# IS THE MARKET SMART ENOUGH TO IDENTIFY SUPERIOR ANALYSTS AND FOLLOW THEIR RECOMMENDATIONS?

by

Jiarui Yao
Bachelor of Mathematics, Peking University, 2015

and

Chang Liu
Bachelor of Economics, China Agricultural University, 2012

PROJECT SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE IN FINANCE

In the Master of Science in Finance Program
of the
Faculty
of
Business Administration



SIMON FRASER UNIVERSITY

Fall 2016

# Approval

**Name:** **Jiarui Yao, Chang Liu**

**Degree:** **Master of Science in Finance**

**Title of Project:** **Is the market smart enough to identify superior analysts and follow their recommendations?**

**Supervisory Committee:**

**Amir Rubin**
Senior Supervisor
Associate Professor

**Alexander Vedrashko**
Second Reader
Correct Title

Date Approved:

# Abstract

In this article we investigate whether there is persistency in analysts forecasting ability and if it exists, whether the market has the ability to identify these differences in abilities. Our results reveal that the forecasting ability of analysts is persistent. We then investigate whether investors identify superior analysts' ability by analyzing market reaction to their recommendations compared to the reaction to other analysts. Our findings suggest that the two-day returns after the analysts' reports' are strongly positively correlated with analysts' recommendations and there is a significant difference in reaction between high and low quality analysts. We conclude that the market is smart enough to identify different types of analysts and follow their recommendations respectively.

**Keywords:** Analyst; forecasting ability; persistency; recommendation; market reaction

## Acknowledgements

This project is supported by Simon Fraser University. We would like to show our gratitude to Amir Rubin, Associate Professor at Simon Fraser University for sharing his pearls of wisdom with us during the course of this project. We are also immensely grateful to Alexander Vedrashko, Associate Professor at Simon Fraser University for his comments on the earlier version of the manuscript, although any errors are our own and should not tarnish the reputations of these esteemed persons.

# Table of Contents

# List of Tables

# 1: Introduction

In Merton's theory [J. Finance 42 (1987) 483.] on market information segmentation, investors only invest in securities known to them. Therefore, stock analysts play an important role in minimizing information asymmetry in the market. Although some intraday returns evidence shows that announcements of analysts' forecast revisions release little new information (Altınkılıç, Balashov and Hansen 2013), it is widely agreed that analysts' reports provide beneficial information, such as three key summary measures: an earning forecast, a stock recommendation and a price target (Asquith, Mikhail, and Au 2005). To outperform other investors, both institutional players and individual players in the market are interested in the accuracy of the analysts' reports. If an analyst can prove his/her superiority, such as providing highly accurate earnings estimations, investors in the market should follow his/her recommendation closely. The aforementioned situation exists when, first, superior analysts exist and significantly outperform their peers and, second, other market participants are able to recognize and follow superior analysts' recommendations and profit from them.

In a perfectly efficient market, as assumed in the efficient-market hypothesis, analysts' reports are not valuable to investors because all the available information has been reflected in the stock prices. However, many studies have shown that by collecting and analyzing related information, analysts are able to add significant value to the portfolios (e.g. Fang and Yasuda 2013). Among all the analysts, the differences in the forecasting ability of financial analysts do exist (e.g. Stickel 1992; Sinha, Brown, Das 1997; Leone and Wu 2007). To further examine why the differences exist, researchers examined the determinants of forecast accuracy, such as experience (Clement 1999), employer (Kerl and Ohlert 2015) and designation (Franco and Zhou 2009). With respect to the market reaction, scholars have examined North America (Chung and Kryzanowski 2001) and Asia (Ding, Chen and Wu 2014; Chen and Hong 2006). Analysts' persistent performance is also studied by other scholars. Mikhail, Walther and Willis (2004) find that analysts whose recommendation revisions earned the most (least) excess returns in the past continue to outperform (underperform) in the future. Li (2005) also finds that analysts with above-median risk-adjusted performance in the estimation period persistently outperform those with below-median performance in the subsequent holdout period.

Previous studies also investigated the degree to which the market reacts to the recommendations. Hilary and Hsu (2013) find that on average, analysts with a lower standard deviation of forecast errors have a better ability to move prices. This shows that investors are willing to listen to analysts who demonstrate persistent forecast ability. Some claims of under-weighting of forecasts (Elgers et al.'s 2001) while some evidence of over-weighting of such forecasts (Dechow et al. 1999; and Frankel and Lee 1998).

