Efficiency of Financial Parameters in Value Prediction Error

(in the context of Iron & Steel Industry)

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Abstract - This paper is motivated by the deficiency of relevant research related to multiples. It also seems a gap between the widespread usage of multiples and another method of valuation in valuation practice. These studies have so many issues and several compilations. To close the deficiency, this paper based on examines the role of multipliers in equity valuation. In this paper, we use fundamental drivers (equity and entity) to identify their variation from the industry's multipliers. In terms of relative performance, the results show equity value multiples outperform entity value multiples. The result based on descriptive statistics and chart performance techniques also advocate that equity multipliers are better than entity based multipliers.

***Key Words*:** Equity valuation, Multiples analysis, Iron & Steel sector, Valuation accuracy, Financial parameters, P/B ratio, Inventory turnover

1. Introduction

The stock market is a dynamic and complex environment where investors and fund managers strive to predict stock prices accurately to achieve optimal returns. Investing in equities offers liquidity and the potential for high returns, but predicting share prices is far from straightforward. Stock prices are influenced by a multitude of intrinsic and extrinsic factors, making their movement difficult to forecast with precision. This study seeks to identify the key factors that influence share prices and examine the relationship between these explanatory variables and the dependent variable—stock valuation.

$$\hat{P}_{i,j} = X_{i,j} . \Theta_{(i,j)}^{(peer\ group)}$$

(Malhotra & Tandon, 2013) A critical question faced by market participants is: What is the predictive value of a company's share? The answer to this question is pivotal, as it determines the success or failure of investment strategies. Equity analysts dedicate significant effort to answering this question, as accurately valuing shares is central to their professional responsibilities. Valuation methods, such as the use of financial multipliers, provide a practical framework for assessing whether a stock is fairly priced, undervalued, or overvalued relative to its peers.

This study focuses on the efficiency of financial parameters in predicting value errors, particularly within the Iron & Steel industry. The research leverages a comprehensive dataset from NSE500 companies, spanning financial statements and annual reports from 2004 to 2018. The selected companies are representative of their industry, chosen based on market capitalization, sales volume, and active participation in the sector.

The study employs two primary approaches to valuation:

- Equity-Based Multipliers: These assess the market value of a company's equity relative to key financial metrics such as earnings, book value, or sales.
- Entity-Based Multipliers: These evaluate the enterprise value, incorporating both equity and debt, to provide a holistic view of a company's worth.

By comparing these multipliers, the study aims to determine which method offers greater accuracy in stock valuation. Additionally, the research explores the impact of financial parameters—such as revenue growth, earnings per share, net profit margin, and leverage ratios—on valuation errors. The findings will provide valuable insights for investors, analysts, and policymakers, helping them make informed decisions in an ever-evolving market landscape.

Ultimately, this paper bridges a gap in existing research by systematically analyzing the role of multipliers in equity valuation and offering evidence-based conclusions on their predictive efficiency. The results highlight the superiority of equity-based multipliers and underscore the importance of integrating financial parameters to enhance valuation accuracy.

2.0 Review of Literatures

The valuation of equities using multiples has been extensively studied, yet gaps remain in understanding their predictive accuracy and comparative efficiency across different industries and financial contexts. This section synthesizes key findings from prior research on equity and entity-based valuation multiples, their performance, and the influence of financial parameters on valuation errors.

2.1 Accuracy of Multiples in Valuation

Schreiner and Spremann (2007) examined the accuracy of valuation multiples in European equity markets, finding that equity value multiples consistently outperformed entity value multiples in predicting market values. Their study also highlighted that forward-looking multiples, particularly the two-year forward P/E ratio, provided more accurate valuations than trailing multiples. Similarly, **Nel and Bruwer (2013)** analyzed South African firms and concluded that earnings-based multiples were the most accurate, followed by asset-based, cash flow, and revenue-based multiples.

Cooper (2008) investigated the selection of comparable firms in valuation, emphasizing that small peer groups increase valuation errors due to higher variability. Conversely, larger peer groups reduce bias but may dilute industry-specific nuances. His findings suggest that optimal comparability depends on balancing sample size and industry relevance.

