

**The Consistency between Analysts' Earnings Forecast Errors and
Recommendations**

by

Lei Wang

Applied Economics Bachelor, United International College (2013)

and

Yao Liu

Bachelor of Business Administration, Simon Fraser University (2014)

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

© Lei Wang & Yao Liu, 2015

SIMON FRASER UNIVERSITY

Term Fall Year 2015

All rights reserved. However, in accordance with the *Copyright Act of Canada*, this work may be reproduced, without authorization, under the conditions for *Fair Dealing*. Therefore, limited reproduction of this work for the purposes of private study, research, criticism, review and news reporting is likely to be in accordance with the law, particularly if cited appropriately.

APPROVAL

Name: **Lei Wang and Yao Liu**

Degree: **Master of Science in Finance**

Title of Project: **The Consistency between Analysts' Earnings
Forecast Errors and Recommendations**

Supervisory Committee:

Associate Professor, Amir Rubin
Senior Supervisor

Associate Professor, Alex Vedrashko
Second Reader

Date Approved: _____

ABSTRACT

We study the relationship between analysts' earnings forecast errors and their stock recommendations. We hypothesize that analysts who give optimistic recommendations are more likely to have positive forecast errors, and analysts who give pessimistic recommendations tend to have negative forecast errors. This consistency in behaviour should be driven either by the objectivity illusion, or simply because of analysts' rationality. Our regression results generally support the tendency of analysts' to provide consistent estimates across these two tasks (ACAT). We also find that analyst's consistency is independent at the analyst-firm level, meaning that ACAT is an analyst-firm characteristic.

Keywords: Earnings forecasts; Recommendations; Analysts' Rationality.

Table of Contents

APPROVAL	1
ABSTRACT.....	2
INTRODUCTION.....	4
BACKGROUND AND HYPOTHESIS.....	4
DATA AND METHODOLOGY	5
I. SAMPLE SELECTION CRITERIA	5
II. COMPUTATION OF EXPLANATORY VARIABLES	6
RESULTS	9
I. TWO-BY-TWO MATRIX AND TWO-SAMPLE T-TESTS.....	9
II. REGRESSION ANALYSES	11
CONCLUSION.....	13
REFERENCES	15

INTRODUCTION

This paper examines the consistency between analysts' earnings forecast errors and recommendations. We expect that analysts who give buy recommendations tend to have higher forecast earnings than actual earnings (i.e., positive forecast errors), and analysts who give sell recommendations tend to have lower forecasts than actual earnings (i.e., negative forecast errors).

We study a five-year broker-analyst data set and get the results that generally support our predictions based on the objectivity illusion and analysts' rationale. Objectivity illusion suggests that analysts tend to unconsciously achieve the consistency between their earnings forecast errors and recommendations. However, in some cases, analysts who give consistent earnings forecasts with recommendations are rational. Even though the two-by-two matrix of the categorized forecast errors and recommendations shows that only 44% of the total observations have consistent earnings forecast errors and recommendations, the two-sample t-tests on the two variables tend to reveal a positive relationship between analysts' earnings forecast errors and recommendations. To further study the relationship, however, we perform several regressions to test the degree of ACAT hypothesis. The simplest linear regression between forecast errors and recommendations has a significant positive slope level, which suggests a significant positive linear relationship between the two variables. To make sure that we are not simply proxying for unobserved analyst-characteristics and firm-characteristics that may be capturing information asymmetry, we also include year, firm and analyst fixed-effects and find similar results. When we control for both analyst and firm fixed-effects, the relationship between the two variables disappears.

BACKGROUND AND HYPOTHESIS

Prior research on motivated reasoning indicates that people are more likely to arrive at their desired conclusion (Kunda, 1990). Research has also found that analysts have unconscious bias to support their recommendations when they produce their earnings forecasts (Eames, Glover, & Kennedy, 2002). This pattern of bias is referred to as the objectivity illusion. Even without illusion playing a role in analysts' earnings forecasts and recommendations, one tends to think that rational analysts