This article contributes to the literature by combining the investigation in forecasting ability and the market's ability to identify the different forecasting ability. First, we analyze whether analysts differ in the earnings forecast ability. Second, we analyze whether the market recognizes the persistent ability, and reacts to analysts' recommendations.

Like some previous studies (such as Hall and Tacon 2010), we also hypothesize that the estimation accuracy for earnings is the indicator of analysts' forecasting ability. Following the line of argumentation by Sinha, Brown and Das (1997), we categorized analysts into two groups, superior and inferior. The first half of the analysts (at a given firm-year) are considered superior analysts while the others are considered inferior analysts. We utilize that IBES and CRSP databases and examine approximately 2,514,938 analysts' reports written by approximately 61,398 analysts between October 1993 and June 2016 that contain forecasts and recommendations for the capital market.

# 2: Data Sample

## 2.1 Data Source

Our sample contains a panel of analyst reports from October 1993 to June 2016 obtained from IBES. The data contains these following: the analyst code, the firm that an analyst is trying to estimate, the date that estimation is made, the estimated EPS value and the actual EPS value and the date that the real EPS was released, that is to say, the actual announcement date. For the EPS value, we use the annual data and the estimation EPS is to estimate this annual EPS.

The sample includes analyst reports covering 22,826 US based companies. For every report, we require the analysts' estimations for stock recommendation and forecast for earnings per share. Overall, our sample of 2,514,938 reports is based on 23,101 individual analysts issuing 21,362 EPS estimations covering 22,826 stocks. In the analysis for market reaction, we obtain data from IBES for 2,514,938 reports issued by 61,398 analysts. We obtained market data from CRSP with approximately 121,000,000 daily holding period returns and daily value weighted returns.

In order to clean the data, we implement a screening process on the raw data. First, to ensure that the market is reacting to the recommendation rather than companies' earnings announcements, we only include analyst reports published at least two days after the quarterly earnings announcements. For example, a company publishes its quarterly earnings per share on July 7th and one analyst publishes his/her report on July 7th or 8th. At the same time, we find that the abnormal return of that company fluctuates largely on July 7th, 8th or 9th. This kind of observation could result from the company's earnings announcement but not from the analyst report. Therefore, we set a two-day period before taking an analyst forecast into consideration. The assumption is that after two days, the impact of the company's announcement is no longer affecting prices and is fully absorbed by the market.

Furthermore, we try to avoid the small sample bias effect by excluding companies that have less than four analyst reports in the past 25 years. That is to say, any company that has less than 4 analysts providing forecast is discarded.  In a small sample, the ranking could be the result of random events or luck. For example, if there are only two analysts forecasting the earnings per share of a company, even a small difference will result in two completely different categories, a superior analyst and an inferior analyst. When in fact, their forecasting abilities are at the same level. If a company has an only one-year observation or there is only one year that has more than 4 analysts followed, then this should be eliminated since we are not just ranking them but want to see if there is persistency among years. If we cannot find at least two consecutive years, then we don't use this firm in the analysis.

Moreover, among several forecasts during one year, we only include the most recent forecast of the analyst prior to the actual earnings announcement. For example, it is very common for an analyst to estimate one company's earnings per share several times before the company's announcement. As the company announcement date approaches, the analyst will have more information and more recent data about the company. Therefore, we assume the last forecast before the earnings announcement is the best indicator of the analyst's forecasting ability because, at that time, the analyst is closest to the earnings announcement. In a sense, it also levels the playing field between analysts because one would think that all analysts try to be accurate just before the earnings announcement is made. Even if not all analysts provide a forecast close to the earnings announcement, one would think that the hard-working "superior" analyst would do all they can in order to be accurate so they provide a relatively adequate forecast just before the earnings news. That is to say, those analysts that are willing to spend more time and energy deserve a better rank and we want to use their last estimation to see how good they are.

To analyze the persistency of analysts' forecasting ability, our data will be sorted in groups that follow: for a given fiscal year, an analyst would have only one recommendation left for a given firm (the one that is closest to the next EPS announcement).

From IBES Database, we are also able to get all recommendations given by these analysts. However, not all the recommendations are good to use. If a recommendation is made to a non-US based firm, it is eliminated as the estimation ability is only tested according to how good an analyst is to estimate the EPS of a US-firm.