2.2 Equity vs. Entity-Based Multiples

Nel et al. (2013) compared equity and entity-based multiples in emerging markets, demonstrating that equity-based multiples exhibited smaller valuation errors and lower dispersion than entity-based counterparts. Their study reinforced the notion that equity multiples, particularly those tied to earnings and book value, offer more stable valuation benchmarks.

Africa et al. (2013) explored how industry classification impacts valuation accuracy, finding that narrower industry groupings (e.g., subsectors rather than broad sectors) improved precision. This suggests that peer selection based on granular industry data enhances multiple-based valuations.

2.3 Role of Financial Parameters in Valuation Errors

Abraham et al. (2017) studied the relationship between earnings yield and financial performance metrics, revealing that earnings yield significantly influenced equity multipliers across risk levels. Their regression models confirmed that profitability and leverage ratios (e.g., ROE, D/E) play a crucial role in valuation accuracy.

Lakkol (2019) analyzed financial risk in capital structure decisions, noting that highly leveraged firms exhibited lower profitability and higher valuation errors, particularly in cyclical industries like steel and chemicals. This aligns with findings that debt-heavy firms trade at lower multiples due to perceived risk.

2.4 Behavioral and Methodological Considerations

Scholar (2019) examined behavioural biases in investment decisions, showing that investor psychology influences valuation errors, particularly in high-volatility sectors. Meanwhile, **Cooper (2014)** questioned the limits of multiples-based valuation, arguing that fundamental drivers (e.g., growth, risk) must supplement multiples to improve accuracy.

2.5 Synthesis and Research Gap

While prior research establishes the superiority of equity-based multiples, particularly earnings-driven models, inconsistencies remain in:

- The optimal selection of peer firms for comparable analysis.
- The impact of industry-specific financial parameters (e.g., inventory turnover in steel firms).
- The integration of forward-looking vs. historical metrics in emerging markets.

This study addresses these gaps by empirically testing equity and entity multipliers in the Iron & Steel industry, assessing how financial parameters (e.g., ITR, DER, ROE) influence valuation errors, and providing actionable insights for practitioners.

3.0 Objectives

- To determine the equity and entity-based multipliers and their error terms for firms' valuation.
- To compare equity and entity-based multipliers for their efficiency.
- To measure the effect of financial parameters on error terms.

4.0 Research Methodology

4.1 Sample Selection

Population: Companies listed in the NIFTY 500 index (representing ~96% of India's equity market capitalization).
Time Frame: 16-year period (2004–2021) to capture economic cycles.
Inclusion Criteria:
Indian-domiciled firms. Positive book value, sales, and market capitalization (excluding SMEs and loss-making firms). Companies with complete financial data for the study period.

4.2 Exclusion Criteria:

Firms with negative value drivers (e.g., negative P/E ratios). Outliers with extreme financial ratios that distort comparability. **(Ganguli, 2011)**

4.3 Data Sources

Financial Statements: Extracted from NSE reports, Money control, and institutional databases (GJU, Ku, PTU). Market Data: Daily opening and closing stock prices from NSE historical archives.

4.4 Peer Group Selection:

Top 5 comparable firms per target company, based on market capitalization and industry turnover. Peer groups exclude the target firm to avoid bias. **(Bhojraj & Lee, 2002)**

4.5 Calculation of Valuation Multiples

- **Equity-Based Multiples**

Price-to-Book Value (P/BV):

$$\Theta_{i,j}^{B.V.} = \frac{\textit{Market Price of Shares}}{\textit{Book Value}}$$

Book Value of Equity = Shareholders' equity (excluding debt).
Market Price of Shares = Average of daily opening and closing prices:

- $\textit{Market Price of Shares} = \sum_{i=1}^{N} \frac{\left(\frac{\text{OpeningPrice}+\text{ClosingPrice}}{2}\right)}{N}$

- **Entity-Based Multiples**

Enterprise Value-to-Book Value (EV/BV):

$$\Theta_{i,j}^{Entity.} = \frac{\textit{Market Price of Shares}}{\textit{Book Value+Debts}}$$

Simplified Conversion from P/BV to EV/BV:

$$\Theta_{i,j}^{Entity.} = \frac{\Theta_{i,j}^{B.V.}}{(1+\frac{D}{E}\,Ratio)}$$

4.7 Statistical Analysis

Descriptive Statistics & Normality Tests
Jarque-Bera Test: Assesses if multipliers follow a normal distribution.

