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# Valuation Accuracy in the Cement Industry: A Comparative Study of Equity and Entity-Based Multipliers

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**Abstract**: - This study establishes that entity-based multipliers, when used in conjunction with significant financial parameters such as Inventory Turnover, Dividend Payout, and Return on Capital Employed, provide a superior framework for equity valuation in the cement industry. The practical implication for investors, analysts, and financial professionals is clear: moving from equity-based to entity-based valuation multiples can substantially improve prediction accuracy and lead to better-informed investment decisions.

Key Words: -B.V.-Book Value, M.V. - Market Value, Entity: - Equity + Debts, Multipliers, Valuation accuracy, Value prediction error, efficiency in value prediction

## 1.1 Introduction

The stock market is an ecosystem defined by its dynamism, where investors and fund managers constantly strive to predict price movements to secure optimal returns. Equity shares, representing ownership in a company, offer the dual advantages of liquidity and the potential to outperform the market. However, the task of predicting share prices is far from an exact science; it is a complex endeavour influenced by a myriad of intrinsic and extrinsic factors. For the thousands of daily participants in stock exchanges, a fundamental question persists: "What is the predictive value of a particular company's share?" The answer to this question often determines the success or failure in achieving investment objectives, making equity valuation the cornerstone of financial analysis **(Stowe, McLeavey, & Pinto, 2009).** Valuation lies at the heart of finance, whether it is the study of market efficiency, corporate governance, or capital budgeting. While a wide spectrum of valuation models exists, ranging from simple to sophisticated, they are often based on different assumptions and fundamentals. These models can be broadly classified into discounted cash flow (DCF) valuation, which relates value to the present value of expected future cash flows; liquidation and accounting valuation, which focus

on existing assets; relative valuation, which estimates value by comparing an asset to 'comparable' assets; and contingent claim valuation, which uses option pricing models **(Damodaran, 2007)**. Despite the theoretical emphasis in academia on models like DCF and residual income valuation (RIV), practitioners frequently find these models sensitive to various assumptions and not always suitable for practical application. Consequently, they often divert to a more straightforward approach: valuation based on multiples **(Schreiner &Spremann, 2007).**

Equity share multipliers, also known as valuation multiples, are a practical and efficient way to estimate the value of a company's shares. A multiplier is simply a ratio that expresses the relationship between the market value of a company's stock and a key financial metric, such as earnings, book value, or sales **(Deng, Easton, & Yeo, 2012)**. The most commonly used multipliers include the Price-to-Earnings (P/E) ratio, Price-to-Book (P/B) ratio, and Price-to-Sales (P/S) ratio. These tools are widely used by analysts and investment bankers in fairness opinions and reports, primarily because of their simplicity and ease of understanding. They allow for a quick relative valuation, comparing a company's valuation with its peers in the same industry, thereby providing insights into market sentiment and potential mispricing.

However, despite their popularity, the use of equity share multipliers is not without limitations. A simplistic application of multiples, without a structured methodology or a sound understanding of their determinants, can lead to trivial and often poor valuation results. Common shortcomings include the reliance on historical data, lack of context for the multiplier value (e.g., a high P/E ratio could indicate growth expectations or an overvalued bubble), and challenges in finding truly comparable firms. Moreover, industry classifications can be ambiguous, and using a single multiplier without justification can produce misleading outcomes. Recognizing these weaknesses, recent research has moved beyond simply using a single multiple to exploring the accuracy of different types of multiples, including equity versus entity-based multiples, forward-looking versus trailing multiples, and the impact of industry classification on valuation accuracy **(Schreiner, 2009; Nel, Bruwer, & Le Roux, 2013).**

This study is motivated by the need to address these gaps and move beyond the simplistic application of valuation multiples. The research is grounded in a comprehensive review of existing literature, which has yielded several critical insights. Studies indicate that equity value multiples often exceed entity value multiples in accuracy, and forward-looking multiples, particularly two-year forward P/E ratios, are superior to trailing ones **(Schreiner &Spremann, 2007)**. Furthermore, the choice of value driver is crucial, with earnings-based drivers often performing the most accurate valuations, followed by assets, cash flow, and revenue **(W. S. Nel &Bruwer, 2013)**. Other research confirms that book value multipliers can provide some of the

lowest mean standard errors among different methods, and that narrower industry classifications lead to more accurate valuations **(Courteau et al., 2003; Nel et al., 2013)**. Key studies have also explored the fundamental determinants of share prices, revealing that variables like earnings yield, dividend per share, and return on equity have significant impacts on share prices and the equity multiplier **(Abraham, Harris, & Auerbach, 2017; Srinivasan, 2012)**.

