

ASSESSING VALUATION MODEL FORECASTING ACCURACY IN HEALTHCARE: A SIMULATED COMPARISON OF CAPM AND DDM

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Abstract

This study addresses the challenges of valuing firms in the volatile healthcare sector by rigorously comparing the forecasting accuracy of the Capital Asset Pricing Model (CAPM) and the Dividend Discount Model (DDM). Employing a controlled synthetic dataset of 100 healthcare firms spanning 2019–2021, we aim to isolate model performance, free from real-world confounding factors. Forecast accuracy is measured using Mean Absolute Error (MAE) and Percentage Absolute Error (PAE). Results indicate CAPM significantly outperforms DDM (e.g., CAPM's average PAE of 3.47% vs. DDM's 8.48%), particularly due to healthcare's variable dividend policies. This research provides empirical evidence from a controlled setting on model suitability, guiding financial practitioners toward more reliable valuation techniques and contributing to the literature on model selection in sector-specific financial contexts.

Keywords: CAPM, DDM, Forecast Accuracy, Valuation Models, Healthcare Firms

1. Introduction

Healthcare firms often exhibit irregular dividend patterns due to high reinvestment demands, regulatory shifts, and innovation-driven growth, posing significant challenges for accurate financial valuation (Damodaran, 2012). These dynamics frequently lead to forecasting errors in models like the Dividend Discount Model (DDM), which assumes stable dividend growth—a condition rarely met in the sector (Penman, 2010; Olweny, 2011). In contrast, the Capital Asset Pricing Model (CAPM), which focuses on systematic market risk, is theoretically better aligned with the sector's volatility (Sharpe, 1964; Lintner, 1965; Fama and French, 2004). Given their foundational roles and contrasting assumptions, a direct comparison of CAPM and DDM in healthcare offers critical insights into model suitability for firms with unstable cash flows.

While theoretical expectations suggest DDM's reliance on consistent dividends will lead to larger forecasting errors, testing this empirically is difficult. Real-world market data is rife with confounding factors—such as shifting market sentiment, firm-specific news, and macroeconomic shocks—that make it impossible to isolate a model's performance from market noise. To overcome this challenge, this study employs a synthetic dataset simulation methodology. This approach allows for a controlled environment where each firm's "true" underlying value is known by design and generated independently of the forecasting models' assumptions. The simulation is modeled over the 2019–2021 period, a timeframe chosen specifically for its unprecedented volatility and structural changes spurred by the COVID-19 pandemic, thus creating a robust stress test for model accuracy.

The analysis provides valuable, actionable insights for financial practitioners in healthcare, where precise valuations underpin critical investment and strategic decisions (Fama and French, 2004). By quantifying the performance of CAPM and DDM in a

controlled simulation tailored to healthcare's unique financial landscape—and under conditions of extreme market stress—this study provides a clear benchmark for model selection. It clarifies which model better navigates volatile cash flows, guiding analysts toward more reliable forecasting tools. The findings also contribute a precise measure of model error that is unobtainable with market data alone, enhancing the broader academic understanding of how valuation models perform in industries with irregular dividend policies.

2. Theoretical Background

Valuation models like the CAPM and DDM are widely studied, yet their performance in healthcare marked by volatile cash flows and irregular dividends—remains under-examined, raising questions about which model works best in this sector (Olweny, 2011; Watts et al., 2024). CAPM's focus on market risk contrasts with DDM's reliance on stable dividends, making them suitable for testing in healthcare's dynamic financial environment (Sharpe, 1964; Gordon, 1962). This review synthesizes key studies and sector-specific challenges to highlight the need for targeted comparisons of CAPM and DDM in healthcare valuation.

2.1 CAPM: Theory and Applications

CAPM, a cornerstone of modern portfolio theory, estimates expected returns using systematic market risk, fitting healthcare's volatility driven by regulatory shifts and innovation (Sharpe, 1964; Fama and French, 2004). Its strength lies in using firm-specific beta to capture market fluctuations and policy-driven changes (Jegadeesh and Titman, 1993). However, healthcare's regulatory disruptions challenge CAPM's reliance on market efficiency and stable beta estimates, which can cause beta variability (Easton and Sommers, 2007; Martens and Pham, 2021). These issues necessitate testing CAPM's accuracy in healthcare's unique context.