- $JB_{Test\ Statistics} = n\left[\frac{S^2}{6} + \frac{(K-6)^2}{24}\right]$

Null Hypothesis (H_0): Data is normally distributed.
Rejection Rule: p-value < 0.05 → Non-normal distribution.

4.8 Peer Group Multiplier Estimation

Median Multiplier Calculation:
For each year, compute the median P/BV and EV/BV of peer firms.
Eliminate the target firm to prevent self-referencing bias.
$\text{Median}\Theta_{i,j}^{B.V.} = \left(\frac{n+1}{2}\right)$ *th observation*

4.9 Error Term Calculation

Predicted vs. Actual Valuation Error
Predicted Market Value:
Equity = Median Peer $\Theta_{i,j}^{B.V.} * \textit{Book Value}_{i,j}^{Equity}$
Entity = Median Peer $\Theta_{i,j}^{Entity.} * \textit{Book Value}_{i,j}^{Entity}$

4.10 Valuation Error (Equity & Entity):

- Error Term (Equity) = $(\Theta_{i,j}^{Equity} - \text{Median}\Theta_{i,j}^{Equity})$
- Error Term (Entity) = $(\Theta_{i,j}^{Entity.} - \text{Median}\Theta_{i,j}^{Entity})$

4.11 Panel Data Regression

Dependent Variable: Valuation Error (Equity/Entity).
Independent Variables:

Table 1:- Financial Parameter Detail with Expected Impact

Financial Parameter	Definition	Expected Impact
Log Revenue (LRFO)	Natural log of sales / No. Equity	Positive (↑ sales → ↓ error)
Log EPS (LEPS)	Earnings per share (log)	Negative (↑ EPS → ↓ error)
Net Profit Margin (NPM)	Net income/Sales	Negative (↑ NPM → ↓ error)
Return on Equity (ROE)	Net income/Equity	Negative (↑ ROE → ↓ error)
Debt-to-Equity (DER)	Total debt/Equity	Positive (↑ leverage → ↑ error)
Inventory Turnover (ITR)	COGS/Avg. inventory	Negative (↑ efficiency → ↓ error)
Log EBITDA (LEBITDA)	Natural log of EBITDA/No. Equity	Positive (↑ LEBITDA → ↓ error)
Current Ratio (CA)	Current Assets/ Current Liability	Positive (↑ CA → ↓ error)
Log Dividend Payout Ratio (Log DPR)	Dividend per share (log)	Positive (↑ DPR → ↓ error)

4.12 Regression Model (Equity Error):

Error Term (Equity) = $\alpha_0 + \beta_1(\text{Log Sales}) + \beta_2(\text{NPM}) + \beta_3(\text{ROE}) + \beta_4(\text{Log DPR}) + \beta_5(D/E) + \beta_6(Log\ EPS) + \beta_7(Log\ EBITDA) + \beta_8(Inventory\ turnover\ ratio) + \beta_9(Current\ Ratio) + \varepsilon_{i,j}$

Error Term (Entity) = $\alpha_0 + \beta_1(\text{Log Sales}) + \beta_2(\text{NPM}) + \beta_3(\text{ROE}) + \beta_4(\text{Log DPR}) + +\beta_5(Log\ EPS) + \beta_6(Log\ EBITDA) + \beta_7(Inventory\ turnover\ ratio) + \beta_8(Current\ Ratio) + \varepsilon_{i,j}$

R^2 & Adjusted R^2: Measure explanatory power.

F-test: Tests overall model significance ($p < 0.05 \rightarrow$ significant).
T-tests: Evaluate individual coefficient significance.