### 1.2 Review of Literature

The academic foundation for equity valuation using multiples, while widely applied in practice, has received surprisingly limited attention in formal academic literature. This gap in research, particularly concerning accounting-based market multipliers, has motivated numerous scholars to examine the accuracy, determinants, and efficiency of various valuation multiples across different markets and conditions. This review synthesizes the key findings from seminal and contemporary studies as discussed in the provided document, organizing them around the central themes of comparing equity versus entity multiples, the role of value drivers, the impact of industry classification, and the fundamental determinants of share prices.

A significant stream of research focuses on comparing the relative accuracy of different types of multiples. In a pivotal study, **Schreiner &Spremann (2007)** examined European equity markets and made several critical observations. Their results conclusively showed that equity value multiples generally provide more accurate valuations than entity value multiples. Furthermore, they found that knowledge-related multiples outperform traditional multiples, and, importantly, forward-looking multiples—specifically the two-year forward price-to-earnings (P/E) multiple—are superior to trailing multiples. These findings, noted to be significant in magnitude and consistent over time, challenge the reliance on historical data. Extending this line of inquiry, **W. S. Nel &Bruwer (2013)** analyzed companies listed on the

Johannesburg Stock Exchange (JSE), representing approximately 91% of the market capitalization. Their research evaluated valuation drivers based on earnings, cash flow, assets, and revenue. The study concluded that earnings-based value drivers performed the most accurate valuations, followed by assets, cash flow, and finally revenue-based drivers. In direct confirmation of **Schreiner & Spremann's** earlier work, **W. Soon Nel et al. (2013)** specifically tested the hypothesis that equity-based multiples offer more accurate results than their entity-based counterparts. Using absolute valuation errors to prevent the netting of positive and negative errors, their findings supported the assumption, demonstrating that equity-based

multiples generally yield more precise estimates of market value. Beyond comparing multiplier types, research has delved into which specific financial metrics serve as the most effective value drivers. A comprehensive study by an author in 2002, titled "Equity Valuation Using Multiples," used data from COMPUSTAT, IBES, and CRSP to evaluate how well different value drivers summarize expected payoffs. The results ranked historical earnings measures second only to forward earnings measures. Cash flow measures and book value were tied for third place, while sales performed the worst in explaining stock prices. This finding underscores the importance of earnings as a key summary statistic for valuation. In a different context, **Ilyukhin (2014)** examined the accuracy of financial multipliers for biopharmaceutical companies in the U.S. market; a sector characterized by income volatility and lengthy research processes. Analyzing a dataset of 73 publicly traded firms from 2002 to 2012, the study found that book value multipliers estimated more accurate values than any other multiple, while cash flow multipliers performed the worst. This suggests that the optimal value driver can vary significantly by industry. Further supporting the need for a multi-faceted approach, **Schreiner (2009)** found evidence that combined multiples can outperform single multiples under certain circumstances, advocating for further exploration of two-factor multiples valuation models.

The accuracy of a valuation multiple is heavily dependent on the correct selection of a peer group. A crucial study by **Nel, Bruwer, & Le Roux (2013)** investigated the impact of industry classification on valuation accuracy. By comparing classifications from broad sector levels (SEC) to more specific sub-industry levels (SUB), the research concluded that using narrower industry classifications leads to more accurate results when using multipliers to predict equity value. This finding highlights the danger of using broad, one-size-fits-all industry multipliers.