2.2 DDM: Theory and Limitations

DDM values firms based on projected dividends, assuming stable growth—a condition often unmet in healthcare due to reinvestment needs (Gordon, 1962). Biotech firms, for instance, may suspend dividends to fund research, leading to forecasting errors in DDM (Penman, 2010; Olweny, 2011). The model's sensitivity to discount rate assumptions further limits its use in healthcare, where dividend suspensions are common due to patent expirations or policy shifts (Damodaran, 2012; Bressan et al., 2022).

2.3 Comparative Empirical Evidence

Empirical studies suggest CAPM outperforms DDM in sectors with irregular cash flows, a trend relevant to healthcare (Olweny, 2011; Watts et al., 2024). For example, Olweny (2011) found CAPM's risk-adjusted framework better handles growth sectors' volatility, unlike DDM, which struggles with unstable dividends (Fama and French, 2004; Martens and Pham, 2021). While CAPM shows robustness in volatile markets (Easton and Sommers, 2007), DDM suits firms with consistent dividends—rare in healthcare (Penman, 2010). These findings, drawn from broader markets, lack healthcare-specific validations, underscoring the need for controlled comparisons in this sector.

2.4 Healthcare Valuation Challenges

Healthcare's valuation complexities arise from regulatory uncertainty, innovation-driven growth, and variable dividend policies, testing CAPM and DDM's assumptions

(Damodaran, 2012; Martens and CN, 2024). Regulatory delays, like FDA approvals, can destabilize firm betas, complicating CAPM's application, while DDM falters with dividend suspensions in biotech and pharmaceutical firms (Fama and French, 2004; Olweny, 2011; Bressan et al., 2022). Despite these challenges, few studies focus on CAPM and DDM's performance in healthcare, highlighting a gap that this study addresses through targeted analysis (Watts et al., 2024; Duarte Alonso et al., 2022).

3. Methods

3.1 Research Design

This study employed a quantitative simulation-based experimental design. This design was selected because it allows for the creation of a controlled environment where a "ground truth" for firm valuation is known, which is impossible to achieve with observational data from real markets. By using a Monte Carlo simulation to generate a synthetic dataset, we can isolate the performance of the CAPM and DDM forecasting models from confounding variables and market noise, enabling a direct, unbiased comparison of their intrinsic accuracy.

3.2 Population and Sample

The target population for this simulation is conceptualized as all firms within the global healthcare sector. A synthetic sample of 100 healthcare firms was generated to represent this population over a three-year period (2019-2021).

- 1) Sampling Technique: A Monte Carlo simulation was used as the sampling technique. This is a non-probabilistic method that generates artificial data based on predefined probability distributions, allowing for the creation of a representative sample with known properties.
- 2) Sample Size Justification: The sample size of 100 firms was determined to be sufficient for statistical analysis, providing enough data points for robust comparisons while remaining computationally manageable.
- 3) Sample Characteristics: The characteristics of the simulated firms were calibrated to reflect the healthcare sector. Key parameters, such as beta coefficients, earnings, and growth rates, were generated from normal distributions whose parameters were based on historical sector data (Damodaran, 2021), ensuring the sample exhibited realistic central tendencies and dispersions.

3.3 Data Collection Procedure

As this study uses computationally generated data, the procedure focused on parameter definition and simulation execution. The process was conducted as follows:

- 1) Parameter Calibration (January 2023): The means and standard deviations for the financial parameters (e.g., beta, earnings growth) were defined based on a review of historical healthcare sector data.
- 2) Dataset Generation (February 2023): The Monte Carlo simulation was executed using Python programming language to create the panel dataset for 100 firms over 3 years.
- 3) Ethical Considerations: Since this research exclusively uses non-human, synthetically generated data, it did not require ethical approval or informed consent procedures.