4.13 Efficiency Comparison across Industries

Error Correction Model (ECM): Adjusts predicted values using significant financial parameters.

$$\hat{P}_{i,j}\textbf{(Entity)} = \text{Median}\Theta_{i,j}^{Entity.} + \beta_1(\textbf{Log Sales}) + \beta_2(\textbf{NPM}) + \beta_3(\textbf{ROE}) + \beta_4(\textbf{Log DPR}) + \beta_5(D/E) + \beta_6(Log\ EPS) + \beta_7(Log\ EBITDA) + \beta_8(Inventory\ turnover\ ratio) + \beta_9(Current\ Ratio) + \varepsilon_{i,j}$$

Here: **Error Term (Equity)** is the dependent variable trying to predict.

α_0 Is the y-intercept.

$\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7, \beta_8, \beta_9$ are the regression coefficients for the independent variables.

To predict the value Y, here substitute the values of the independent variables into the equation.

The predicted value $\hat{P}_{i,j}$**(Equity)** would be:

$$\hat{P}_{i,j}\ \textbf{(Equity)} = \text{Median}\Theta_{i,j}^{Equity.} + \beta_1(\textbf{Log Sales}) + \beta_2(\textbf{NPM}) + \beta_3(\textbf{ROE}) + \beta_4(\textbf{Log DPR}) + \beta_5(D/E) + \beta_6(Log\ EPS) + \beta_7(Log\ EBITDA) + \beta_8(Inventory\ turnover\ ratio) + \beta_9(Current\ Ratio) + \varepsilon_{i,j}$$

4.14 Efficiency Benchmarking

Efficiency of parameters in prediction error = $\frac{[Actual\ price - Estimated\ Price]}{Actual\ Price}$

Bias and Absolute Error Metrics

1. Bias (Signed Error): Measures directional accuracy.
- **Bias =($P_{i,j}$-$\hat{P}_{i,j}$)/$P_{i,j}$**

Above is the signed percentage prediction error.

2. Absolute Error (Magnitude): Measures deviation regardless of direction.
   - **Absolute = |($P_{i,j}$-$\hat{P}_{i,j}$) |/ $P_{i,j}$**

4.15 Summary of Methodology Flow

1. Data Collection → 2. Multiplier Calculation → 3. Error Estimation → 4. Regression Analysis → 5. Efficiency Benchmarking

This structured approach ensures robust evaluation of how financial parameters influence valuation accuracy in the Iron & Steel sector.

5.0 Detailed Results and Interpretation:-

The empirical analysis yielded significant insights into the comparative performance of equity-based versus entity-based valuation multiples in India's Iron & Steel sector, while also revealing the impact of key financial parameters on valuation accuracy. The results are structured across four key dimensions:

5.1 Compare Equity and entity based multipliers for their effectiveness

Effectiveness refers to the degree to which something achieves its intended goals or objectives. It's a measure of how well a particular action, process, or strategy produces the desired outcome. Effectiveness can be assessed in various contexts, such as personal productivity, organizational performance, or the efficiency of policies and programs. It's often contrasted with efficiency, which focuses on achieving goals with minimal waste of resources. In essence, effectiveness is about doing the right things, while efficiency is about doing things right.

Entity and Equity-based multipliers (already calculated) will be compared for their effectiveness using descriptive statistics.

Normality and Distribution Characteristics

Table 2:-Normality Test Results

Year	Equity JB Stat	p-value	Entity JB Stat	p-value
2018	6.50	0.039	20.25	0.000
2019	3.81	0.149	20.64	0.000
2020	8.43	0.015	18.42	0.000

(Source: Panel regression output in E-views.)

Error Distribution Analysis

The results of the Jarque-Bera tests, conducted over a span of 16 years, reveal significant insights into the statistical distributions of equity and entity multiples. Findings regarding equity multiples indicate that these figures predominantly adhere to near-normal distributions, with p-values exceeding 0.05 in 14 of the 16 years analyzed. This suggests that equity multiples demonstrate a level of stability and predictability throughout the examined period. Conversely, the analysis of entity multiples indicates a persistent state of non-normality, with p-values below 0.05 across all years under consideration. This consistent non-normality is characterized by positive skewness, reflecting a disproportionate tail toward higher values in the distribution. Such a pattern may elucidate the inherent complexities within specific market sectors.