Complementing this, **I. Cooper (2008)** explored the trade-off between using many versus few comparable firms. Analyzing a large sample of 49,757 firm-years from 1982 to 2006, the research found that the primary cause of higher error in forecasts made with small numbers of comparables is the greater frequency of very large errors when the sample size (n) is small. The study concluded that it is not possible to reliably choose a small number of comparables based solely on industry characteristics. Later, **I. A. Cooper (2014)** extended this work by focusing on the choice of comparables and weighting schemes, reaffirming that multipliers based on forward earnings predict stock prices remarkably well, with the model achieving within 15% price prediction error for about half of the sample.

Several studies have moved beyond the mechanics of multiples to examine the broader fundamental and behavioral determinants of share prices. In the Indian context, **Srinivasan (2012)** employed panel data techniques on six major sectors of the Indian economy from 2006 to 2011. The empirical results revealed that dividend per share had a negative and significant impact on share prices for the manufacturing, pharmaceutical, energy, and infrastructure sectors, confirming that fundamental ratios are essential for assessing stocks across different industry groups. From a different perspective, **Abraham, Harris, & Auerbach (2017)** analyzed 3,013 observations of NASDAQ stocks across 12 sectors and 101 industries from 2010 to 2014. Using multiple regressions, they found that earnings yield significantly influenced the variation in the equity multiplier at all risk levels, following a linear functional form. The study also confirmed that earnings yield was a significant predictor of return on assets, return on equity, and economic value added. Expanding the scope to behavioral finance, **Scholar (2019)** conducted a survey of 727 clients from a brokerage house in Surat, India, using Structural Equation Modelling (SEM). The results indicated a positive relationship between personality traits and behavioral biases, and further found a positive relationship between behavioral biases and both investment performance and reinvestment intention. Finally, **Lakkol, Commerce, and (2019)** analyzed the impact of financial risk on debt-equity mix decisions across five sectors (Chemical, Engineering, Food, Media, and Entertainment) over seven years. The study found that high-risk firms across sectors use higher debt and exhibit low profitability, while a negative relation between financial risk and debt was found specifically in the food and media sectors. Collectively, this body of literature establishes that valuation accuracy depends not on a single multiple in isolation, but on a careful selection of the multiplier type (equity vs. entity, forward vs. trailing), the appropriate value driver (earnings, book value), a narrowly defined peer group, and a thorough understanding of industry-specific financial and behavioral factors.

### 1.3 Objectives of the Study

Based on the research framework outlined in the above discussion, this study pursues the following four primary objectives:

1. **To determine the equity and entity-based multipliers and their error terms for firms' valuation.**
2. **To compare equity and entity-based multipliers for their effectiveness.**

### 1.4 Research Methodology

#### 1.4.1 Scope of the Study

The scope of this study is restricted exclusively to companies listed on the National Stock Exchange (NSE) of India that are included in the NIFTY 500 index. The NIFTY 500 serves as the census for the study, from which the sample is drawn. This ensures a broad and representative base of large-cap, mid-cap, and small-cap companies across diverse sectors of the Indian economy.

#### 1.4.2 Time Frame

The time frame for the present study spans 17 years, from 2007 to 2023. Multipliers are calculated for this entire period and are used to determine the expected market value of sample companies within the same time frame.

#### 1.4.3 Sample Design

To accurately estimate multipliers, peer groups must consist of at least 5 to 10 firms, representing 40% to 80% of the market capitalization of the relevant industry. Whenever possible, peer groups are formed based on market capitalization and do not include the target firm **(Bhojraj & Lee, 2002)**. To facilitate the selection of peer groups, this study includes NIFTY 500 companies.

To estimate a robust model, the following firms are excluded from the sample:

1. Non-Indian domiciled firms.
2. Firms with book value, sales, or market capitalization categorized as SME (Small and Medium Enterprise) firms.
3. Firms with negative value drivers (e.g., loss-making firms with a negative price-to-earnings ratio).

The objective is to create a sample that can estimate coefficients with confidence, omitting observations where financial ratios indicate extreme situations; as such firms are not comparable with others in the sample.