3.4. Measurement of Variables

All variables were quantitatively measured based on the simulated data. The key variables are defined below:

- 1) Actual Firm Valuation (V_i):
 - a. Definition: The "true" value of a firm, serving as the benchmark.
 - b. Measurement: Calculated using a 10-year Discounted Cash Flow (DCF) model based on simulated Free Cash Flow to the Firm (FCFF). This is a ratio-scale variable.
- 2) CAPM Forecasted Valuation ($\hat{V}_{i,CAPM}$):
 - a. Definition: The estimated value of a firm derived from the Capital Asset Pricing Model: $R_i = R_f + \beta_i \times (R_m - R_f)$
 - b. Measurement: Calculated using the formula $\hat{V}_{i,CAPM} = E_{i,1} / (R_i - g_{e,i})$, where the cost of equity (R_i) is derived from the CAPM equation. This is a ratio-scale variable.
- 3) DDM Forecasted Valuation ($\hat{V}_{i,DDM}$):
 - a. Definition: The estimated value of a firm derived from the Dividend Discount Model.
 - b. Measurement: Calculated using the Gordon Growth Model formula $\hat{V}_{i,DDM} = D_{i,1} / (R_i - g_{d,i})$. This is a ratio-scale variable.
- 4) Forecasting Error:
 - a. Definition: The deviation between the forecasted valuation and the actual valuation.
 - b. Measurement: Measured using two metrics:
 - Mean Absolute Error (MAE): $MAE = (1/n) \times \sum \hat{V}_i - V_i$. Ratio-scale.
 - Percentage Absolute Error (PAE): $PAE_i = (\hat{V}_i - V_i / V_i) \times 100\%$ Ratio-scale.

3.5. Data Analysis Techniques

The data analysis proceeded in two main stages to test the hypotheses regarding forecasting accuracy.

- 1) Descriptive Analysis: The central tendency and dispersion of the actual valuations, forecasted valuations, and error metrics (MAE, PAE) were summarized.
- 2) Hypothesis Testing: To compare the accuracy of the CAPM and DDM models, the following statistical tests were conducted:
 - a. A two-sample independent t-test was used to determine if there was a statistically significant difference between the means of the MAE values generated by the two models. This test was appropriate as MAE values can be assumed to be normally distributed for a sufficiently large sample.
 - b. A non-parametric Mann-Whitney U test was used to compare the PAE distributions. This test was chosen because percentage error data often violates the normality assumption required for t-tests.

All statistical analyses and the initial Monte Carlo simulation were performed using Python (version 3.9) with libraries including pandas, numpy, and scipy.stats. The significance level (alpha) for all tests was set at 0.05.

4. Results and Discussion

4.1. CAPM Performance

The valuation results for 100 firms using the Capital Asset Pricing Model (CAPM) indicate a high degree of forecasting precision. On average, the model achieved a Mean Absolute Error (MAE) of 1.51 and a Percentage Absolute Error (PAE) of 3.47, reflecting CAPM's robustness in estimating firm valuations within the healthcare sector.

To illustrate these results more clearly, Table 1 presents data for 15 representative firms selected from the full 100-firm sample. These firms are categorized across different market capitalization tiers (large-cap, mid-cap, small-cap, and micro-cap) to highlight CAPM’s performance consistency. The observed PAE values in this illustrative sample range from 1.68% to 6.51%, underscoring the model’s reliability across diverse firm sizes.