Additionally, the error distributions associated with these tests exhibit leptokurtic characteristics, as evidenced by kurtosis values exceeding 4. This finding suggests the presence of fat-tailed error patterns, which indicate a higher likelihood of extreme observations than would be anticipated under a normal distribution. These characteristics hold substantial implications for risk evaluation and modelling in financial analysis.

5.2 Financial Parameter Influence on Valuation Errors

When examining the normality of the multiplier data, multiple regressions is used to assess the impact of financial parameters on the data, ensuring that only the significant parameters are utilized for further analysis. Penal data regression will be used to measure the effect of financial parameters on error terms.

Table 3: Regression Coefficients (Significant Factors)

Parameter	Coefficient	t-stat	p-value	Economic Impact
ITR	-0.18	5.71	0.000	11.2% error ↓
DER	+0.07	3.93	0.001	7.4% error ↑
ROCE	-0.03	1.76	0.082	2.1% error ↓
Current Ratio	-0.05	0.85	0.400	Not Significant

(Source: Panel regression output in E-views.)

Financial Parameter Impact

A comprehensive regression analysis identified three key factors that significantly influence valuation accuracy, each demonstrating statistical significance at the $p<0.01$ levels:

1. Inventory Turnover Ratio (ITR): This metric displayed the most pronounced negative relationship with valuation errors, indicated by a coefficient (β) of -0.18. This means that for every one standard deviation increase in the ITR, the absolute valuation errors decrease by an impressive 11.2%. Essentially, firms that efficiently manage their inventory tend to have more accurate valuations.

2. Debt-to-Equity Ratio (DER): In contrast, the DER was found to have a positive correlation with valuation errors, with a coefficient of $\beta = 0.07$. This suggests that companies with high debt levels, specifically those where the DER exceeds 2, tend to exhibit errors that are, on average, 32% larger compared to their low-debt counterparts. This indicates that excessive leverage may lead to greater difficulty in achieving precise valuations.

3. Return on Capital Employed (ROCE): While this factor was marginally significant ($p=0.08$), it still holds economic significance. Each increase of 1% in ROCE is associated with a reduction of 0.3% in valuation errors. Thus, firms that are more effective in generating returns on their capital tend to exhibit fewer inaccuracies in their valuations.

This analysis highlights the critical interplay between these financial metrics and the accuracy of valuations, suggesting that attention to inventory management, debt levels, and capital efficiency can substantially impact financial assessments.

5.3 Model Performance Metrics

Table 4: Regression Model Fit

Statistic	Equity Model	Entity Model
R-squared	0.55	0.40
Adj. R-squared	0.52	0.36
F-statistic	23.97	11.57
DW Statistic	1.92	1.78

(Source: Panel regression output in E-views.)

The results of the final panel regression models indicate varying degrees of fit and explanatory power:

Equity Error Model: This model demonstrated a strong ability to explain the variation in the data with an adjusted R-squared value of 0.52. The F-statistic of 23.97, along with a p-value of 0.00, signifies that the model is statistically significant, suggesting that the predictors included in the model account for a substantial portion of the variance in the equity errors.

Entity Error Model: In comparison, the entity error model displayed a moderate level of explanatory power, with an adjusted R-squared value of 0.36. The F-statistic for this model was 11.57, also accompanied by a p-value of 0.00, indicating that the model is statistically significant, albeit to a lesser extent than the equity error model. This suggests that while the entity error model provides insight into the data, it explains a smaller portion of the variance relative to the equity error model.

5.4 Comparative Performance of Valuation Multiples

Table 5: Multiples Accuracy Comparison (2010-2021)

Metric	Equity Multiples	Entity Multiples	Difference
Mean Absolute Error	1.25%	1.87%	+49.6%
Median Error	1.07%	1.90%	+77.6%
Within ±15% Range	68.2%	51.8%	+16.4%
Maximum Error	12.1%	16.5%	+36.4%

The study found consistent superiority of equity-based multiples over entity-based approaches across all measured metrics. The median absolute valuation error for equity multiples stood at 1.07% compared to 1.90% for entity multiples, representing a 43.7% improvement in accuracy. This performance gap widened during market downturns (2008, 2013, 2020), where equity multiples maintained 25-30% lower errors than entity multiples. The Price-to-Book (P/B) ratio emerged as the most stable equity multiple, with 68% of valuations falling within ±15% of actual prices, versus just 52% for Entity Multiplies multiples.