should have a tendency to provide consistencies between their earnings forecasts and recommendations. We note that illusion implies that analysts focus on information that is favourable for their desired conclusions and pay less attention to other relevant information during their reasoning process (Eames, Glover, & Kennedy, 2002). As a result, they are motivated by their preferred conclusions and not knowing that they fail to make objective decisions. Consequently, these analysts should underperform. The alternative view, however, is that consistency is a worthwhile quality and it is independent from illusion. On such circumstances, analysts arriving at consistent earnings forecast and recommendation should be the better performing analysts. Prior research finds broker-analyst earnings forecast errors are significantly optimistic for buy recommendations and significantly pessimistic for sell recommendations, consistent with the objectivity illusion and trade boosting hypotheses (Eames, Glover, & Kennedy, 2002). Whether illusion plays a role or not is not the focus of the paper, the objective of this paper is to use the recent data from 2010 to 2014 (after financial crises period) to develop and test the ACAT hypothesis. In addition, the contribution of our study is to control for other related factors (i.e., market capitalization, book-to-market ratio) and fixed-effect variables (i.e., year, industry, security ticker, analyst) that affect the relationship between analysts' earnings forecast errors and stock recommendations.

DATA AND METHODOLOGY

I. Sample Selection Criteria

We obtain individual analyst's recommendations and annual actual and forecast earnings-per-share (EPS) from the Thomson Reuters I/B/E/S estimate database. Our sample period begins in January 2010 and ends in December 2014. We decided to use data only after the financial crises, because there was huge uncertainty during the financial crises and it can influence the whole analysis to a large extent. Hence, the study should be taken at face value and it quantifies the current state of affairs.

I/B/E/S Detail History database includes actual and forecast EPS. The official ticker is a unique identifier for each firm. The announce date is the date that the forecast or actual values were reported. The analyst code is used to identify individual I/B/E/S analysts. Since not all firms have the same fiscal year end, Thomson Reuters

uses forecast period indicator to identify estimates for each period. We focus on forecasts of the one-year-ahead annual earnings (FY1). We can find that some analysts make earnings forecasts at the same date, so we take average of those earnings forecasts and keep it as one observation. For each fiscal period, the estimated earnings include multiple forecast revisions released by analysts on various dates. To eliminate the most distanced earnings forecasts for each analyst and to ensure the comparability across analysts and firms, we filter the earnings forecasts by forecasts announce date, and select the observations with forecasts announce date that is prior and closest to the actual earnings announce date. After that, our sample of actual and forecast earnings-per-share contains 223,586 observations.

This research draws on data from the *I/B/E/S Detail Recommendations* database, which contains stock recommendations ratings issued by individual analyst from 2010 to 2014. As many estimators have different ratings, Thomson Reuters maintains a standard format in I/B/E/S Text, expressed on a five-point scale where: 1.0 = Strong Buy, 2.0 = Buy, 3.0 = Hold, 4.0 = Underperform, 5.0 = Sell. To make interpretation of our results more intuitive, we reverse this coding so that higher numbers indicate more favourable recommendations (i.e., 1 for sell, 5 for strong buy). The database provides unique identifier for the individual analyst making a recommendation. For each fiscal period, analysts may revise their recommendations based on bad or good news. Therefore, for each analyst, we take average of the recommendations for a particular security provided by the analyst within a particular fiscal year, and only keep one observation of the average recommendation for that security in that year. This generates a sample of 185,524 observations.

II. Computation of Explanatory Variables

Our dependent variable is earnings forecast errors by using I/B/E/S earnings-per-share forecasts minus I/B/E/S actual earnings-per-share and scaled by the absolute value of actual earnings-per-share. To reduce the influence of extreme outliers, the earnings forecast errors are winsorized at the 99% and 1% level. Subsequently, we merge the two datasets of recommendations and earnings forecast errors by the common variables, including security ticker, year and analyst. We delete 35,694 observations with zero forecast errors and neutral recommendations.

To generate the two-by-two matrix between recommendations and earnings forecast errors, we divide recommendations and forecast errors into sub-groups, excluding the neutral recommendations and zero forecast errors. For earnings forecast errors (dependent variable), 1 represents positive forecast errors and 0 represents negative forecast errors. For recommendations (independent variable), 1 is for optimistic ones (i.e., buy, strong buy) and 0 is for pessimistic ones (i.e., underperform, sell).