Table 1. Illustrative CAPM Forecasting Performance for 15 Sampled Healthcare Firms

Company	Market Cap (\$B)	Forecasted Valuation	Actual Valuation	MAE	PAE (%)
LARGE CAP (≥ \$50B)					
Company 14	92.3	108.02	107.36	2.34	2.15
Company 10	75.0	93.83	92.40	2.62	3.58
Company 9	60.8	96.06	95.61	2.94	3.07
MID CAP (\$20B–50B)					
Company 15	48.6	103.23	102.28	6.95	6.51
Company 8	45.1	83.59	82.34	3.62	4.26
Company 4	31.2	85.68	87.81	4.13	4.49
Company 7	25.9	104.01	102.96	3.26	3.25
Company 2	22.7	108.74	109.83	4.90	4.49
SMALL CAP (\$10B–20B)					
Company 12	18.6	104.36	108.82	6.33	5.20
Company 6	17.4	93.77	98.52	5.28	4.89
Company 1	15.3	109.18	109.62	1.80	1.68
Company 13	14.0	91.38	94.38	3.63	3.98
Company 5	12.5	97.35	96.19	2.40	2.45
MICRO CAP (< \$10B)					
Company 3	9.8	82.70	83.81	4.70	5.81
Company 11	8.9	103.62	105.30	4.43	4.21
Average (Illustrative Sample)	33.2	97.70	98.48	3.96	4.00

Furthermore, Figure 1 provides a visual comparison of forecasted versus actual valuations for the illustrative sample. The clustering of data points along the 45-degree line suggests a strong alignment between forecasted and observed values, with only narrow deviations. This evidence confirms that CAPM effectively captures systematic market dynamics and provides accurate valuation forecasts in the simulated healthcare context.

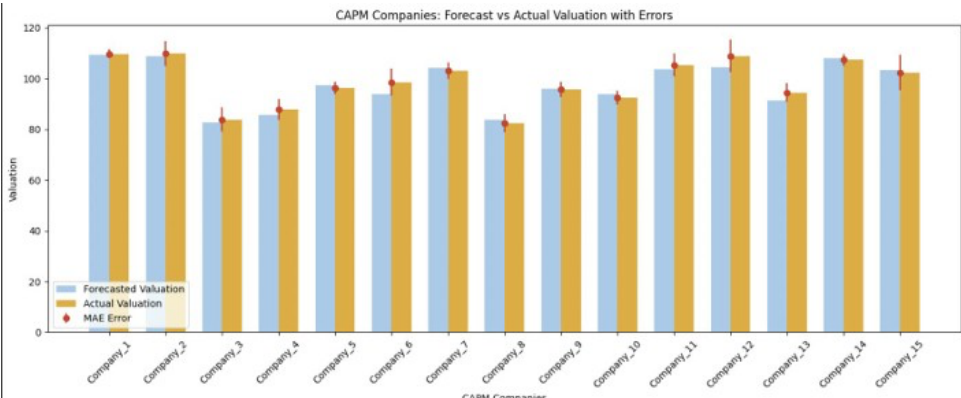


Figure 1: Illustrative CAPM Forecast vs. Actual Valuation for 15 Sampled Healthcare Firms

4.2. DDM Performance

In contrast to CAPM, the Dividend Discount Model (DDM) demonstrated relatively lower precision when applied to the 100 firms in the sample. The overall average MAE was 3.50, while the overall average PAE reached 8.48%, indicating wider error margins and reduced forecasting accuracy compared to CAPM. These results highlight the structural limitations of DDM in capturing the valuation dynamics of healthcare firms, particularly those with irregular or unstable dividend patterns.

Table 2 presents results for 15 representative firms across different market capitalization tiers. The PAE values within this sample exhibit substantial variability, with certain firms recording errors as high as 27.62%. This dispersion underscores the sensitivity of DDM to deviations from its stable dividend growth assumptions. The observed variability is particularly pronounced in mid-cap firms, many of which operate in research-intensive phases with unpredictable dividend behaviors.