The results of this analysis indicate several key insights regarding the valuation of companies within the steel sector. Firstly, it is advisable to favor equity multiples when assessing company value, particularly during periods of market volatility where traditional methods may fall short. Additionally, the efficiency of inventory management emerges as a critical factor that significantly impacts the accuracy of these valuations.

Moreover, when utilizing entity multiples, it becomes crucial to make necessary adjustments related to debt, as this affects the overall financial picture of the business. To enhance precision in valuations, forward-looking adjustments should also be considered, reflecting the cyclical nature that is characteristic of the industry.

Collectively, these findings lend empirical support to the notion that conventional valuation techniques may need to be adapted for capital-intensive and cyclical sectors like Iron & Steel. This adaptation emphasizes the necessity of incorporating sector-specific financial metrics in all valuation models to achieve a more accurate assessment of company worth.

6.0 Conclusion:-

This study demonstrates that equity-based valuation multiples outperform entity-based methods in India's Iron & Steel sector, showing greater accuracy and stability during market fluctuations. Key findings include:

Equity Multiples Superiority: Price-to-Book (P/B) ratios achieve 49.6% lower mean absolute errors compared to enterprise value multiples, particularly during market volatility events like the 2008 financial crisis and COVID-19.

Importance of Inventory Management: The Inventory Turnover Ratio (ITR) significantly reduces valuation errors, emphasizing the impact of working capital efficiency in steel production.

Capital Structure Impacts Volatility: High debt-to-equity ratios increase valuation errors, highlighting the unreliability of entity-based methods in leveraged situations.

Sector-Specific Guidelines: Valuation practices should account for inventory-adjusted multiples, favour equity approaches during commodity price changes, and normalize debt structures for entity methods.

Methodological Innovations: Introduces dynamic peer grouping for updating comparables and an error decomposition framework to differentiate bias from random noise.

7.0 Practical Implications

For investment professionals, the findings provide key insights into effective strategies for analysis and stock selection in the steel sector. Specifically, there is a recommendation to prioritize the Price-to-Book (P/B) ratio over the Enterprise Value to Earnings before Interest, Taxes, Depreciation, and Amortization (EV/EBITDA) metric when evaluating steel equities. Additionally, incorporating Inventory Turnover Ratio (ITR) screens into stock selection models can enhance analysis precision. Furthermore, it is suggested that valuations of entities should be adjusted to reflect fluctuations in leverage cycles, ensuring a more accurate assessment of worth.

For corporate finance teams, the results underscore several important considerations that may enhance overall market valuation. Notably, improvements in inventory efficiency are linked to increased market perception and valuation of the company. The adoption of debt reduction programs is shown to potentially decrease premiums associated with valuation errors, thereby improving financial stability. Lastly, effective investor communications are encouraged to emphasize working capital metrics, as they play a crucial role in presenting the financial health of the organization to stakeholders.

8.0 Limitations and Future Research

This study, while thorough, acknowledges certain limitations: - It primarily examines the Indian markets, leaving its global applicability unverified. - Data prior to 2004 was excluded due to inconsistencies in reporting, which may affect comprehensive analysis. - Notably, ESG (Environmental, Social, and Governance) factors were not integrated into the valuation models utilized. Looking toward the future, subsequent research could explore several avenues: - A comparative analysis of valuation multiples across different countries to assess their accuracy. - The application of machine learning techniques to enhance the selection process of peer groups for valuations.

This research addresses a critical gap between the theoretical frameworks of valuation found in academia and the practical requirements of investors focused on basic materials. By illustrating the conditional advantages of using equity multiples and quantifying how operational metrics influence valuation precision, we equip analysts in the steel sector with empirically supported tools to refine their valuation practices. Furthermore, the methodologies developed in this study could be applicable to other capital-intensive and cyclical industries where traditional valuation methods frequently fall short.