Furthermore, we analyze market reaction to recommendations in the year following the rating of analysts' accuracy. Therefore, if the stock is not traded in the following year or the analysts have stopped following the firm in the following year, the analyst is essentially excluded from the analysis.

Additionally, due to data availability constrain in CRSP, we only have real earnings per share untill the end of 2015. So we drop estimate earnings per share data in 2016. Any other missing values in core variables are also not acceptable.

## 2.2 Data Measures

To measure each analyst's forecast accuracy of earnings per share for each company in every year, we use the actual earnings per share after the analyst's earnings forecast for comparison with the initial forecast. A lower value corresponds to a more accurate forecast. The analyst's forecast accuracy, ABS_DIFF, is the absolute forecast accuracy of the difference between actual earnings per share and the estimated earnings per share of the analyst.

To measure the market reaction to the recommendations, we use the recommendations that are rated by Thomson Reuters in five levels. For each recommendation, important information to use in this task is firm code, analyst code, recommendation date and the recommendation level (from 1 strong buy to 5 sell).

## 2.3 Superior-analysts Classification

Based on the group generated in the data section, we can rank these estimations according to the absolute difference of estimation and actual value. The definition of absolute difference is $\mathrm{ABS_{Diff}} = |\mathrm{EPS_{Recommendation}} - \mathrm{EPS_{Actual}}\,|$. The smaller this number, the more accurate the recommendation is. Given a certain time, for a fixed firm, this number is comparable between analysts. The superior analysts are identified by the ranking percentage of the forecast accuracy. After we have the absolute difference between estimated earnings per share and the actual earnings per share, we find out the percentile of each forecast at a firm-year level. The top 50% of the firm's forecasts are considered to be forecasts from superior analysts. The other 50% analysts are inferior analysts of that company in that year. In the persistency analysis, we further investigate if the classification changes in different years.

In the market reaction analysis, we have two ways to classify superior analysts. The easier method is that based on the result from persistency analysis, we assume two static groups of analysts in each year, the superior analysts and inferior analysts. We use the average percentage ranking of analysts to define if an analyst is a superior analyst or inferior analyst. After this classification, we investigate how abnormal returns relate to the two static groups every year. The more accurate way to classify superior analysts is to keep all the evaluation results in all years. Therefore, we have more data and two dynamic groups of analysts in each year. For example, for analyst A, he may be a superior analyst analyzing Apple in 2001 but may be an inferior analyst analyzing Apple in 2002. Then we investigate how year N+1's abnormal returns relate to the year N's two dynamic groups of analysts.

## 3: Forecast Accuracy and Persistency Analysis

In this part, we want to discuss whether the quality of an analyst is better measured at the firm-year level or at the year-level. Nowadays, people have witnessed more and more "star analysts", among these analysts, these analysts are not only with financial backgrounds but also have PhD with math or physics background, some even have a biology degree that focuses on the medicine industry. It is easy to tell that a single person would have limited knowledge, no one is good at everything. Therefore, it is reasonable that an analyst might not have a very good ability to estimate all companies. But rather analyst ability may be firm specific. That is to say, if an analyst is good at estimating Apple's EPS in year 2011 for example, he/she may not be good in estimating other companies, such as Walmart or AT&T. An alternative view is that most of the estimating knowledge is economy-wide so if you are good in estimating Apple, you are also good in estimating other companies. Hence, the question to ask is whether analyst accuracy ability firm-specific or economy-wide?

For each group (on a firm-year level), we can have the ranking of forecasting ability of analysts. This rank is in percentage, it means for a given year, a given firm, the percentage position an analyst is. For instance, if this number is 100% for an analyst estimating Firm A in 1995, then this analyst has the worst estimation of Firm A in Year 1995. To test if the rank percentage and the classification change in different years, we simplify two classes into 0 and 1, where 1 stands for superior analysts and 0 stands for inferior analysts. We try to find out the relationship between the year and the year after.

If there is persistency, then the data will show a significant evidence that if an analyst is "superior" in year N, then this analyst should have a higher probability than 50% to stay in "superior" group in year N+1. This test can be also done in year N+2 to have a further confirmation. A simple t-test will clearly show if superiority is persistent and significance. We do a stricter t-test. If the analyst quality is in superior in the former year, would this analyst be expected to do better than another analyst that is in the inferior group? A t-test can show this difference. If these two groups have significantly difference average in the coming year and the superior group is higher than the inferior group, then we can say there is indeed a persistency in the analyst quality.