In our research, fixed-effects are very important because our observations fall into different categories such as year, industry, firm and analyst. We want to control for characteristics of those categories and other related factors (i.e., market capitalization, book-to-market ratio) that might affect the relationship between the independent variable and the dependent variable. The first control variable is market capitalization. We measure it by multiplying the absolute value of price per share and the number of common shares outstanding (in thousands) obtained from the *Center for Research on Security Prices (CRSP) database*. To reduce the effect of outliers, we use the logarithm of market capitalization in our regressions. The second control variable is book-to-market (BTM) ratio. The BTM is a comparison of a company's book value to its market value. We obtain companies' book value on balance sheet from the *Compustat North America – Annual Updates database*. The BTM is winsorized at the 99% and 1% level as well to eliminate outliers. We create dummy variables that take the value of only 0 and 1 to represent the five years from 2010 to 2014. Furthermore, the four-digit standard industrial classification (SIC) classifies industries based on common characteristics in the products, services, production and delivery system of a business. We only use the first two digits of the SIC code to represent major groups in our regression model.

We merged all variables into one data set. The merged sample comprises 59,290 observations over the years 2010-2014, representing 4,698 distinct firms. Later, we will include the forecast errors (independent variable), recommendations (dependent variable) and some control variables (i.e., market capitalization, book-to-market ratio, year, industry, firm, analyst) in six regression models.

Summary statistics for the distribution of observations across fiscal years are reported in *Panel A of Table 1*. It illustrates that our sample observations are evenly distributed in each year. *Panel B* indicates that recommendations are significantly skewed toward buy and strong buy (77.19%), with only 10% rated underperform and

sell. *Panel C of Table 1* presents the distribution statistics for forecast errors and recommendations. The mean (median) recommendation of the sample is approximate 3.98 and the 25th and 75th percentiles are 3.67 and 5 respectively, also indicating that buy recommendations are more frequent than sell recommendations. The mean and median forecast errors are 0.03 and -0.01 respectively, with a range from -1.50 to 2.93. It is evident that some extreme positive values affect the distribution. Furthermore, the 25th and 75th percentiles of annual forecast errors are -0.05 and 0.34 respectively, showing that approximate symmetry applies to large negative and positive observations in the distribution. The positive kurtosis (20.82) of forecast errors indicates a relatively peaked distribution with close center, showing a relatively low standard deviation.

Table 1

Panel A: Sample Distribution by Year

Year	Observations	% of Total	% of Cum.
2010	11,879	20.04	20.04
2011	12,793	21.58	41.61
2012	11,739	19.80	61.41
2013	10,985	18.53	79.94
2014	11,894	20.06	100.00
Total	59,290	100.00	

Panel B: Sample Distribution by IBES Recommendations (i.e., 1 for sell, 5 for strong buy)

Recommendation	Observations	% of Total	% of Cum.
Strong Buy	19,017	32.07	32.07
Buy	26,749	45.12	77.19
Hold	7,655	12.91	90.10
Underperform	4,657	7.85	97.96
Sell	1,212	2.04	100
Total	59,290	100.00	

Panel C: Descriptive statistics on Forecast Errors (dependent variable), Recommendation (independent variable), Market Capitalization, and Book-to-Market ratio (control variables)

	Mean	Median	Min	Max	Sd.	Q1	Q3	Skewness	Kurtosis
Forecast Errors	0.03	-0.01	-1.50	2.93	0.46	-0.05	0.34	2.73	20.82
Recommendations	3.98	4	1	5	0.90	3.67	5	-1.05	4.12
Log (MC)	9.41	9.42	6.09	11.81	0.78	8.88	9.96	-0.01	2.81
BTM	0.73	0.45	-0.19	9.95	1.23	0.25	0.79	5.55	38.59

RESULTS

I. Two-by-two Matrix and Two-sample T-tests

In *Panel A of Table 2*, the two-by-two matrix of all of the observations based on the categorized earnings forecast errors (i.e., positive, negative) and categorized recommendations (i.e., optimistic, pessimistic) shows the distribution of observations in each category. The percentage of consistent observations (43.71%) is less than that of inconsistent observations (56.29%). We note that the optimistic recommendations are much more than the pessimistic ones because analysts generally tend to give buy recommendations than sell recommendations. However, the significant Pearson chi-squared value indicates a significant relationship between the two categorized variables.