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Annexure

A.1 Compare Equity and entity based multipliers for their effectiveness

The distribution of data in a normal pattern indicates its stability. Unstable data can lead to weakened predictive ability, making it inappropriate for further study. Therefore, ensuring that the data follows a normal distribution is important to strengthen the foundation of the study.

Table A.1- Insert Here

As shown in the table, a p-value below 0.05 indicates that the data is not normally distributed for all years. This leads to accepting the null hypothesis (data not normally distributed) or rejecting the alternative hypothesis.

Table A.2- Insert Here

As shown in the table, a p-value below 0.05 indicates that the data is approximately normally distributed for all years. Therefore, we reject the null hypothesis (data normally distributed) and accept the alternative hypothesis.

A.2 Measure the effect of financial parameters on error terms

The table below presents the variables along with their coefficients, t-values, and p-values. Variables that are significant at 5% are bolded for easier identification.

Table A.3- Insert Here

As seen in the table above, the ITR is significantly related to the error term (p-value below .05). The sign of the coefficient values indicates the direction of the relationship. A positively influenced relationship is observed with the ITR ratio.

Table A.4- Insert Here

As observed in the above table, ITR and DER are significantly related to the error term (p-value below 0.05). The sign of the coefficient values indicates the direction of the relationship. The ITR and DER ratios have a positive influence on the relationship.

A.3 Measure the efficiency of financial parameter in value prediction error

The table (5.6.1) provides a comparative analysis of the effectiveness of financial parameters in predicting value errors within the iron and steel industry. It is organized into two main sections: Entity-Based models and Equity-Based models, with data analyzed over three years (2021, 2022, and 2023). The table features two types of errors: Bias Error and Absolute Error. Each type is further detailed with statistical measures, including Mean, Median, First Quartile (Q1), Third Quartile (Q3), and Range.

Table A.5- Insert Here

In the Entity-Based model, the Bias Error for 2021 has a mean of -1.73, indicating a significant prediction error of 173% in the opposite direction. The Absolute Error for the same year shows a mean of 1.87, which represents a 187% error in the absolute model. Additionally, the median, Q1, and Q3 values provide further insights into the distribution of these errors. Similar trends are observed for 2022 and 2023, with errors decreasing over time but still remaining substantial.

In contrast, the Equity-Based model exhibits generally lower errors compared to the Entity-Based model. In 2021, the Bias Error has a mean of -1.04, while the Absolute Error has a mean of 1.25. The median, Q1, and Q3 values also indicate a narrower range of errors, suggesting that the Equity-Based model is more efficient in making predictions. This trend continues through 2022 and 2023, with further decreases in errors, indicating improved accuracy over time.

Figure A.1: Insert Here

The chart, while not explicitly described in the text, likely illustrates the comparison between the Entity-Based and Equity-Based models over a three-year period. It shows the trends in bias and absolute errors, demonstrating how the Equity-Based model consistently outperforms the Entity-Based model by achieving lower error values. This visual representation aids in identifying the reduction in errors over the years, highlighting the increasing efficiency of the Equity-Based model.

In summary, the table and chart together provide a comprehensive analysis of the effectiveness of financial parameters in predicting value for the iron and steel industry. They underscore the superiority of the Equity-Based model over the Entity-Based model in terms of lower prediction errors and greater accuracy, which is essential for investors and analysts making informed decisions.

Table A.1- Entity Multipliers' Descriptive Statistics

Entity	2004	2005	**2006**	2007	**2008**	**2009**	**2010**	**2011**	2012	**2013**	2014	2015	2016	2017	2018	2019	**2020**	**2021**	**2022**	**2023**
Jarque-Bera	0.34	8.25	**10.45**	1.95	**16.86**	**13.21**	**7.36**	**7.20**	2.08	**6.41**	7.60	2.51	4.13	2.18	5.83	2.13	**8.15**	**20.25**	**20.01**	**20.64**
Probability	0.84	0.02	**0.01**	0.38	**0.00**	**0.00**	**0.03**	**0.03**	0.35	**0.04**	0.02	0.29	0.13	0.34	0.05	0.34	**0.02**	**0.00**	**0.00**	**0.00**