### 1.4.4 Objective-Wise Methodology

**Objective 1: To determine equity and entity-based multipliers and their error terms for firms' valuation.**

For this objective, the Price/Book Value formula is used to calculate multipliers for sample companies in each industry over the 17-year period. For equity-based multipliers, the 'Book Value' includes only the book value of equity. For entity-based multipliers, the 'Book Value' implies the book value of equity plus debts. The study uses industry turnover and market capitalization to identify the peer group. From an initially identified set of 10 companies, the top 5 companies that best fit the peer group assumptions are selected. Each company is represented by "i" and time by "j".

The fundamental valuation multiple is calculated as:

- $$\Theta_{i,j}^{B.V.} = \frac{MarketPriceofShares}{BookValue} \quad (1)$$

The key assumption in equation (1) is that the valuation multiple ΘijB.V.$\Theta ijB.V.$ is appropriate for the target companies. The market price of shares is calculated as the average of opening and closing prices:

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

The median price-to-value-driver ratio of peer group companies is used to calculate single multipliers, excluding predictor firms. The median is calculated as:

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- $\text{Median}\theta_{i,j}^{B.V.} = \left(\frac{n+1}{2}\right) th\ observation$ (3)

This median value is referred to as the Peer Group multiplier. The Peer Group multiplier is used to predict the market value of sample companies. The predicted value is then compared with the actual market value to find the Error Term:

- **Error Term =** $(\theta_{i,j}^{B.V.} - \text{Median}\theta_{i,j}^{B.V.})$ **(4)**

For entity-based multipliers, a similar function is used. The entity-based multiplier is derived from the equity-based multiplier by incorporating debt. The relationship between equity and entity multipliers is established as follows:

- $\theta_{i,j}^{Entity.} = \frac{MarketPriceofShares}{BookValue+Debts}$ **(5)**

- $\theta_{i,j}^{Entity.}(BookValue + Debts) = MarketPriceofShares$ **(6)**

Equating the market values from both approaches:

- $\theta_{i,j}^{Entity.}(BookValue + Debts) = \theta_{i,j}^{B.V.}.BookValue$ **(7)**

Dividing the right-hand side by Book Value:

- $\theta_{i,j}^{Entity.} = \frac{\frac{\theta_{i,j}^{B.V.}.BookValue}{BookValue}}{(\frac{BookValue+Debts}{BookValue})}$ **(8)**

This simplifies to:

- $\theta_{i,j}^{Entity.} = \frac{\theta_{i,j}^{B.V.}}{(1+\frac{Debts}{BookValue})}$ **(9)**

Which can be expressed in terms of the Debt-to-Equity ratio:

- $\theta_{i,j}^{Entity.} = \frac{\theta_{i,j}^{B.V.}}{(1+\frac{D}{E}Ratio)}$ **(10)**

The median price-to-value-driver ratio of peer group companies is used to find single entity multipliers. The error term for the entity-based model is then:

- **Error Term (Entity) = ( $\Theta_{i,j}^{Entity.}$–Median$\Theta_{i,j}^{Entity.}$)** **(11)**

**Objective 2: To compare equity and entity-based multipliers for their effectiveness.**

For this objective, the equity and entity-based multipliers already calculated in Objective 1 are compared using descriptive statistics. The characterization of the data includes skewness and kurtosis.

**Skewness** measures the symmetry of the data distribution. It is calculated as:

- **Skewness =** $\frac{\sum_{i=1}^{N}\left(\Theta_{i,j}^{B.V.} - \textbf{Mean}\ \Theta_{i,j}^{B.V.}\right)^{3}}{\delta^{3}\ N}$ **(12)**

Where Mean Θi,jB.V.Θ*i*,*jB*.*V*. is the mean, *δδ* is the standard deviation, and N is the number of data points. Symmetric data has skewness near zero. Negative skewness indicates a long-left tail, while positive skewness indicates a long right tail.

**Kurtosis** measures the "tailedness" of the data distribution:

- **Kurtosis =** $\frac{\sum_{i=1}^{N}\left(\Theta_{i,j}^{B.V.} - \textbf{Mean}\ \Theta_{i,j}^{B.V.}\right)^{4}}{\delta^{4}\ N}$ **(13)**

High kurtosis indicates heavy tails or outliers, while low kurtosis indicates light tails.