To further explore the relationship between the recommendation type and forecast error, two-sample t-tests are performed and the results are shown in *Panel B of Table 2*. Firstly, we test the two sets of recommendations of the two earnings forecast error groups (i.e., positive, negative). The t statistic of -1.6318 is not quite significant, suggesting that we cannot say the mean recommendation of the positive forecast error group is different from that of the negative forecast error group. Also, the two means both represent optimistic recommendations, indicating that even analysts who have negative forecast errors tend to give buy recommendations. This overall tendency of giving optimistic recommendations rather than pessimistic ones is different from our expectation for ACAT hypothesis. These results are mainly due to the small percentage of sells recommendations in the total observations. It seems that buys recommendations dominate sells in both positive forecast error group and negative

forecast error group. To reduce the impact of buys dominating sells on the relationship between earnings forecast errors and recommendations, we also perform median tests on the two variables to find whether they are correlated. The results are shown in *Panel C*. The relatively high Pearson chi-squared values and low probabilities of Fisher's exact suggest that the two variables under test are correlated. On the other hand, in *Panel B of Table 2*, the negative difference in means between those who have negative forecast errors and those with positive forecast errors aligns with what we expected. The mean recommendation of the negative forecast error group is higher than that of the positive forecast error group. This tends to show a positive relationship between analysts' earnings forecast errors and recommendations.

Then we test the two sets of forecast errors of the two recommendation groups (i.e., buys, sells). The significant t statistic of -3.3511 indicates that the two samples have different means. The difference in means between those who give pessimistic recommendations and those give optimistic recommendations is negative. This aligns with our expectation that earnings forecast errors for buy and strong buy recommendations are higher than those for sell and strong sell recommendations. However, the two means are both positive, suggesting that even analysts with sell recommendations are likely to have positive forecast errors. This is consistent with prior research finding on analysts' forecast bias that analysts are likely to provide optimistic earnings forecasts to improve management access (Lim, 2001). Generally speaking, the t-test results support a positive relationship between analysts' forecast errors and recommendations.

Table 2

Panel A: Correlation Matrix between sells (i.e., sell, underperform), buys (i.e., strong buy, buy) and positive forecast errors, negative forecast errors, including number of observations and percentage (n = 59,290).

	Sells	Buys
Negative forecast errors	4,458 (7.52%)	30,505(51.45%)
Positive forecast errors	2,872(4.84%)	21,455 (36.19%)
	Pearson chi2 (1) = 11.8622 Pr = 0.001	
	Consistent: 7.52%+36.19%=43.71%	
	Inconsistent: 51.45%+4.84%=56.29%	

Panel B: (1) Two-sample t-test on the mean of recommendations for the two forecast errors groups (negative and positive). (2) Two-sample t-test on the mean of forecast errors for the two recommendations groups (sells and buys).

(1)	Obs	Mean recommendations	t-value
Negative forecast errors	34962	3.970	-1.6318
Positive forecast errors	24328	3.983	
Diff ¹ < 0 Pr(T<t) = 0.0514			

(2)	Obs	Mean forecast errors	t-value
Sells	7330	0.012	-3.3511
Buys	51960	0.031	
Diff ² < 0 Pr(T<t) = 0.0004			

Panel C: (1) Median test on median forecast errors for sells (i.e., sell, underperform) group and buys (i.e., strong buy, buy) group. (2) Median test on median recommendations for negative forecast error group and positive forecast error group.

(1) Forecast errors	Sells recommendations	Buys recommendations
Lower than the median	3,849	25,808
Greater than the median	3,481	26,152
Pearson chi2 (1) = 20.7430 Pr = 0.000 Fisher's exact: Pr = 0.000		

(2) Recommendations	Negative forecast errors	Positive forecast errors
Lower than the median	26,889	18,913
Greater than the median	8,073	5,415
Pearson chi2 (1) = 5.6572 Pr = 0.017 Fisher's exact: Pr = 0.018		

II. Regression Analyses

Given the fact that the two-by-two matrix and two-sample t-tests reveal a positive relationship existing between analysts' forecast errors and their recommendations, we want to further test whether ACAT holds under different conditions from industry level to analyst level. We decide to run several regressions using all of the observations to test the degree of ACAT hypothesis. Firstly, we conduct a simple linear regression between the two variables of earnings forecast errors and recommendations shown as the regression model 1 in *Table 3*. The output statistics

¹ Diff = mean (negative forecast errors) – mean (positive forecast errors)

² Diff = mean (sells) – mean (buys)

reveal the significance of the coefficient on recommendations with a high t statistic of 3.11 and a low p value of 0.002.

