy access to firm-specific information and produce better earnings forecasting. Our paper contributes to the literature on the informativeness of analyst coverage and provides an effective approach to quantify the relationship between analysts and public firms.

Keywords: Analyst Coverage; Unique Linkages; Informativeness; Earnings Forecasting Accuracy.

1. Introduction

Analysts’ earnings forecasting accuracy has been a frequent topic in financial and accounting research. Accumulating literature discusses the determinants of earnings forecasting accuracy. Earnings forecasting accuracy is proved to increase with analysts’ experience [1], analysts’ prior earnings forecasting performance, the availability of new information [2], and decrease with decision fatigue [3], goodwill impairment charges [4] and reputation concerns. Besides, the title of star analysts [5], fair value measurements [6], and geographical proximity to firms [7] result in analysts’ better earnings forecasting accuracy.

However, few pieces of research explore the impact of the relationship between analysts and target firms on the earnings forecasting accuracy, for that relationship is hard to be quantified directly with data. Close connection with target firms have a positive impact on the analyst’s information environment and improve the analyst’s ability to make accurate predictions. In this paper, we investigate the ties between analysts and public firms, and the subsequent effect on analysts’ forecasting performance.

Compared with the cultural orientation in the West, China is a typical relationship-oriented emerging market economy. Relationship plays an important role in economic and social development by providing business information and market opportunities through personal connections. The Chinese stock market provides an ideal environment to study the special relationship between analysts and companies.

Our empirical research is based on the assumption that analysts with limited resources and energy pay more attention to those listed firms with frequent communication. Analyst coverage proxies reflect all observable and unobservable information between analysts and stocks. We measure the unique linkage between analysts and firms by eliminating the technical analysis information attributable to the firm’s financial characteristics and analysts’ characteristics from analyst coverage based on a simple characteristic-based model. Then, we examine the effect of the unique linkages on analysts’ earnings forecasting accuracy. The empirical results suggest that analysts who maintain intense interactions with target firms have better earnings forecasting performance with less forecasting volatility and higher forecasting accuracy. Our study provides a novel perspective on quantifying the relationship between analysts and public firms based on the informativeness of analyst coverage and adds directly to the growing literature on the determinants of earnings forecasting accuracy.
The remainder of the paper is as follows. Section 2 describes the methodology and data. Section 3 reports the empirical results. Section 4 concludes.

2. Methodology and Data

2.1 Measure of Unique Linkages between Analysts and Firms

Analyst coverage is confirmed to contain information about expected returns [8]. The unique linkages between analysts and firms are measured by separating the observable technical components attributable to firm’s financial characteristics and analysts’ characteristics from analyst coverage. Specifically, we calculate the unique linkages between analyst \( i \) and firm \( j \) in year \( t \) by estimating the following regressions:

\[
\text{Coverage}_{i,j,t} = \beta_0 + \beta_1 \text{Size}_{i,t} + \beta_2 \text{Turnover}_{i,t} + \beta_3 \text{Return}_{i,t} + \beta_4 \text{VO}_{i,t} + \beta_5 \text{MB}_{i,t} + \beta_6 \text{Star}_{i,t} \\
+ \beta_7 \text{Exp}_{i,t} + \beta_8 \text{Gender}_{i,t} + \beta_9 \text{Degree}_{i,t} + \beta_{10} \text{Brokerage}_{i,t} + \beta_{11} \text{Year}_{i,t} + \beta_{12} \text{Industry}_{i,t} + \epsilon_{i,j,t} \tag{1}
\]

where \( \text{Coverage}_{i,j,t} \) denotes analyst coverage of analyst \( i \) for stock \( j \), calculated as the natural logarithm of one plus the number of research reports published by analyst \( i \) on stock \( j \) in the year \( t \). Control variables include \( \text{Size} \) (natural logarithm of market value), \( \text{Turnover} \) (cumulative share turnover), \( \text{Return} \) (cumulative market-adjusted return), \( \text{VO} \) (price volatility), \( \text{MB} \) (market-to-book ratio), \( \text{Star} \) (dummy variable of star analysts), \( \text{Exp} \) (analysts’ career experience), \( \text{Gender} \) (dummy variable of analysts’ gender), \( \text{Degree} \) (dummy variable of analysts’ education level), \( \text{Brokerage} \) (natural logarithm of the number of analysts employed by the same brokerage firm), year dummy and industry dummy.

The residual component of analyst coverage after removing technical analysis and analysts’ characteristics, calculated as the standard residuals of the Eq. (1), is selected as the proxy of the close relationship between analysts and firms.

2.2 Measure of Earnings Forecasting Accuracy

The simple measure of earnings forecasting accuracy, absolute forecasting accuracy, is calculated as the absolute difference between forecasted earnings per share (\( \text{EPS} \)) and the actual \( \text{EPS} \) based on the following model:

\[
\text{AFA}_{i,j,t} = |\text{FEPS}_{i,j,t} - \text{AEPS}_{j,t}|/\text{P}_{j,t} \tag{2}
\]

where \( \text{FEPS} \) denotes the forecasted \( \text{EPS} \), \( \text{AEPS} \) denotes the actual \( \text{EPS} \), and \( \text{P} \) is the close price.