The **Jarque-Bera (JB) test** is used to determine whether the sample data comes from a normally distributed population. The test statistic is defined as:

- $JB_{TestStatistics}$ **= n** $\left[\frac{S^2}{6} + \frac{(K-6)^2}{24}\right]$ **(14)**

Where n is the number of observations, S is the sample skewness, and K is the sample kurtosis.

The hypotheses are:

- **H0 (Null Hypothesis):** Data is normally distributed.
- **H1 (Alternate Hypothesis):** Data is NOT normally distributed.

A regression model with error term as a dependent variableand selected financial parameters as independent variables as given below, was developed.

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

This model was extrapolated to predict the estimated prices. This estimated price was used for calculating efficiency in value prediction error.

- **Efficiency of parameters in prediction error =** $\frac{[Actual\ price - Estimated\ Price]}{Actual\ Price}$ **(15)**

To compare the ability of different value drivers to predict equity prices, two common error metrics are employed: **Bias** and **Absolute error**.

**Bias** is the signed percentage prediction error, which indicates the direction of the error:

- **Bias** $=(P_{i,j}-\hat{P}_{i,j})/P_{i,j}$ **(16)**

**Absolute Error** is the absolute percentage prediction error, which indicates the magnitude of the error regardless of direction:

- **Absolute** $= |(P_{i,j}-\hat{P}_{i,j})| / P_{i,j}$ **(17)**

For the book value of equity, the bias is derived as:

- $Bias^{BV}_{i,j} = (\Theta^{x}_{i,j}BV_{i,j} - \hat{P}_{i,j}) / \Theta^{x}_{i,j}BV_{i,j}$ **(18)**

Similarly, the absolute percentage prediction error is:

- $\hat{P}_{i,j}=X_{i,j}\ .\ \mathrm{Median}\,\mathbf{of}\,\Theta^{xB.V.}_{i,j}$ **(19)**

These metrics are calculated for each company and year, and then aggregated. The comparison between entity-based and equity-based models is performed by analyzing the mean, median, first quartile (Q1), and third quartile (Q3) of the bias and absolute errors. A lower absolute error and a bias closer to zero indicate a more efficient and accurate valuation model.

**1.5 Results and Discussion** This section presents the detailed findings of the study as they apply to the cement industry. The cement industry plays a pivotal role in global construction by providing the primary binding agent used in concrete, the most widely used construction material worldwide. Through the blending and heating of raw materials such as limestone, clay, shale, iron ore, and sand, the industry creates the foundation for countless remarkable structures and infrastructures. The analysis below is structured according to the four objectives of the study, with a specific focus on the cement companies sampled from the NIFTY 500 index over the period 2007 to 2023.

### 1.5.1 Comparison of Equity and Entity-Based Multipliers for Effectiveness

The second objective of the study was to compare equity and entity-based multipliers for their effectiveness. Effectiveness refers to the degree to which something achieves its intended goals or objectives. In this context, a more effective multiplier is one that produces more stable, predictable, and reliable valuations. The first step in this comparison was to test the normality of the data distribution for both types of multipliers. A normal distribution indicates data stability, whereas unstable data can lead to weakened predictive ability, making it inappropriate for further study.

**Hypotheses Tested:**

- **Null Hypothesis (H0):** Data is distributed but not normally distributed.
- **Alternate Hypothesis (H1):** Data is distributed and normally distributed.

The Jarque-Bera test was employed to assess normality. A p-value above 0.05 indicates that the data is approximately normally distributed, leading to rejection of the null hypothesis.