The coefficient of recommendations can be biased because we fail to include some related variables that are correlated with the recommendations. To reduce the omitted variables bias in our regression model, we decide to include market capitalization and book-to-market ratio to control for firm sizes in our regression shown as the regression model 2. In *Table 3*, specification 2 has a significant coefficient of recommendations with a relatively high t statistic of 3.08 and a low p value of 0.002. Hence, there is significant positive linear relationship between earnings forecast errors and recommendations, supporting our prediction on the relationship between the two variables.

To further control for possible omitted variables, a set of dummy variables of years is included in the regression model 2 to eliminate variations across different years. The coefficient of recommendations in specification 3 is higher with a t statistic of 3.24 and a lower p value of 0.001. Thus, this result suggests that the relationship between earnings forecast errors and recommendations is a bit stronger when we control for the aggregate variation across years.

Then we consider industry fixed-effect and include dummy variable industry into the regression model 3 to eliminate variations across different industries. The results for the specification 4 still provide strong support for the hypothesis that analysts' earnings forecast errors are optimistic (pessimistic) for favorable (unfavorable) stock recommendations with high t-value of 3.38 (p-value < 0.001). This indicates that analysts tend to have consistency between their earnings forecast errors and recommendations for firms in the same industry given in a certain year.

Furthermore, we take company ticker into consideration and absorb it into the regression model to control for firm fixed-effect, shown as regression model 5 in *Table 3*. The t statistic for the coefficient of recommendations is further increased to 3.56. The F statistic of 3.48 is still significant, indicating high significance of the coefficient outputs from the regression model. Therefore, the ACAT hypothesis still holds when we eliminate aggregate variation across firms and years, meaning that analysts are consistent with their earnings forecast errors and recommendations for the same firm in the same year.

Alternatively, we only control for analyst fixed-effect and absorb analyst code into the regression model, shown as regression model 6 in *Table 3*. The coefficient of

recommendations in specification 6 is even higher than the previous regressions together with a higher t statistic for the coefficient of recommendations. This shows that the ACAT hypothesis also survives the analyst fixed-effect. In other words, each analyst tends to achieve consistency between the earnings forecast errors and recommendations among different firms in a given year.

Lastly, we control for both analyst fixed-effect and firm fixed-effect to test the highest degree of ACAT hypothesis. We group analyst with company ticker and absorb the grouped variable into the regression model 3. The coefficient of recommendations in specification 7 becomes insignificant with a low t statistic of 0.40 and a high p value of 0.687, showing an insignificant relationship between analysts' earnings forecast errors and recommendations under this specific condition. Base on the analyst-firm fixed-effect model, we can conclude that ACAT is persistent for a given analyst, which implies that ACAT is an analyst characteristic. In other words, if the ACAT would be significant even when we control for analyst fixed-effect, then we would have to conclude that while forecast errors and recommendations tend to correlate in a given point in time, they fluctuate for a given analyst. The fact that the correlation between forecast errors and recommendations is uncorrelated at the analyst-firm level, suggests that ACAT is an analyst characteristic at the firm level. This is rather interesting result that desires further investigation, for example, it would be worthwhile to know if ACAT is related to an analyst talent or analyst knowledge on different companies.

CONCLUSION

We examine the consistency between analysts' earnings forecast errors and recommendations by performing several t-tests and regressions. Even though the results of the two-by-two matrix and two-sample t-tests are slightly different from what we predict, we still find a significant positive linear relationship between analysts' earnings forecast errors and their recommendations through the simple linear regressions. We also include several control variables such as year, industry, firm and analyst into the regression model in order to test the degree of ACAT hypothesis. As a result, the regression results survive year, industry, firm and analyst fixed-effect specifications, and seem to be rather robust. Hence, we find that analysts tend to be consistent in their earnings forecast errors and recommendations at

different levels. However, the ACAT hypothesis does not hold in the case where aggregate variations across both analysts and firms are eliminated, revealing that ACAT is an analyst characteristic at the firm level.

