

Rankings of Financial Analysts and I/B/E/S Earnings Consensus

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ABSTRACT

The I/B/E/S (Institutional Brokers' Estimate System) database is a comprehensive resource containing detailed data from financial analysts, including individual estimates, consensus values, historical actuals, company guidance, and advanced analytics. It compiles forecasts on future earnings for publicly traded companies, with coverage spanning thousands of companies over several decades. This research assesses analyst performance through their earnings per share (EPS) forecasts, creating a dynamic ranking system that tracks each analyst's accuracy relative to peers over time. Analysts' performances are evaluated on their quarterly EPS forecasts for a range of companies, with rankings reflecting both company-specific forecast performance and overall accuracy across multiple companies. The ranking system also identifies high- and low-performing analysts, examining links between their forecast longevity and ranking stability. Our study introduces an enhanced consensus forecasting approach, which outperforms individual forecasters and existing consensus estimates from Bloomberg platform. Using dynamic weighting based on analyst rankings, our rank-based aggregation produces a continuously updated EPS consensus estimate, identifying the most accurate EPS forecasts for each ticker.

Keywords

analyst estimates, performance evaluation, data aggregation, reputation system, earnings forecasting

1 INTRODUCTION

Research on the accuracy and impact of financial analyst forecasts has drawn significant attention due to its essential role in guiding investment decisions and shaping market sentiment. Analyst forecasts, particularly on earnings per share (EPS), provide key insights into corporate performance, influencing equity valuations and market movements. While EPS serves as a widely trusted indicator of a company's profitability and financial health, studies reveal persistent biases in analyst forecasts that can undermine their reliability. Factors such as information asymmetry, behavioral tendencies like herding and overconfidence, and conflicts of interest often skew these estimates. Databases like the Institutional Brokers Estimate System (IBES) aggregate these forecasts to provide consensus estimates, yet even these can reflect systematic biases. In response, recent research has proposed advanced techniques, including iterative filtering algorithms and machine learning models, to improve forecast accuracy and reduce bias. Despite these innovations, the need for enhanced, unbiased models for ranking and evaluating analysts remains critical, marking an ongoing area for exploration and refinement. (Machuga2002) (Harris2019) (Kua2022a)

In this paper, we apply a structured framework of techniques to rank financial analysts based on the accuracy of their earnings per share (EPS) forecasts across multiple companies. Leveraging the iterative filtering algorithms from (Kua2022a) and (Laureti2006), we enhance the precision of consensus estimates by calculating key parameters for each analyst, including individual variance (V_i), market variance (V_j) and the reliability index (C_i). These parameters culminate in a composite score that summarizes each analyst's overall performance, allowing us to adjust for prediction discrepancies and recognize patterns of reliability over time. This approach incorporates interval days, forecast accuracy, and reliability scores, resulting in a comprehensive evaluation of analyst effectiveness. Our data source is the IBES database for EPS analysts' estimates on companies such as AMZN, AAPL, MSFT, IBM, and ORCL, supplemented by actual EPS values from Bloomberg. By merging these datasets, we conduct a consistent analysis on combined data. We standardize the reliability index values to ensure comparability across years and analysts and we account for the sparsity of the EPS data estimates over specific periods. The final composite score for each analyst represents the mean of the standardized reliability index values over several decades, while alternative proposed ranking models incorporate cross-company consistency, timeliness, and weighted accuracy metrics. Through this analysis, we aim to establish a robust ranking system that reliably identifies top-performing analysts.

2 METHODOLOGY AND RESULTS

This section outlines the methodology developed to rank financial analysts based on their earnings per share (EPS) estimates for various companies. To create a comprehensive model over the available datasets, we apply a structured framework of

methodologies. The model is built on the principles of Iterative Filtering Algorithms for Computing Consensus Analyst Estimates based on (Kua2022a) and Information Filtering via Iterative Refinement (Laureti2006). These methodologies were used to compute key parameters such as V_i (individual variance), V_j (market variance), and C_i (Reliability Index) for each analyst, culminating in the calculation of a composite score to rank the analysts effectively. To finalize the ranking process, we develop an algorithm that incorporates C_i , composite scores, interval days, and the accuracy of each analyst.