Furthermore, we measure the relative forecasting accuracy \( \text{RFA} \) by scaling the absolute forecasting accuracy to be 1 for the most forecasting accuracy and 0 for the least forecasting accuracy, which mitigates stock characteristic effects on forecasting accuracy for the comparison between different stocks.

2.3 Data and Samples

We selected all the research reports announced from January 1, 2007, to December 31, 2017 on all A-shares stocks listed on the Shanghai and Shenzhen Stock Exchange as the initial samples. Then we remove the research reports that (1) analysts only make one earnings forecasting on the same stock in one year; (2) only one analyst follows in one year. Earnings forecasting data and firm financial data are obtained from China Stock Market and Accounting Research (CSMAR) and Resset database.

The summary statistics of all variables in our sample are provided in Table 1.
Table 1. Descriptive statistics

| Variable   | Mean  | Std.Dev | Min | 5%    | 50%    | 95%   | Max   |
|------------|-------|---------|-----|-------|--------|-------|-------|
| RFA        | 0.624 | 0.343   | 0   | 0     | 0.728  | 1     | 1     |
| Coverage   | 1.059 | 0.443   | 0.693| 0.693 | 1.099  | 1.946 | 3.850 |
| Size       | 23.611| 1.521   | 20.301| 21.747| 23.314 | 26.491| 30.895|
| Turnover   | 4.992 | 4.621   | 0.000| 0.167 | -0.471 | -0.003| 0.984 |
| Return     | 0.098 | 0.518   | -1.679| -0.471| -0.003 | 0.984 | 14.604|
| VO         | 0.029 | 0.024   | 0.007| 0.016 | 0.027  | 0.048 | 2.095 |
| MB         | 0.504 | 0.263   | 0.111| 0.152 | 0.456  | 0.990 | 4.565 |
| Anal       | 3.021 | 0.629   | 1.099| 1.792 | 3.091  | 3.892 | 4.500 |
| Level      | 0.438 | 0.223   | 0.008| 0.099 | 0.428  | 0.820 | 2.579 |
| Volume     | 21.205| 1.268   | 13.347| 21.185| 23.347 | 26.265| 26.265|
| Exp        | 3.389 | 2.564   | 0   | 0.400 | 2.748  | 8.540 | 15.213|
| Star       | 0.222 | 0.415   | 0   | 0     | 0      | 1     | 1     |
| Gender     | 0.276 | 0.447   | 0   | 0     | 0      | 1     | 1     |
| Degree     | 2.996 | 0.470   | 1   | 2     | 3      | 4     | 4     |
| Brokerage  | 6.362 | 0.864   | 0   | 4.779 | 6.477  | 7.482 | 7.766 |
| Stocknum   | 3.036 | 0.836   | 0   | 1.609 | 3.091  | 4.344 | 5.394 |

3. Empirical Results

Column (1) of Table 2 reports the OLS estimation results of Eq. (1), which suggests that analyst coverage is significantly increasing in firm size, firms’ cumulative return, the title of star analysts, analysts’ career experience, education level and the brokerage size, and decreasing in share turnover, price volatility, market-to-book ratio. Then, we get the unique linkages between analysts and target firms which is denoted by the standard residuals.

Considering the information sharing among analysts from the same brokerage institutions, we consider the coverage of all analysts from the same brokerage firms on the same target firms, BroCoverage, as the alternative variables of Coverage. Correspondingly, the standard residuals of regression in Column (2), BroLinkage, is denoted as the alternative variable of Linkage.

Next, we examine the impact of the unique linkage between analysts and firms on analysts’ forecasting accuracy following the estimated regression in Eq. (3):

\[
RFA_{i,t} = \beta_0 + \beta_1 Linkage_{i,t} + \beta_2 Anal_{i,t} + \beta_3 Size_{i,t} + \beta_4 MB_{i,t} + \beta_5 Level_{i,t} + \beta_6 Volume_{i,t} + \beta_7 Year_{i,t} + \beta_8 Star_{i,t} + \beta_9 Exp_{i,t} + \beta_{10} Gender_{i,t} + \beta_{11} Degree_{i,t} + \beta_{12} Stocknum_{i,t} + \beta_{13} Brokerage_{i,t} + \epsilon_{i,t} \]