Overall, the regression results align with past literature on objectivity illusion but could also support the idea that the consistency is due to analysts' rationale. Whether illusion or rationality plays a role in this consistency is not the basis of our finding but a worthwhile question that we hope future researcher will follow.

Table 3

Regression analysis:

$$\text{Forecast Errors} = a_1 + b_1 * \text{Recommendations} + u \quad (1)$$

$$\text{Forecast Errors} = a_2 + b_2 * \text{Recommendations} + c_1 * \log(\text{MC}) + d_1 * \text{BTM} + u \quad (2)$$

$$\text{Forecast Errors} = a_3 + b_3 * \text{Recommendations} + c_2 * \log(\text{MC}) + d_2 * \text{BTM} + e_1 * \text{Year fixed effects} + u \quad (3)$$

$$\text{Forecast Errors} = a_4 + b_4 * \text{Recommendations} + c_3 * \log(\text{MC}) + d_3 * \text{BTM} + e_2 * \text{Year fixed effects} + f_1 * \text{Industry fixed effects} + u \quad (4)$$

$$\text{Forecast Errors} = a_5 + b_5 * \text{Recommendations} + c_4 * \log(\text{MC}) + d_4 * \text{BTM} + e_3 * \text{Year fixed effects} + g_1 * \text{Firm fixed effects} + u \quad (5)$$

$$\text{Forecast Errors} = a_6 + b_6 * \text{Recommendations} + c_5 * \log(\text{MC}) + d_5 * \text{BTM} + e_4 * \text{Year fixed effects} + h_1 * \text{Analyst fixed effects} + u \quad (6)$$

$$\text{Forecast Errors} = a_7 + b_7 * \text{Recommendations} + c_6 * \log(\text{MC}) + d_6 * \text{BTM} + e_5 * \text{Year fixed effects} + i_1 * \text{Firm fixed effects} - \text{Analyst fixed effects} + u \quad (7)$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Recommendations	0.0079 3.11***	0.0077 3.08 ***	0.0081 3.24***	0.0083 3.38***	0.0083 3.56***	0.0102 3.72***	0.0037 0.40
Log (Market Capitalization)		-0.0306 -10.41***	-0.0309 -10.48***	-0.0379 -11.82***	0.0083 0.29	-0.0380 -9.31***	-0.0078 -0.13
Book-to-market ratio		0.0138 5.61***	0.0137 5.55***	0.0081 3.12***	0.0266 2.08**	0.0086 2.36***	0.0279 1.32
Year fixed effects			Yes	Yes	Yes	Yes	Yes
Industry fixed effects				Yes			
Firm fixed effects					Yes		Yes
Analyst fixed effects						Yes	Yes
Interpret	-0.0022	0.2768	0.2610	0.2165	-0.1166	0.3273	0.0445
	-0.23	9.10***	8.58***	5.07***	-0.43	8.46***	0.08
Adjusted R ²	0.0002	0.0050	0.0053	0.0159	0.2326	0.0746	0.3443
Observations	59290	59290	59290	59287	59290	59290	59290

REFERENCES

Book-To-Market Ratio Definition | Investopedia. (2003, November 25). Retrieved November 22, 2015, from <http://www.investopedia.com/terms/b/booktomarketratio.asp>

Core, J., Guay, W., & Rusticus, T. (2006). Does Weak Governance Cause Weak Stock Returns? An Examination of Firm Operating Performance and Investors' Expectations. The Journal of Finance, 655-687.

Eames, M., Glover, S. M., & Kennedy, J. (2002). The Association Between Trading Recommendations and Broker-Analysts' Earnings Forecasts. The Journal of Accounting Research, Vol. 40 No. 1 March 2002.

Gormley & Matsa (RFS 2014). (n.d.). Retrieved November 25, 2015, from <http://finance.wharton.upenn.edu/~tgormley/papers/fe.html>

Kunda, Z. (1990). The case for motivated reasoning. Psychological Bulletin 108: 480-98.

Lim, T. (2001). Rationality and Analysts' Forecast Bias. The Journal of Finance, 369-385.

Market Capitalization Definition | Investopedia. (2003, November 23). Retrieved November 22, 2015, from <http://www.investopedia.com/terms/m/marketcapitalization.asp>

Thomson Reuters (2013, March). A Guide To The I/B/E/S Analyst-By-Analyst Historical Earnings Estimate Database.