Data

The data for this research is sourced from the IBES database, with focus on the analyst earnings estimates for EPS (Earnings Per Share) for AMZN, AAPL, MSFT, IBM, and ORCL, and the Bloomberg database for actual EPS of the companies. The dataset includes analyst codes, forecast dates, actual earnings, and forecasted earnings across each year's four quarters, spanning the years from 2000 to 2023. We merge the IBES and Bloomberg databases for each company and then we proceed with the analysis of the combined data.

Methodology for Ranking Analysts Using Iterative Filtering Algorithms

Based on the Iterative Filtering Algorithms for Computing Consensus Analyst Estimates (Kua2022a) and Information Filtering via Iterative Refinement (Laureti2006), we calculate the C_i (Reliability Index), which is used to rank analysts. The following sections will elaborate on this methodology in detail.

Reliability Index (C_i) Calculation

The reliability index, denoted as C_i , represents the relative reliability of the i^{th} analyst's earnings per share (EPS) estimates over j quarters. It is calculated using the formula:

$$C_i = \frac{1/V_i}{\sum(1/V_j)} \quad (1)$$

Variance of Individual Analyst (V_i) Calculation

To compute V_i for each analyst i , we first calculate the variance of their estimates over the four quarters each year. The formula for variance is:

$$V_{i,y} = \frac{\sum(X_{iq} - T_q)^2}{n} \quad (2)$$

where: X_q is the EPS estimate provided by the analyst for quarter q , T_q is the actual EPS value for quarter q , n is the total number of estimates provided by the analyst for that year, and y represents a specific year.

The term V_i captures how closely the analyst's estimates align with the actual EPS values across multiple quarters. Lower V_i values indicate more accurate estimates.

Variance of All Analysts in a Quarter (V_j)

For each quarter q , we compute the variance V_j , which reflects the overall variability in EPS estimates provided by all analysts for a specific quarter. The formula for the variance of all analysts in a quarter is:

$$V_j = \frac{\sum_{i=1}^n (X_{i,q} - T_q)^2}{n} \quad (3)$$

Reliability Index (C_i)

Once V_i is calculated for each analyst and V_j is calculated for all analysts per quarter, we compute the reliability index C_i for each analyst using Equation 1. This formula compares the variance of each analyst to the variance of all analysts in each quarter. Analysts with lower variance (i.e., those whose estimates are closer to the true EPS) will have a higher C_i indicating greater reliability.

Standardization and Handling the Sparsity of Analysts' Estimates

After calculating the reliability index C_i for each analyst across multiple years, we standardize these values to ensure comparability over time. Standardization scales the C_i values by subtracting the mean and dividing them by the standard deviation for each year, resulting in a distribution with a mean of 0 and a standard deviation of 1. This transformation allows for a more accurate comparison across analysts, and it is represented by:

$$Z_{i,y} = \frac{C_i - \mu_y}{\sigma_y} \quad (4)$$

where $Z_{i,y}$ is the standardized C_i for a specific year y , μ_y is the mean, and σ_y is the standard deviation. The sparsity of analysts' estimates is addressed by preventing analysts from being penalized for years without predictions and ensuring a smooth standardization process. Finally, data restructuring allows each analyst to be represented by rows with years as columns, which

streamlines composite score calculations over time.

Calculate the Composite Score

The composite score is computed as the mean of the standardized C_i values for each analyst across the available years. This provides a summary score reflecting each analyst's performance over time in a single number. Analysts with higher scores demonstrate greater consistency in their estimations and are ranked higher. The formula for the composite score is:

$$CompositeScore = \frac{\sum_{i=1}^n Z_i}{n} \quad (5)$$

where Z_i is the standardized C_i value for year i and n is the number of years the analyst made predictions.

Ranking Based on Composite Score, Reliability Index, Interval Days Weight, and Accuracy

After calculating key indices for each analyst across multiple companies, we turn to examining various methodologies for ranking financial analysts. Each approach offers a unique lens on performance evaluation, using different metrics and weighting techniques to capture distinct aspects of analyst effectiveness. In this section, we provide a detailed overview of these ranking methods, explaining both the rationale behind each approach and their implementation in code. Our goal is to determine the most accurate model for identifying top-performing analysts.

Ranking Analysts Based on Composite Score (Company-Specific Ranking)

This model ranks analysts for each company based on their final composite score, which represents their overall performance. After computing the composite scores for each analyst, we rank them individually for each company and identify the top 20 analysts. However, this approach has certain limitations. It does not incorporate the interval days between predictions, which is a critical factor in assessing the timeliness and reliability of an analyst's forecasts. As a result, while useful, this method may not be the most accurate for practical EPS estimation, as it overlooks the temporal aspects that can significantly influence an analyst's performance.