**Table 1.5.1 - Equity Multipliers' Descriptive Statistics**

| Year | Jarque-Bera | Probability | Year | Jarque-Bera | Probability |
|---|---|---|---|---|---|
| 2007 | 1.44 | 0.49 | 2016 | 3.25 | 0.20 |
| 2008 | 0.32 | 0.85 | 2017 | 1.46 | 0.48 |
| 2009 | 0.01 | 0.60 | 2018 | 0.33 | 0.51 |
| 2010 | 1.83 | 0.66 | 2019 | 1.11 | 0.95 |
| 2011 | 0.75 | 0.69 | 2020 | 0.09 | 0.58 |
| 2012 | 0.08 | 0.58 | 2021 | 1.52 | 0.47 |
| 2013 | 1.26 | 0.53 | 2022 | 0.25 | 0.88 |
| 2014 | 0.56 | 0.75 | 2023 | 0.37 | 0.83 |
| 2015 | 0.71 | 0.70 | - | - | - |

As shown in the table, the probability values (p-values) for the Jarque-Bera test for equity multipliers across all years from 2007 to 2023 are consistently above the 0.05 significance

level. For example, in 2007 the probability was 0.49, in 2010 it was 0.66, and in 2023 it was 0.83. This indicates that the null hypothesis of non-normal distribution is rejected, and the alternative hypothesis is accepted. Therefore, the equity multiplier data for cement companies is approximately normally distributed for all years, providing a stable foundation for further regression analysis.

**Table 1.5.2 - Entity Multipliers' Descriptive Statistics**

| Year | Jarque-Bera | Probability | Year | Jarque-Bera | Probability |
|---|---|---|---|---|---|
| 2007 | 0.87 | 0.65 | 2016 | 1.91 | 0.23 |
| 2008 | 0.81 | 0.67 | 2017 | 1.12 | 0.35 |
| 2009 | 1.18 | 0.91 | 2018 | 2.45 | 0.48 |
| 2010 | 1.42 | 0.49 | 2019 | 1.30 | 0.86 |
| 2011 | 0.01 | 0.60 | 2020 | 0.69 | 0.43 |
| 2012 | 1.04 | 0.60 | 2021 | 1.96 | 0.62 |
| 2013 | 1.22 | 0.54 | 2022 | 0.21 | 0.90 |
| 2014 | 1.12 | 0.57 | 2023 | 0.04 | 0.98 |
| 2015 | 1.08 | 0.58 | - | - | - |

Similar to the equity multipliers, the entity multipliers also show probability values consistently above 0.05 for all years from 2007 to 2023. For instance, the probability in 2004 was 0.65, in 2013 it was 0.54, and in 2023 it was 0.98. This confirms that the entity multiplier data is also approximately normally distributed. Consequently, the null hypothesis is rejected, and the alternative hypothesis is accepted. Both equity and entity multipliers for the cement industry exhibit normal distribution, validating their suitability for the subsequent panel data regression analysis to measure the effect of financial parameters on error terms.

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### 1.5.2 Efficiency in Value Prediction Error

This section uses an error correction model that includes only the statistically significant coefficients identified in the previous objective. The efficiency is measured using two metrics: **Bias** (signed percentage error, indicating direction) and **Absolute Error** (magnitude of error). The analysis compares the performance of Entity-Based and Equity-Based models for the years 2021, 2022, and 2023.

**Table 1.5.3 - Efficiency of Financial Parameters (Cement Industry)**

| | | Bias Error | | | | | Absolute Error | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Year | Mean | Median | Q1 | Q3 | Range | Mean | Median | Q1 | Q3 | Range |
| Entity Based | 2021 | -0.70 | -0.39 | -0.32 | -0.92 | 0.61 | 0.75 | 0.39 | 0.90 | 0.29 | 0.62 |
| | 2022 | -0.95 | -0.92 | -0.59 | -1.14 | 0.55 | 0.95 | 0.92 | 1.04 | 0.75 | 0.29 |
| | 2023 | -0.69 | -0.49 | -0.18 | -0.80 | 0.62 | 0.70 | 0.49 | 0.75 | 0.17 | 0.59 |
| Equity Based | | | | | | | | | | | |
| | 2021 | -3.62 | -2.56 | -1.73 | -3.28 | 1.55 | 3.62 | 2.56 | 3.28 | 1.73 | 1.55 |
| | 2022 | -3.76 | -3.45 | -2.60 | -4.23 | 1.64 | 3.76 | 3.45 | 4.23 | 2.60 | 1.64 |
| | 2023 | -3.33 | -2.94 | -2.53 | -3.92 | 1.39 | 3.33 | 2.94 | 3.92 | 2.53 | 1.39 |

**Entity-Based Model Performance:**

- **Bias Error:** In 2021, the mean bias error was -0.70, indicating that the entity-based model underestimated the actual value by 70% on average. The median bias was -0.39, meaning half the observations had underestimations of 39% or less. In 2022, the mean bias worsened to -0.95 (95% underestimation), but improved slightly in 2023 to -0.69. The negative sign across all years indicates consistent underestimation, but the magnitude is relatively contained.