The regression results of unique linkages between analysts and target firms on earnings forecasting accuracy are shown in Column (1) of Table 3. The significantly positive coefficient of Linkage suggests unique linkages with firms improves analysts’ earnings forecasting accuracy. Columns (4) reports the robustness results of BroLinkage on forecasting accuracy.
Table 2. Unique linkages between analysts and firms

| Variable | (1) Coverage | (2) BroCoverage |
|----------|-------------|-----------------|
| Size     | 0.053***    | 0.078***        |
|          | (49.316)    | (54.350)        |
| Turnover | -0.005***   | -0.006***       |
|          | (-12.920)   | (-11.866)       |
| Return   | 0.020***    | 0.028***        |
|          | (8.250)     | (8.859)         |
| VO       | -0.234***   | -0.383***       |
|          | (-4.646)    | (-5.698)        |
| MB       | -0.140***   | -0.221***       |
|          | (-26.012)   | (-30.734)       |
| Star     | 0.095***    | 0.139***        |
|          | (35.168)    | (38.612)        |
| Exp      | 0.015***    | -0.012***       |
|          | (34.837)    | (-20.904)       |
| Gender   | -0.001      | 0.259***        |
|          | (-0.325)    | (139.987)       |
| Degree   | 0.075***    | 0.078***        |
|          | (54.089)    | (54.350)        |
| Brokerage| -0.706***   | -2.019***       |
|          | (-22.997)   | (-50.376)       |
| Constant | 167,902     | 167,902         |
| R-squared| 0.081       | 0.203           |

The t-statistics are reported in parentheses under the estimated coefficients. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

To eliminate concerns of non-information-driven forecasting on results, we design the RFA_Mean and RFA_Volatility, the mean value and volatility of relative earnings forecasting corresponding to the same value of Linkage. Columns (2) and (3) examine the relationship between unique linkages and RFA_Mean as well as RFA_Volatility. The results indicate that maintaining a close relationship with the target firm improves analysts’ forecasting performance with less forecasting volatility and higher forecasting accuracy.
Table 3. Unique linkages and earnings forecasting accuracy

| Variable  | (1) RFA | (2) RFA_Mean | (3) RFA_Volatility | (4) RFA |
|-----------|---------|--------------|--------------------|--------|
| Linkage   | 0.059*** | 0.063***     | -0.026***          | 0.041*** |
|           | (74.740) | (450.583)    | (-305.217)         | (49.136) |
| BroLinkage| 0.059*** | 0.001***     | -0.001***          | 0.060*** |
|           | (32.700) | (7.878)      | (-7.998)           | (33.167) |
| Anal      | 0.012*** | 0.001***     | -0.001***          | 0.013*** |
|           | (12.357) | (9.206)      | (-25.405)          | (12.549) |
| Size      | -0.052***| 0.000        | 0.002***           | -0.049***|
|           | (-10.838)| (0.256)      | (10.475)           | (-10.165)|
| MB        | -0.008   | -0.001***    | 0.000              | -0.011* |
|           | (-1.334) | (-2.983)     | (0.306)            | (-1.788)|
| Level     | -0.008   | -0.001***    | 0.000              | -0.009***|
|           | (-7.238) | (-7.552)     | (6.361)            | (-7.792)|
| Volume    | 0.007    | 0.001        | -0.000             | 0.003 |
|           | (1.027)  | (1.170)      | (-1.265)           | (0.458)|
| In dumb   | 0.006*** | 0.002***     | -0.002***          | 0.005** |
|           | (2.935)  | (9.523)      | (-17.532)          | (2.162)|
| Star      | -0.005***| 0.000***     | -0.000             | -0.005***|
|           | (-14.261)| (6.012)      | (-19.617)          | (-16.012)|
| Exp       | 0.009*** | 0.000**      | 0.000              | 0.009*** |
|           | (4.746)  | (2.900)      | (0.331)            | (5.121)|
| Gender    | 0.004**  | 0.000        | 0.000**            | 0.005*** |
|           | (2.058)  | (0.058)      | (2.224)            | (2.597)|
| Degree    | 0.010*** | 0.000***     | -0.000             | 0.018*** |
|           | (8.731)  | (5.848)      | (-1.175)           | (15.030)|
| Stocknum  | 0.009*** | 0.001***     | -0.002***          | 0.041*** |
|           | (7.965)  | (10.590)     | (-35.459)          | (49.136)|
| Brokerage | 0.255*** | 0.617***     | 0.371***           | 0.262*** |
|           | (8.083)  | (257.334)    | (266.155)          | (8.249)|
| Constant  | 167,902  | 167,902      | 167,848            | 167,902 |
| Observations |        |              |                    |        |
| R-squared | 0.057    | 0.868        | 0.756              | 0.042  |

The t-statistics are reported in parentheses under the estimated coefficients. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

4. Conclusion

We innovatively quantity the relationship between analysts and listed firms by removing the mechanical component summarized by observable firm characteristics and analyst characteristics from the standard analyst coverage proxies. We find that analysts closely associated with target firms maintain easy access to firm-specific information. Besides, unique linkage with target firms improves information precision and leads to better earnings forecasting performance with less forecasting volatility and higher forecasting accuracy. Our paper contributes to the literature on the informativeness of analyst coverage and expands the determinants of earnings forecasting accuracy.
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