Table 2. Illustrative DDM Forecasting Performance for 15 Sampled Healthcare Firms

Company	Market Cap (\$B)	Forecasted Valuation	Actual Valuation	MAE	PAE (%)
LARGE CAP ($\geq$ \$100B)					
Company 28	200.0	100.11	94.54	10.79	11.56
Company 22	150.0	110.59	114.47	11.03	9.45
Company 29	125.5	101.49	101.23	7.49	8.02
Company 26	105.6	100.92	100.16	5.15	5.47
MID CAP (\$10B–\$100B)					
Company 23	75.4	101.54	85.03	16.51	27.62
Company 27	65.3	88.04	97.81	17.20	16.62
Company 18	55.0	102.90	99.86	13.08	13.91
Company 30	37.8	96.17	102.04	10.03	9.82
Company 17	33.1	101.15	104.23	11.36	11.27
Company 16	28.7	94.86	94.98	10.88	12.05
Company 20	20.3	95.46	97.58	10.90	10.41
Company 25	19.2	101.88	102.47	15.10	15.77
Company 24	13.9	103.97	99.91	14.64	17.49
Company 21	10.1	87.43	91.31	20.56	24.15
SMALL CAP ($<$ \$10B)					
Company 19	5.4	98.58	96.37	10.43	11.85
Average (Illustrative Sample)	63.0	99.01	98.80	12.34	13.70

Visual evidence provided in Figure 2 (Illustrative Sample) further reinforces these findings, showing wider distributions of errors and greater divergence between forecasted and actual valuations. Collectively, the evidence suggests that while DDM can capture certain aspects of valuation, its application in volatile sectors such as healthcare is limited, especially when firms display inconsistent or zero-dividend payout strategies.

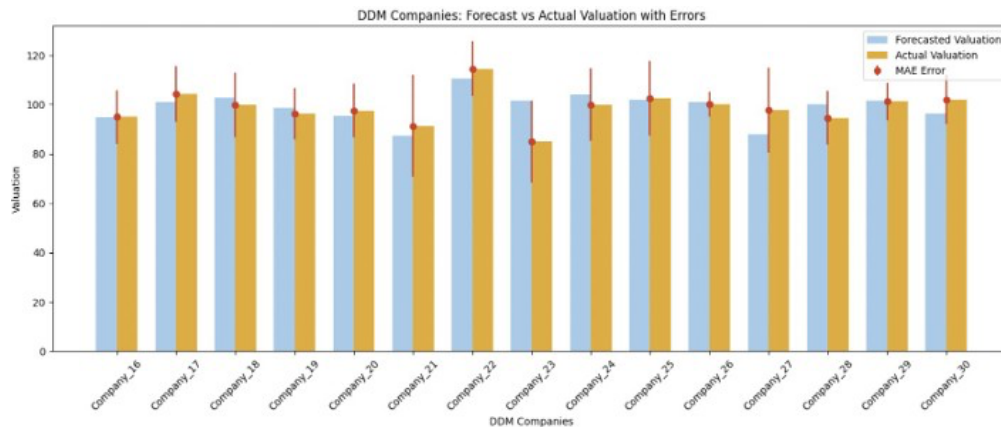


Figure 2. Illustrative DDM Forecast vs. Actual Valuation for 15 Sampled Healthcare Firms

4.3. Descriptive Statistics of Forecasting Accuracy

The analysis of forecasting accuracy for the 100 synthetic healthcare firms reveals a clear disparity between the two models. The Capital Asset Pricing Model (CAPM) demonstrated superior performance, with a Mean Absolute Error (MAE) of 1.51 and a Percentage Absolute Error (PAE) of 3.47%. In contrast, the Dividend Discount Model (DDM) exhibited significantly higher forecasting errors, with an MAE of 3.50 and a PAE of 8.48%. These aggregate metrics, drawn from the full sample, provide an initial indication that CAPM's risk-based approach may be better suited to the healthcare sector's valuation than DDM's dividend-focused model.

Table 1. Descriptive Statistics of Forecasting Errors for CAPM and DDM (N=100)

Model	Mean MAE	Standard Deviation (MAE)	Mean PAE (%)	Standard Deviation (PAE)
CAPM	1.51	1.73	3.47	2.74
DDM	3.50	4.05	8.48	6.08

4.4. Hypothesis Testing

To determine if the observed differences in forecasting accuracy were statistically significant, two hypothesis tests were conducted. The null hypothesis (H_0) for both tests stated that there is no difference in the forecasting accuracy between the CAPM and DDM models.