- **Absolute Error:** The mean absolute error in 2021 was 0.75 (75% average deviation from actual value). This decreased to 0.70 in 2023, showing slight improvement. The median absolute error in 2023 was 0.49, meaning half the predictions were within 49% of the actual value. The Q1 and Q3 values show that 25% of errors were below 17% and 25% were above 75% in 2023, indicating some variability in prediction accuracy.

**Equity-Based Model Performance:**

- **Bias Error:** The equity-based model performed substantially worse. In 2021, the mean bias error was -3.62, representing a massive 362% underestimation. This worsened to -3.76 in 2022 before improving slightly to -3.33 in 2023. The median bias of -2.56 in 2021 means that half the observations had underestimations exceeding

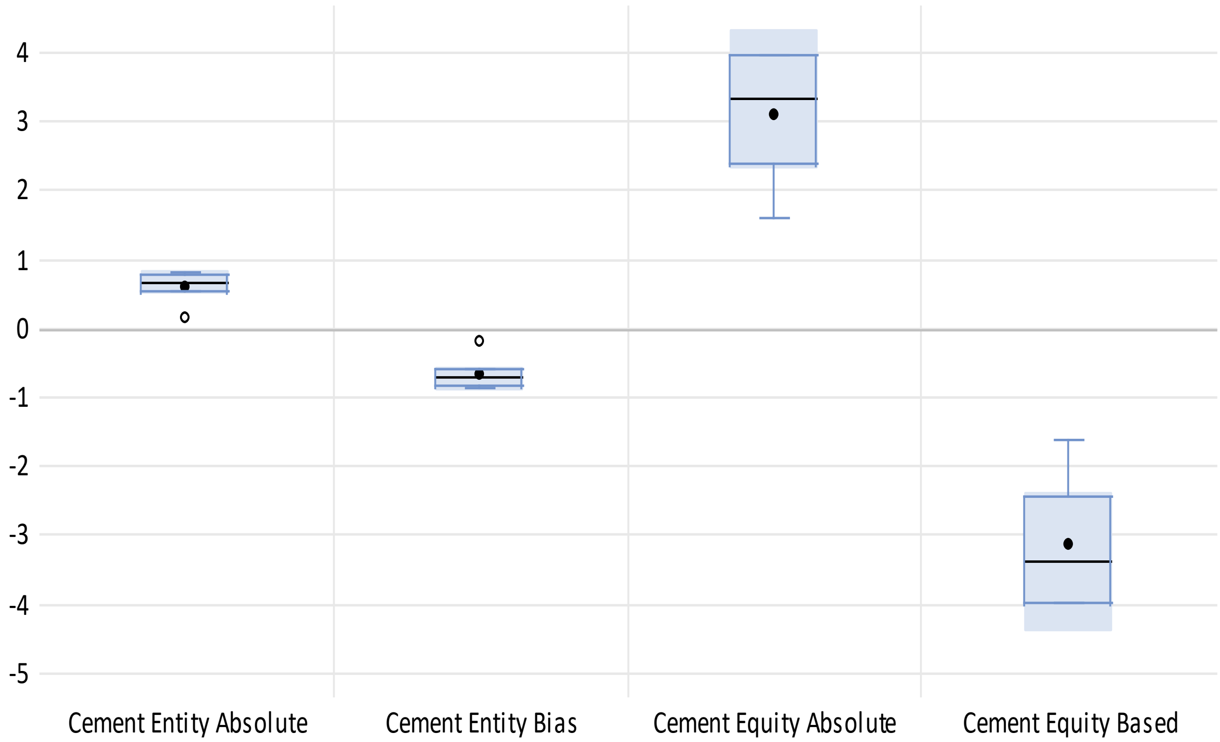
  256%. These values are approximately 4 to 5 times larger than those of the entity-based model.