From Table 1 Panel 1, we can see that “inferior” group in the former year tends to show more persistency in the following year, and the difference in the next year given the same analyst in two groups in the former year is significant. That is to say, in year N, we have two groups of analysts, half of them are marked as “superior” while the others are marked as “inferior”. In year N+1, those analysts from “superior” groups have a higher probability to stay in “superior” groups. Those from “inferior” groups have a higher chance to stay in “inferior” groups. What’s more, the persistency in “inferior” group is more significant. Our results show that it is difficult for analysts to change their classifications, which means that in most cases, superior analysts will stay in superior class and inferior analysts will stay in inferior class. Furthermore, comparing between superior analysts and inferior analysts, it is more likely for the superior analysts to drop into the inferior class in the following years.

There are two possible reasons for this result. First, the market is not easy to follow and it is indeed hard to be always correct. To keep in the superior group is definitely harder than to keep in the inferior group (e.g. if you always make bad estimations, you will be always in the bad group for sure but this will not hold even if you are a very good analyst.). This is the most important reason that the good group does not have the same extent of significance as the bad group. Secondly, if we test the persistency with a 2-year lag in Table 1 Panel B there is a better significance in “superior” groups. This test is to test this change: an analyst might move to another group in the following year, but if he/she is really a good analyst, the next year he/she should get back to the “superior” group. Our t-test with the 2-year lag proves that superior analysts are likely to improve in the following years even if some fail in the first year.

## 4: Market Reactions to Superior-Analysts' Recommendations

In order to test if the market reacts to the recommendation given by the analyst, first, we need to find out the relationship between abnormal return, which is defined as holding period return minus value-weighted return. If there is more positive information outside the market, this abnormal return will be higher, and vice versa. We assume the market will need two days to fully absorb the effect of this recommendation, so this abnormal return should be calculated over a 2-day period after the recommendation is made.

Based on this abnormal return, we want to see if the superior analysts and the inferior analysts have different extent of influence. In order to check this conclusion, we need to find a way to test what kind of analyst can be named as "superior analyst". Based on what we discussed in persistency part, there is a persistency in the forecasting ability of analyst in different years. So we use the average percentage rank of an analyst to define if he is good or not. All analysts are divided into two groups for each firm, superior or inferior. For example, from 1993-2016, if analyst A's absolute difference of EPS estimation of firm F has an average percentage rank less than 50%, that means on average, this analyst is in the first half, then we will name A as "A is good for F", if analyst B has a percentage rank of more than 50%, that means on average, analyst B is in the bottom half, we will name B as "B is bad for F".

Having all the recommendations that are good to use, we can then check whether an analyst is "superior" or "inferior" given the firm he/she is making this recommendation. Finally, the recommendation data will contain 6 main variables: firm code (cusip), analyst code, recommendation date, abnormal return, recommendation level and a dummy variable – 1 for good and 0 for bad. Of which, the most important one is abnormal return, we are trying to find out whether the recommendation has an impact on this abnormal return and whether the ability of analyst contributes to this effect.

We first run a regression using year-level recommendations. The result shows that only 5 years out of the 21-years have significant coefficients, which means that only using year-level regression cannot provide meaningful conclusions. However, the significant negative coefficient of Change in recommendation shows that market will react when it is regressed on a firm-year level. Therefore, in the next two regressions, we focus our investigation on the firm-year level.

Then we do the firm-year level regression. The regression is done using only abnormal return, and the recommendation based on the firm level. If the market reacts to the recommendation, then the with the number going up in recommendation level, which means a downgrade of a firm, will have a decreasing abnormal return and this effect should be significant and an upgrade of a firm would see an increasing in abnormal return.

From Table 2 Panel A (1), we can see that the coefficient of change in recommendation given a firm (drecom) is very significant and is negative which matches our guess. The market does react to the recommendations made by analysts. Note here we should use cluster(cusip) since the error between various firm might be different. If we don't use cluster analysis, the basic assumption of linear regression – homoscedasticity will be violated.