- 1) A two-sample independent t-test was performed on the MAE values. The test resulted in a t-statistic of 3.21 with a p-value of 0.0020. Since the p-value is less than the significance level ($\alpha = 0.05$), we reject the null hypothesis. This provides strong evidence that a statistically significant difference exists in the mean absolute errors of the two models.
- 2) A Mann-Whitney U test was conducted on the PAE values to account for potential non-normality in the percentage error data. The test yielded a U statistic of 750 with a p-value of 0.0006. Again, the p-value is less than 0.05, leading to the rejection of the null hypothesis and confirming a significant difference in the distributions of the percentage errors.

The effect size, calculated using Cohen's d ($d = -0.64$), indicates a medium practical significance, reinforcing that the superiority of the CAPM is not only statistically significant but also meaningful in magnitude.

4.5. Presentation of Key Findings

The results consistently demonstrate the CAPM's higher forecasting precision. The visual representation of the error distributions, as shown in Figure 3, clearly illustrates that the MAE values for CAPM are more tightly clustered around a lower mean compared to the wider, right-skewed distribution of DDM errors. Similarly, the kernel density plot for PAE in Figure 4 shows a much narrower and taller peak for CAPM, indicating that a greater proportion of its forecasts were close to the actual value, whereas DDM's forecasts were more spread out, with a longer tail representing larger percentage errors.