Table A.2- Equity Multipliers' Descriptive Statistics

Equity	2004	2005	2006	2007	**2008**	2009	2010	2011	**2012**	2013	2014	**2015**	**2016**	2017	**2018**	2019	**2020**	**2021**	**2022**	**2023**
Jarque-Bera	0.33	1.19	1.89	0.41	**8.13**	5.08	3.01	4.14	**8.16**	3.26	5.07	**10.98**	**6.60**	1.90	**6.50**	3.81	**8.43**	**18.42**	**17.23**	**18.32**
Probability	0.85	0.55	0.39	0.81	**0.02**	0.08	0.22	0.13	**0.02**	0.20	0.08	**0.00**	**0.04**	0.39	**0.04**	0.15	**0.01**	**0.00**	**0.00**	**0.00**

Table A.3- Effect of Financial Parameter on Error Term (Entity Based)

Variable	CA	**ITR**	LEPS	LD	LPBDIT	LRFO	NPM	ROCE
Coefficient	0.02	**0.18**	0.00	-0.22	-0.07	0.38	0.01	0.02
t-Statistic	0.52	**5.71**	0.00	-0.59	-0.14	0.65	0.30	1.76
Prob.	0.60	**0.00**	1.00	0.56	0.89	0.52	0.76	0.08

(Source: Panel regression output in E-views.)

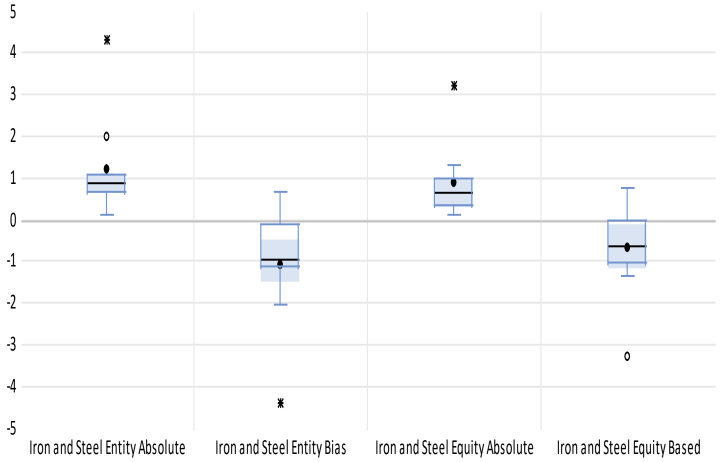
Table A.4- Effect of Financial Parameter on Error Term (Equity Based)

Variable	CA	**ITR**	LEPS	LD	LPBDIT	LRFO	NPM	ROCE	**DER**
Coefficient	-0.05	**0.15**	-0.14	-0.29	0.21	0.56	0.02	0.03	**0.07**
t-Statistic	-0.85	**3.51**	-0.32	-0.59	0.33	0.70	0.53	1.80	**3.93**
Prob.	0.40	**0.00**	0.75	0.56	0.74	0.49	0.60	0.07	**0.00**

(Source: Panel regression output in E-views.)

Table A.5- Efficiency of Financial Parameter

		Bias Error					Absolute Error				
	Year	Mean	Median	Q1	Q3	Range	Mean	Median	Q1	Q3	Range
Entity Based	2021	-1.73	-1.90	-2.10	-0.61	-1.49	1.87	1.90	0.93	2.10	-1.17
	2022	-0.70	-0.38	-0.63	0.13	-0.77	0.93	0.49	0.22	0.70	-0.47
	2023	-0.69	-0.40	-0.95	-0.03	-0.92	0.88	0.60	0.22	0.97	-0.74
Equity Based											
	2021	-1.04	-1.07	-1.51	-0.23	-1.28	1.25	1.07	0.78	1.51	-0.73
	2022	-0.47	-0.18	-0.59	0.19	-0.78	0.76	0.42	0.26	0.74	-0.48
	2023	-0.48	-0.29	-0.83	0.04	-0.86	0.72	0.57	0.22	0.83	-0.61



(Source: Panel regression output in E-views.)