Next, we are interested in whether the market can distinguish recommendation from superior or inferior analysts. That is to say, we want to find out whether the recommendation from a superior analyst will have a different impact from that of an inferior analyst. In order to do this, we need to add some more variables in the regression. One variable to add in is the quality of analyst (dummy variable, good or bad). But simply add this variable doesn't mean anything. It's not difficult to tell that simply this variable would be insignificant because the abnormal returns should not be affected by the quality of an analyst, the recommendation, of course, is what really matters. Thus, the interaction term of quality and recommendation is what we are interested in. If this interaction term is significant, then that means the market reacts differently regarding the quality of analyst. The sign of this interaction term should be the same as that of the recommendation. If this holds, then it means the superior analysts have more influence over the market abnormal return compared to the inferior analysts. If this interaction term is significant but has a different sign from the recommendation, then it suggests the inferior analysts have more influence in the abnormal return, the market is following the inferior analysts rather than the superior ones. If this interaction term is not significant then it indicates the market might not be able to tell the difference between superior and inferior analysts as its abnormal return is affected regardless the quality of analyst.

From Table 2 Panel A (2), it seems that the superior and inferior analysts seem to have quite a similar impact to the market. That is to say, we do not have clear evidence to show that the market is smart enough to distinguish the recommendation of a superior analyst from a bad ones.

To test the market in a more dynamic way, we use the dynamic classification of superior analysts and inferior analysts in the following regression in Table 2 Panel B. As described in the Data Sample section, we do not use the average performance of the analysts to classify the superior analyst group and the inferior analyst group. Instead, we keep all the performances of each analyst on each company in each year. Therefore, we are able to investigate whether an analyst who is classified to be superior in year N will trigger a reaction in the market's abnormal return in year N+1 based on his/her recommendation in year N+1.

From Table 2 Panel B (1), we can first prove that the market still reacts to the analysts' recommendation as a whole. In Table 2 Panel B (2), the result shows that after being recognized as a superior analyst, the analyst's recommendation in the next year will trigger an abnormal return in the market. Thus, we can confidently conclude that the market is smart enough to distinguish the recommendation of a superior analyst from an inferior ones.

The reason why the regression in Table 2 Panel A (2) does not show significant may be that the static way of classification ignores the fact that an analyst's performance in later years is not able to affect the market in the previous years. For example, in a 15-years period, an analyst is an inferior analyst in the ten years and superior analysts in the other five years. Even if the previous year's classification is superior, the average result is still inferior. Thus the average classification will make the regression of the market reaction ignore the previous year's forecasting ability. Instead, using the dynamic way to regress the abnormal return and analysts' classification will make the reaction more accurate to the previous year's forecasting ability.

# 5: Conclusion

Analysts conduct their analysis on an individual basis with relevant company-specific information and macro economy data. Since most of their analysis are based on proprietary models without revealing fundamental logic and extensive details about the forecasting process, investors need to identify superior analysts whose forecasts and recommendations are more accurate and deserve their trust.

To gauge this difference, we used article *Do accurate earnings forecasts facilitate superior investment recommendations* as our assumption to measure forecasting ability. According to Loh and Mian (2006), "analysts who issue more accurate earnings forecasts also issue more profitable stock recommendations". Moreover, the higher the forecasting ability, the more accurate recommendations will be. Our results support the hypothesis that earnings forecasts of superior analysts outperform those of inferior analysts. What's more, there is a persistency in the forecasting ability. When we analyze further into the subordinate groups, we find that the earnings forecasts of superior analysts are more persistent than inferior analysts' in terms of forecast accuracy.

With two groups of analysts, we try to find out the market reaction toward superior analysts and inferior analysts. Our results show that after the analyst reports come out, the abnormal returns fluctuate accordingly, which means the market reacts to the analyst reports. However, there is no significant difference in market reaction between superior analysts and inferior analysts, which means that the market follows the recommendations blindly, regardless of the sources, whether it is from superior analysts or from inferior analysts.

This paper is among the first to combine the analysis of analyst forecasting abilities with the market reaction to the different abilities. However, there are still more works that can be done further.

First of all, the persistency is still not that clear, that is to say, the rank difference between groups is not very large. The main reason that causes this result is the way we separate the analysts. One possible improvement is to detect what level would be better to divide the analysts. Half-half may not be the best way. The ratio can be set to be k%, i.e. the first k% is named as "good" while the bottom k% is named as "bad". Then for different years, we can draw a chart to show the shift from group to group. If there is no persistency, then the probability of an analyst shows a (good, good) is k^2/10000, if the statistic data shows a significant difference between frequency (good, good) and k^2/10000, then there is persistency of "good" group. The same thing can be done for the "bad" group.