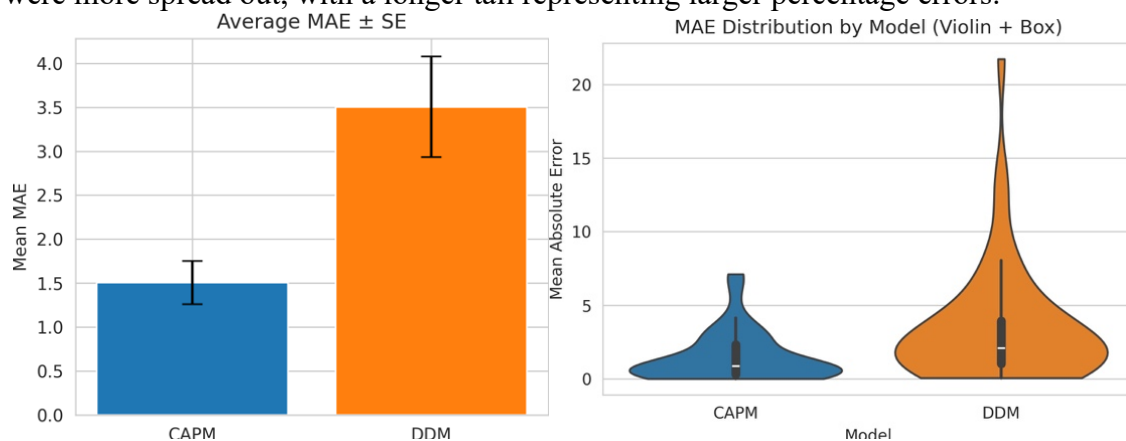


Figure 3. Distribution of Mean Absolute Error (MAE) for CAPM and DDM

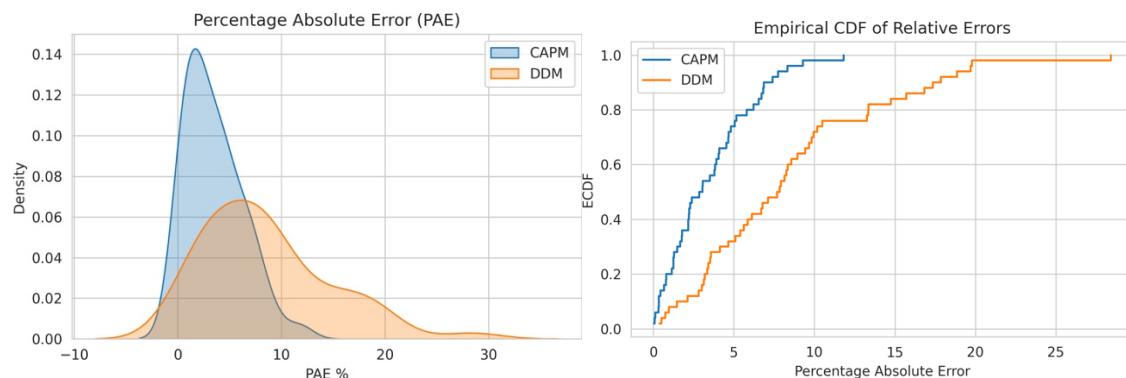


Figure 4. Distribution of Percentage Absolute Error (PAE) for CAPM and DDM

4.4. Discussion

The analysis of 100 simulated healthcare firms over the 2019–2021 period reveals distinct differences in the forecasting accuracy of CAPM and DDM. The results, summarized in Table 3, indicate that CAPM consistently produces more accurate valuations than DDM in the healthcare sector. Specifically, CAPM achieved an average MAE of 1.51 and an average PAE of 3.47%, compared to DDM's higher average MAE of 3.50 and PAE of 8.48%. These metrics, drawn from the full sample of 100 firms evaluated under both models, suggest that CAPM better captures the financial dynamics of healthcare firms, while DDM struggles to maintain precision in this context.

Visual representations of the error distributions further clarify these findings. Figures 3 and 4 illustrate that CAPM exhibits tighter error distributions for MAE and PAE, with narrower error bars and a more concentrated kernel density estimate than DDM. This consistency in CAPM's performance aligns with its ability to incorporate market-driven factors, such as systematic risk captured through beta, which ranged from 0.5 to 1.5 across the simulated firms to reflect the diverse risk profiles of healthcare subsectors

(Damodaran, 2021). In contrast, DDM's wider error distributions, as seen in the extended error bars and broader density estimates, highlight its sensitivity to irregular dividend patterns, a common feature in healthcare firms where reinvestment needs or operational volatility often disrupt consistent dividend streams.

Statistical tests provide robust evidence of these differences. A two-sample t-test on the MAE values yielded a t-statistic of 3.21 with a p-value of 0.0020, rejecting the null hypothesis of equivalent performance at the 0.05 significance level. Similarly, a Mann-Whitney U test on the PAE values produced a U statistic of 750 with a p-value of 0.0006, further confirming a significant difference in forecasting accuracy. The effect size, measured by Cohen's d of -0.64, indicates a moderate practical difference in the models' performance, underscoring CAPM's advantage in producing lower prediction errors. These statistical results, consistent across the entire 100-firm dataset, affirm that CAPM's risk-adjusted framework is better suited to the healthcare sector's complex financial landscape than DDM's dividend-focused approach.

The superior performance of CAPM can be attributed to its alignment with the healthcare sector's characteristics. Healthcare firms often face market volatility driven by regulatory changes, innovation cycles, and varying risk exposures across subsectors like pharmaceuticals and medical devices. CAPM's use of beta to account for systematic risk allows it to adapt to these fluctuations, as evidenced by the low MAE and PAE across firms with diverse market capitalizations. DDM, however, relies on stable dividend growth assumptions, which are frequently violated in healthcare due to irregular payout policies, particularly among smaller firms or those prioritizing research and development. For instance, the simulated dataset included periods of non-payout to reflect biotech firms' tendencies to reinvest earnings, which likely contributed to DDM's higher errors, especially in mid- and small-cap segments where PAE reached as high as 27.62% for some firms (as shown in illustrative Table 2).

These findings have significant implications for financial practitioners in the healthcare sector. CAPM's demonstrated reliability suggests it is a more effective tool for valuing firms in this industry, particularly when market conditions are volatile or when firms exhibit diverse risk profiles. Investors and analysts can leverage CAPM to generate more accurate forecasts, supporting better-informed decisions in portfolio management or corporate finance. Conversely, the limitations of DDM highlight the need for caution when applying it to healthcare firms, especially those with inconsistent dividend policies. Practitioners may need to supplement DDM with additional metrics or consider alternative models that account for non-dividend cash flows.