- **Absolute Error:** The absolute errors for the equity-based model are equally concerning. The mean absolute error in 2021 was 3.62 (362% average deviation), increasing to 3.76 in 2022. Even the best-performing quartile (Q1) in 2021 showed absolute errors of 1.73 or 173%, which is still more than double the worst-performing quartile of the entity-based model. The ranges (1.39 to 1.64) indicate consistently high errors across all observations.

**Comparative Analysis:**

The entity-based model consistently exhibits lower bias and absolute errors compared to the equity-based model. For example, in 2021, the entity-based model had a mean bias error of -0.70 versus -3.62 for equity-based – a reduction in error magnitude of approximately 81%. Similarly, the mean absolute error of 0.75 for entity-based compared to 3.62 for equity-based represents an 79% improvement in accuracy. This pattern holds across all three years, strongly indicating that entity-based multipliers are more efficient and accurate for valuing cement industry companies.

**Figure 1: Equity and Entity's Error Comparison in Cement Industry**




(Note: The bar chart where each bar represents the error value for a specific type of error and model. The Entity-Based model displays shorter bars for both absolute and bias errors, indicating smaller deviations from actual values. In contrast, the Equity-Based model shows much taller bars, reflecting significantly larger errors.)

The analysis of this industry leads to several important conclusions. First, multipliers alone are not powerful enough to value stocks accurately.

Most conclusively, **entity-based multipliers are more efficient than equity-based multipliers** for the cement industry, as they produce consistently lower prediction errors. The bar chart visually confirms this, illustrating that the absolute and bias errors in the entity-based model are substantially smaller than those in the equity-based model. This indicates that the entity-based model is more effective at estimating firm value, making it the preferred choice for financial forecasting and better decision-making for companies in the cement industry.

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## 1.6 Conclusion

This study was undertaken to address a fundamental challenge in financial analysis: accurately valuing equity shares. While valuation lies at the heart of finance, practitioners often find traditional models like Discounted Cash Flow (DCF) and Residual Income Valuation (RIV) to be sensitive to assumptions and impractical for routine use. Consequently, they frequently turn to valuation multiples for their simplicity and ease of understanding. However, the simplistic application of these multiples, without a structured methodology or consideration of their determinants, often leads to poor and unreliable valuations. This research sought to move beyond this simplistic approach by systematically analyzing equity and entity-based multipliers, identifying the financial parameters that influence valuation errors, and comparing the efficiency of these multipliers in predicting market value.

The normality tests confirmed that data for both equity and entity-based multipliers are approximately normally distributed across all years. The Jarque-Bera test consistently produced p-values above 0.05 (e.g., 0.49 for equity in 2004 and 0.98 for entity in 2023), leading to rejection of the null hypothesis of non-normal distribution. This indicates that the multiplier data is stable and suitable for further parametric regression analysis.

Third, and most significantly, the error correction model conclusively demonstrated that entity-based multipliers are substantially more efficient and accurate than equity-based multipliers for the cement industry. The entity-based model produced a mean bias error of -0.70 in 2021, -0.95 in 2022, and -0.69 in 2023, with corresponding absolute errors of 0.75, 0.95, and 0.70. In contrast, the equity-based model produced dramatically larger errors: mean bias errors of -3.62, -3.76, and -3.33, with absolute errors of 3.62, 3.76, and 3.33 for the same years. This represents an approximate 80% improvement in accuracy when using entity-based multipliers. The entity-based model's errors are consistently smaller across all metrics—mean, median, first quartile (Q1), and third quartile (Q3)—indicating that incorporating debt into the valuation multiple provides a more comprehensive and reliable assessment of a company's true worth.

The practical implication for investors, analysts, and financial professionals is clear: moving from equity-based to entity-based valuation multiples can substantially improve prediction accuracy and lead to better-informed investment decisions.

### 1.9 References


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