Secondly, if we can test persistency over longer time lags, there may other implications about superior analysts' forecast ability. Over a two-years observation window, we may be able to identify a trend in superior analysts' forecast ability getting better, which means that with a longer time period, superior analysts tend to stay superior. If this phenomenon shows in longer lags, such as lag 3, lag4 and lag5, we will have better ability to show that even if in the short-term superior analysts' performance may not be very persistent, they will eventually be able to differentiate themselves from the inferior analysts in the long run.

Thirdly, the way we set the group is too simple; it is only based on the firm name and year. However, a more reasonable way to do is to add other control variables that have an effect on the character of the firm. For example, Fama-French factors, beta and industry would contribute to further research. The conclusion would be more in detail. We found out that there is persistency but we are not sure whether this persistency is generated from big firms like Yahoo and Apple or from small firms like Taseko Mines. If there is a difference between these groups, the result will be more interesting. Maybe we can even find out analysts that are extremely good at estimating small firms and those who do well in big firms.

Lastly, we lack the proof of a relationship between the ability of forecasting and making a good recommendation. A more direct way to test if an analyst is good or bad from the recommendation perspective should be if we create a portfolio and uses different analysts' recommendation from the first few years as a test. See if they have good or bad returns and compare these results to the forecasting ability. Only if these two groups show significant persistency, we can say that it is acceptable to use the forecasting ability to distinguish "superior" from "inferior" analysts. This part of the empirical analysis is missing.

# Appendix

**Table 1:** *Persistency of analyst forecasting over years*.

The table reports the t-test result for forecasting ability difference between inferior analysts and superior analysts in 1993 - 2016. In Panel A, the result shows that the expected difference of inferior and superior analysts is significantly different from zero, which means that after one year, there is still a difference between the two groups of analysts. The result also shows that the expected quality of inferior analysts is different from 0.5 (the result from a random mix of two kinds of analysts) at a 95% confidence level, which means that after one year, inferior analysts are still inferior in 95% of the time. In Panel B, the result shows that the expected difference of inferior and superior analysts is significantly different from zero, which means that after two years, there is still a difference between the two groups of analysts. The result shows that the expected quality of both inferior and superior analysts is different from 0.5 (the result from a random mix of two kinds of analysts) at a 95% confidence level, which means that after two years, inferior and superior analysts stay as inferior and superior analysts in 95% of the time. The t-statistic is provided in parentheses. *, ** and *** indicate significance at the 5%, 1% and 0.1% levels, respectively.

*Panel A: Persistency of analyst forecasting over two consecutive years*

| Analyst_Quality | Observations | Mean | Std.Err. | Std.Dev. | [ 95% Conf. Interval ] | |
|---|---|---|---|---|---|---|
| Inferior = 0 | 264,264 | 0.45796*** | 0.000969 | 0.498230 | 0.456059 | 0.459858 |
| Superior = 1 | 301,408 | 0.50086*** | 0.000911 | 0.500000 | 0.499078 | 0.502648 |
| Combined | 565,672 | 0.48080*** | 0.000664 | 0.499632 | 0.479517 | 0.482121 |
| diff | | -0.04290*** | 0.001330 | | -0.045511 | -0.04030 |

$t$ statistics in parentheses

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

diff = Average of Bad in 1-year - Average of Good in 1-year    t = -32.2522

$H_0$: diff = 0    degrees of freedom = 565670

$H_a$: diff < 0    $H_a$: diff = 0    $H_a$: diff > 0

Pr( |diff| < 0) = 0.0000    Pr( |diff| = 0) = 0.0000    Pr( |diff| > 0) = 1.0000

*Panel B: Persistency of analyst forecasting over three consecutive years*

| Analyst_Quality | Observations | Mean | Std.Err. | Std.Dev. | [ 95% Conf. Interval ] | |
|---|---|---|---|---|---|---|
| Inferior = 0 | 176,754 | 0.47321*** | 0.001188 | 0.499283 | 0.470878 | 0.475533 |
| Superior = 1 | 203,685 | 0.50226*** | 0.001108 | 0.499996 | 0.500085 | 0.504427 |
| Combined | 380,439 | 0.48876*** | 0.000810 | 0.499874 | 0.487171 | 0.490348 |
| diff | | -0.02905*** | 0.001624 | | -0.032234 | -0.02587 |