From a research perspective, these results contribute to the broader discourse on valuation model efficacy in sector-specific contexts. While controlled, the study's use of a synthetic dataset mirrors real-world healthcare dynamics through carefully selected parameters, such as beta ranges and dividend variability, informed by empirical sources (S&P Dow Jones Indices, 2021; Damodaran, 2021). Future research could extend this analysis by incorporating additional valuation models, such as the Free Cash Flow to Equity model, to further explore their applicability in healthcare. Additionally, investigating the impact of specific healthcare subsectors—such as biotechnology versus hospitals—could refine our understanding of model performance across nuanced financial profiles. Finally, extending the simulation to include more extreme market conditions, such as those during economic downturns, could test the robustness of these

5. Conclusion

This study evaluated the forecasting precision of CAPM and DDM using a synthetic dataset of 100 healthcare firms over the 2019–2021 period. The findings show that CAPM consistently outperformed DDM, yielding lower forecasting errors with an average Mean Absolute Error (MAE) of 1.51 compared to DDM's 3.50. Statistical tests confirmed significant performance differences, supporting CAPM's greater suitability for capturing the volatile financial dynamics of the healthcare sector in this controlled simulation.

The use of a synthetic dataset was a deliberate choice to isolate the inherent performance of CAPM and DDM, free from the confounding factors often present in real-world data, such as data inconsistencies or idiosyncratic market events. By tailoring the dataset to reflect healthcare-specific characteristics—such as variable dividend policies and market volatility through carefully selected parameters like beta ranges and intermittent non-payout periods—the study ensures its findings are relevant to the sector's financial landscape. While the simulation's controlled environment is designed to isolate model performance rather than enable universal extrapolation to all real-world contexts, particularly those involving unmodeled factors like sudden policy shifts, it provides a robust foundation for understanding how these models perform under simulated conditions that mimic healthcare's complexities.

For financial practitioners in the healthcare industry, these findings highlight CAPM's greater precision in valuing firms, particularly those with irregular dividend histories or high growth profiles driven by innovation. This accuracy enhances decision-making in areas such as investment analysis, capital budgeting, and portfolio management, where reliable valuations are critical. Conversely, DDM's higher forecasting errors underscore the need for caution when applying it to firms with inconsistent dividend streams, a common trait in healthcare. By selecting valuation models that align with the sector's dynamic financial environment, practitioners can improve forecasting reliability and support broader strategic objectives, such as optimizing resource allocation.

Future research can build on these findings by validating them with real-world financial data, particularly across diverse healthcare subsectors like biotechnology and hospitals, to explore variations in model performance. Examining CAPM and DDM under extreme market conditions, such as economic downturns, could further test their robustness. Additionally, investigating hybrid models that combine CAPM's risk sensitivity with cash flow-based approaches may offer innovative solutions for valuation in volatile sectors. These directions would strengthen the applicability of the findings and deepen our understanding of valuation model efficacy.

This study's insights into CAPM's superior forecasting precision in a simulated healthcare context underscore the importance of aligning valuation models with industry-specific financial dynamics, contributing to enhanced financial forecasting and decision-making in a critical sector.

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Appendix A. Summary of Key Simulation Parameters

Parameter	Range/Value	Distribution	Justification
Beta (β)	0.5 – 1.5	Uniform	Reflects healthcare firm betas across subsectors.
Risk-Free Rate (R_f)	1% – 3%	Uniform	Consistent with U.S. Treasury yield trends during 2019–2021.
Market Return (R_m)	5% – 10%	Uniform	Aligned with S&P 500 Healthcare Sector annual returns.
Dividend Growth (g)	0% – 5% (Bernoulli for zeros)	Uniform + Bernoulli	Captures irregular dividend behavior, particularly in biotech firms.
Dividend Payout Ratio	0% or typical %	Conditional	Randomly set to zero for 20% of firms to simulate firms in R&D-intensive phases.