Ranking Based on Average Composite Score and Consistency Across All Companies (Global Analyst Ranking)

This model ranks analysts by assessing their performance across multiple companies, focusing on both their average composite score and the consistency of their predictions. The goal is to evaluate an analyst's reliability and effectiveness across various firms, providing a more comprehensive view of their overall performance. The formula to calculate the average composite score C_{avg} for each analyst is:

$$C_{avg} = \frac{\sum_{k=1}^K C_k}{n} \quad (6)$$

where K is the number of companies and C_k is the composite score for each company.

In addition to calculating the average composite score, we also assess the consistency and stability of the analyst's performance across different companies. Analysts with more stable and convergent scores are ranked higher, as consistency is an important indicator of long-term reliability. By incorporating both the average composite score and consistency, this method provides a more robust and comprehensive ranking. It accounts for an analyst's overall performance across multiple companies, offering a broader and more reliable perspective compared to the company-specific ranking, which may rely on isolated results from individual firms.

Ranking Based on Reliability Index C_i and Interval Days: Rewarded Composite Score Model

In this model, we adjust the Reliability index C_i by incorporating a reward factor that accounts for the interval days Δt between an analyst's estimation and the actual reporting date. Analysts who provide timely estimates, particularly those made well in advance of the reporting date, are rewarded with a higher score. The reward factor $R = \Delta t / 365$. This model aims to prioritize analysts who not only provide accurate predictions but also offer timely insights. The rewarded composite score is then calculated as:

$$C_{reward} = \frac{\Delta t}{365} * C_i \quad (8)$$

where C_i is the Reliability index calculated earlier. After computing the rewarded composite score for each analyst, we rank them for each company. While this method introduces a timeliness factor, the results presented inconsistencies and potential errors in the reward factor.

Ranking Based on Weighted Score Combining C_i , Interval Days, and Accuracy (Weighted Model)

This is a more advanced model where we combine three key factors: C_i (Reliability Index), Interval Days (Δt), and Accuracy to calculate a weighted score for each analyst's estimations. The accuracy is measured as the absolute difference between the

analyst's prediction and the actual EPS value. The formula for the weighted score W_i is:

$$W_i = W_a * Accuracy + W_n * \left(\frac{\Delta t}{365} \right) + W_c * C_i \quad (9)$$

where W_a , W_n and W_c are the weights assigned to accuracy, interval days, and C_i respectively. After calculating the weighted score for each analyst's estimation, we rank the analysts using two approaches:

- Best Weighted Score: We select the highest weighted score for each analyst across all estimations and rank them accordingly.
- Average Weighted Score: We calculate the average of all weighted scores for each analyst and rank them based on this average. The formula for the average weighted score:

After comparing the results of both methods, we concluded that ranking analysts based on the average weighted score provides a more reliable and consistent approach for evaluating their overall performance.

Results

The results from our various analyst ranking models demonstrate significant differences in effectiveness and practicality. The simplest model, shown in Figure 1, ranks analysts based on their average Reliability Index (C_i) for each company, such as MSFT. While this approach provides a straightforward ranking based on the analysts' consistency in their EPS estimates, it has notable limitations. Without normalization and additional factors, such as accuracy and interval days, this method fails to capture the full scope of an analyst's performance. Consequently, while it provides an initial ranking, its insights are limited and lack practical applicability. In contrast, as shown in Figure 2, the model based on the composite score for each analyst improves ranking accuracy by summarizing their performance over time. This model is more refined than the basic Reliability Index approach, yet it still lacks consideration for timeliness, which is critical for effective financial forecasting. The most robust results were achieved using the weighted score model, as shown in Figures 3 and 4 (displaying the top 30 percent of analysts for MSFT). This model combines C_i , interval days, and accuracy, providing a comprehensive assessment of each analyst's performance across companies. By incorporating each factor's contribution to reliability, this approach ensures that top-ranked analysts demonstrate both accuracy and timeliness, making it a more reliable and practical ranking method.