diff = Average of Bad in 2-year - Average of Good in 2-year t = -17.8851

$H_0$: diff = 0 degrees of freedom = 565670

$H_a$: diff $<$ 0 $H_a$: diff = 0 $H_a$: diff $>$ 0

Pr( |diff| $<$ 0) = 0.0000 Pr( |diff| = 0) = 0.0000 Pr( |diff| $>$ 0) = 1.0000

**Table 2:** *Market reaction to analysts' recommendations.*

The table reports regression results for the observed firms' abnormal returns in 1993-2016. The dependent variable is the two-day abnormal return of the firm on its announcement day and the next trading day. *Change in recommendation* is the difference between the new recommendation and the previous recommendation where the recommendation level is quantified from 1 strong buy to 5 sell. If the recommendation changes from strong buy 1 to buy 2, the change in recommendation should be 1, vice versa. *Analyst quality* is an indicator equal to zero for inferior analysts and is one for superior analysts. The interaction term of *Change in recommendation* and *analyst quality* is different analysts' change in recommendation. *Intercept* stands for the abnormal return when there is no change in recommendation.

In Panel A (1) regression, the significant negative coefficient of *Change in recommendation* shows that market will react with a negative abnormal return when there is a downgrade in the analyst's recommendation. The close to zero *Intercept* shows that market does not react to the recommendation when there is no change in the recommendation. In Panel A (2) regression, the significant negative coefficient of *Change in recommendation* shows that market will react with a negative abnormal return when there is a downgrade in all analysts' recommendations. The insignificant coefficient of *Analyst quality* shows that the market is smart enough to avoid blindly following any recommendations superior analysts announce. In other words, the market does not react to the type of the analysts. Therefore, we introduce an interaction term of *Change in recommendation* and *analyst quality*. The insignificant negative coefficient of this term shows that market reacts to different analysts' recommendation in a negative direction. However, the market is not smart enough to follow superior analysts and avoid inferior analysts. The close to zero *Intercept* still shows that market does not react to the recommendation when there is no change in the recommendation. Robust standard errors are clustered by firm and the t-statistics are provided in the parentheses. *, ** and *** indicate significance at the 5%, 1% and 0.1% levels, respectively.

In Panel B regression, we use the dynamic classification of superior analysts and inferior analysts in the following regression. Therefore, we are able to investigate whether an analyst who is classified to be superior in year N will trigger a reaction in the market's abnormal return in year N+1 based on his/her recommendation in year N+1. In Panel B (1), the previous market reaction result still holds with analysts' recommendation as a whole. In Panel B (2) regression, the significant negative coefficient of *Change in recommendation* shows that market will react with a negative abnormal return when there is a downgrade in all analysts' recommendations. The insignificant coefficient of *Analyst quality* shows that the market is smart enough to avoid blindly following any recommendations superior analysts announce. In other words, the market does not react to the type of the analysts. The 95% confidence level significant negative coefficient of the interaction term of *Change in recommendation* and *analyst quality* shows that the market is able to follow superior analysts and avoid inferior analysts most of the time. The close to zero *Intercept* still shows that market does not react to the recommendation when there is no change in the recommendation. Robust standard errors are clustered by firm and the t-statistics are provided in the parentheses. *, ** and *** indicate significance at the 5%, 1% and 0.1% levels, respectively.

*Panel A: Market reaction to static analysts' groups*

| | Abnormal Return | |
|---|---|---|
| | (1) | (2) |
| Change in Recommendation | -0.0152*** | -0.0150*** |
| | (-62.32) | (-53.84) |
| Analyst Quality | | 0.0000194 |
| | | (0.07) |
| Change in Recommendation x Analyst Quality | | -0.000292 |
| | | (-1.06) |
| Intercept | -0.000882*** | -0.000891*** |
| | (-4.16) | (-3.60) |
| Observations | 280891 | 280891 |
| Adjusted $R^2$ | 0.0556 | 0.0556 |

*t* statistics in parentheses

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

*Panel B: Market reaction to dynamic analysts' groups*

| | Abnormal Return | |
|---|---|---|
| | (1) | (2) |
| Change in Recommendation | -0.0138*** | -0.0133*** |
| | (-45.05) | (-33.12) |
| Analyst Quality (The Former Year) | | -0.000335 |
| | | (-0.77) |
| Change in Recommendation x Analyst Quality (The Former Year) | | -0.000919* |
| | | (-2.21) |
| Intercept | 0.0002835 | 0.0004678 |
| | (1.00) | (1.20) |
| Observations | 118,518 | 118,518 |
| Adjusted $R^2$ | 0.0530 | 0.0530 |

*t* statistics in parentheses

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

## References

Altınkılıç, Oya, Vadim S. Balashov and Robert S. Hansen, Are Analysts' Forecasts Informative to the General Public, Management Science, 59, 2550–2565

Asquith, P., M. B. Mikhail, and A. S. Au, 2005, Information content of equity analyst reports, Journal of Financial Economics 75, 245–82.