Figure 1, Ranking of Analysts Based on Average for MSFT

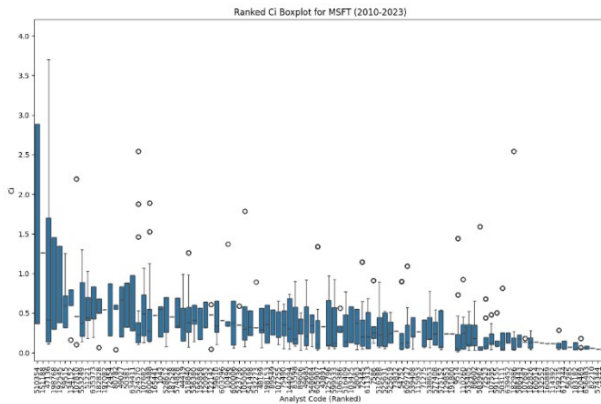


Figure 2, Ranking of Analysts Based on Composite Scores for MSFT

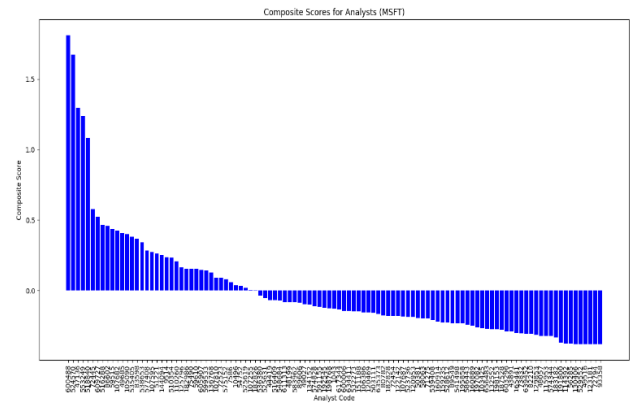
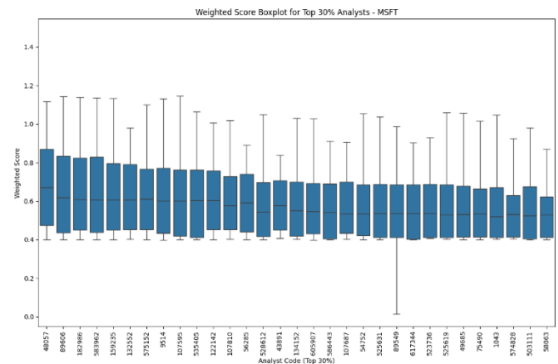


Figure 3, Ranking of Analysts by Weighted Score for MSFT



Figure 4, Top 30% Analysts by Weighted Score for MSFT



3 CONCLUSIONS

Enhanced Accuracy and Practicality of the Weighted Score Model: Compared to simpler ranking methods based solely on average Reliability Index (C_i) or composite scores, the weighted score model, which incorporates C_i , interval days, and accuracy, provides a more robust and realistic evaluation of analyst performance. By addressing both the consistency and timeliness of estimates, this model aligns closely with real-world investment needs, making it a practical choice for accurately ranking financial analysts. **Limitations of Traditional Ranking Approaches:** The results demonstrate that traditional methods, such as ranking by average C_i or composite scores alone, fail to capture essential dimensions of performance, such as timeliness and accuracy. These limitations echo findings from previous research that emphasizes the need for multi-faceted metrics. Without these additional factors, rankings may not truly reflect analysts' reliability or relevance in a fast-paced market. **Future Potential for Improved Analyst Ranking Systems:** The successful application of iterative filtering algorithms and the weighted score model indicates a promising direction for future research. By integrating more comprehensive measures like accuracy, interval days, and reliability into a single score, this study opens avenues for developing even more sophisticated analyst ranking systems. Future research could explore refining these models further or adapting them to other types of financial forecasting metrics.

4 FUTURE WORKS

In the next phase of this research, we aim to enhance the accuracy of earnings per share (EPS) estimations by identifying the best-performing analysts and incorporating machine learning (ML) models to improve predictive methods. Building upon the weighted score ranking model, our focus will be to develop approaches that can provide reliable EPS estimates on a timely basis, which is crucial for applications in both investment portfolio management and sell-side analytics.

By applying advanced ML techniques, we plan to refine the estimation process to identify the optimal forecast at a specific time and to improve the reliability and timing of these predictions. This approach has significant potential to support data-driven decision-making for institutional investors, analysts, and other financial professionals seeking to leverage EPS estimates for various strategic objectives. Additionally, future research could explore adapting these ML-enhanced models to identify actionable signals, enhancing their utility across both investment and forecasting domains.

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