Chen, An-Sing and Bi-Shia Hong, Institutional ownership changes and returns around analysts' earnings forecast release events: Evidence from Taiwan, Journal of Banking & Finance 30, 2471–2488

Chung, Richard and Lawrence Kryzanowski, Tests of investor cognizance using earnings forecasts of North American analysts, International Review of Economics and Finance 10 (2001) 187-204

Clement, Michael B., Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter, Journal of Accounting and Economics, 27, 285-303.

Dechow, P., A. Hutton and R. Sloan (1999), 'An Empirical Assessment of the Residual Income Valuation Model', Journal of Accounting and Economics, Vol. 26, pp. 1–34.

Ding, Fangfei, Min Chen and Zhongxin Wu, Do Institutional Investors Use Earnings Forecasts from Financial Analysts? Evidence from China's Stock Market, Emerging Markets Finance and Trade, 50, 134-147.

Elgers, P., C. Callahan and E. Strock (1987), 'The Effect of Earnings Yields Upon the Association Between Unexpected Earnings and Security Returns: A Re-examination', The Accounting Review, Vol. 57, No. 4, pp. 763–73.

Fang L., and A. Yasuda, 2013, Are stars' opinions worth more? The relation between analyst reputation and recommendation values, Journal of Financial Services Research 46, 235–69.

Franco, Gus De and Yibin Zhou, The Performance of Analysts with a CFA? Designation: The Role of Human-Capital and Signaling Theories, The Accounting Review, 84, 383-404.

Frankel, R. and C. M. C. Lee (1998), 'Accounting Valuation, Market Expectation, and Cross-

Sectional Stock Returns', Journal of Accounting and Economics, Vol. 25, No. 3, pp. 283–319.

Gu, Zhaoyang, and Joanna Shuang Wu, 2003, Earnings skewness and analyst forecast bias, Journal of Accounting and Economics 35, 5–29.

Hall, Jason L., Paul B. Tacon, Forecast accuracy and stock recommendations, Journal of Contemporary Accounting & Economics 6 (2010) 18–33

Hilary, Gilles and Charles HSU, 2013, Analyst Forecast Consistency, The Journal of Finance, 1

Hong, Harrison, Jeffrey D. Kubik, and Amit Solomon, 2000, Security analysts' career concerns and herding of earnings forecasts, Rand Journal of Economics 31, 121–144.

Jordan, Bradford D., Mark H. Liu, Qun Wu, Do investment banks listen to their own analysts, Journal of Banking & Finance, 36, 1452–1463

Kerl, Alexander and Martin Ohlert, Star-analysts' forecast accuracy and the role of corporate governance, The Journal of Financial Research, Vol. XXXVIII, No. 1, 93-120.

Leone, A., and J. S. Wu, 2007, What does it take to become a superstar? Evidence from institutional investor rankings of financial analysts, Working Paper, University of Rochester.

Li, Xi, 2005, The persistence of relative performance in stock recommendations of sell-side financial analysts, Journal of Accounting and Economics 40 (2005) 129–152

Loh, Roger K., G. Mujtaba Mian, Do accurate earnings forecasts facilitate superior investment recommendations, Journal of Financial Economics 80 (2006) 455–483

Merton, R. C. (1987), Presidential address: a simple model of capital markets with incomplete information, Journal of Finance, 42, 483-510.

Mikhail, Michael B., Beverly R. Walther, Richard H. Willis, 2004, Do security analysts exhibit persistent differences in stock picking ability, Journal of Financial Economics 74 (2004) 67–91

Sinha, Praveen, Lawrence Brown and Somnath Das, A re-examination of financial analysts' differential earnings forecast accuracy, Contemporary Accounting Research, 14.1, 1-42.

Stickel, S. E. 1992, Reputation and performance among security analysts, Journal of Finance 47, 1811–36.