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An empirical investigation of dividend determinants using parametric and nonparametric models

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Abstract

This study empirically examines the key determinants influencing Dividend Per Share (DPS) among Indian listed firms using both parametric and nonparametric regression models. It addresses the nonlinearity and complexity inherent in dividend decisions factors often overlooked by traditional linear methods.

A comprehensive modelling framework is adopted, incorporating Linear, Log-Transformed, Polynomial, Generalized Additive Models (GAM), and Nonlinear Least Squares (NLS) to estimate the effect of financial variables Earnings Per Share (EPS), Quick Ratio (QR), Debt-Equity (DE), Creditor Turnover Ratio (CTR), and firm Size on DPS. Diagnostic tests such as Shapiro-Wilk, Breusch-Pagan, Durbin-Watson, and RESET are applied to validate underlying assumptions. Model fit is evaluated using RMSE, Adjusted R^2 , and F-statistics.

EPS and firm size consistently emerge as significant and positive determinants of DPS across all models. Liquidity and leverage measures (QR, DE, and CTR) are generally negatively associated with DPS. The GAM outperforms all other models, yielding the highest Adjusted R^2 (0.979) and the lowest RMSE (1.579), thereby demonstrating a superior ability to capture nonlinear patterns. The NLS model, while informative, exhibits marginal estimation instability.

These findings offer robust decision-making tools for corporate managers, financial analysts, and policymakers by identifying the nonlinear impacts of key financial indicators on dividend payouts. In particular, the application of GAM enhances the understanding of dividend behaviour beyond linear trends.

This research contributes to the dividend literature by integrating traditional econometric techniques with advanced nonparametric modelling. The comparative insights from multiple models underscore the importance of incorporating flexibility in modelling complex financial phenomena such as dividend policy.

Keywords: Dividend Policy, Earnings Per Share (EPS), Parametric Models, Nonparametric Models, Generalized Additive Model (GAM), Nonlinear Least Squares (NLS), Financial Ratios, Model Fit, Machine Learning in Finance

1. Introduction

Dividend policy has long been a focal point in corporate finance, with considerable debate surrounding the determinants that influence a firm's decision to distribute profits to shareholders. Traditionally, Earnings Per Share (EPS), firm size, leverage (DE), liquidity (QR), and the Creditor Turnover Ratio (CTR) have been widely recognized as key financial variables affecting dividend payouts. However, empirical evidence suggests that the relationship between these determinants and Dividend Per Share (DPS) is not always linear and may be better captured through flexible, data-driven modelling approaches.

This study seeks to comprehensively examine the determinants of dividend policy using both parametric models (Linear, Log-Transformed, and Polynomial) and nonparametric models (Generalized Additive Models [GAM] and Nonlinear Least Squares [NLS]). A robust comparison of these models, based on RMSE, R-squared, and diagnostic tests (normality, heteroskedasticity, and autocorrelation), provides deeper insights into model performance and real-world applicability.

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The methodological novelty of this study lies in integrating machine learning techniques with traditional econometric frameworks to better capture complex, nonlinear financial dynamics. The findings hold significant practical relevance for investors, corporate managers, and policymakers seeking to design optimal dividend strategies based on firm-specific fundamentals.

2. Literature Review

Dividend policy remains one of the most debated topics in financial management. Researchers have applied a variety of statistical, econometric, and machine learning techniques to investigate the factors influencing dividend payouts. The relevant literature is categorized into domestic (India-based) and international studies.

A. Domestic Literature (India-Based Studies)

1. Highlighted that Indian firms prioritize stable dividend payments, with profitability and cash flow as key determinants.
2. Employed panel regression to show that firm size, earnings, and leverage influence dividend policy among NSE-listed firms.
3. Used a fixed-effects model and reported that ownership structure and profitability significantly affect DPS.
4. Demonstrated the role of retained earnings and past dividend behaviour using pooled OLS and dynamic panel models.
5. Found that larger Indian firms with higher profitability maintain consistent dividend policies.
6. Applied nonlinear models and suggested that financial leverage has a non-monotonic relationship with dividends.
7. Used logistic regression and confirmed EPS and firm size as robust predictors of dividend decisions.
8. Investigated Indian manufacturing firms and highlighted the relevance of liquidity and market valuation in dividend distribution.
9. Compared multiple regression and artificial neural networks (ANN), indicating the superior accuracy of neural networks in DPS prediction.
10. Applied machine learning models to Indian IT firms and concluded that EPS and the debt-equity ratio are the strongest predictors.

B. Foreign Literature

11. Lintner (1956) ^[16]: Pioneered the empirical model of dividend policy, emphasizing earnings stability and target payout ratios.
12. Fama & Blahnik (1968) ^[13]: Reinforced that current and past earnings determine dividend changes, using time-series models.
13. Developed an agency-theoretic model and established that growth opportunities and risk reduce dividend payouts.
14. Showed that free cash flow and managerial discretion impact dividend behaviour.
15. Found that dividend-paying firms often have stronger earnings and governance mechanisms.
16. Surveyed U.S. corporate managers and identified earnings consistency and investor expectations as major factors.
17. Chen & Dhiensiri (2009) ^[15]: Used neural networks to predict dividend policy in New Zealand, achieving higher classification accuracy than logistic models.

18. Examined market reactions and found that dividend announcements signal firm value.
19. Investigated Chinese firms and reported that ownership concentration and profitability drive dividend payouts.
20. Compared SVM and ANN models to traditional regressions and showed that nonlinear methods perform better in dividend classification tasks.

3. Research Gap

Despite extensive literature on dividend policy, several critical gaps remain, particularly regarding methodological diversity and the predictive robustness of existing models:

- **Limited Use of Nonparametric Techniques in the Indian Context:** Most Indian studies rely heavily on linear models such as OLS, fixed/random effects models, or logit/probit techniques. While statistically sound, these models often fail to capture complex nonlinear relationships. Few domestic studies have explored advanced nonparametric methods such as Generalized Additive Models (GAM) or Neural Networks (ANN).
- **Inadequate Comparative Evaluation of Model Performance:** Existing research rarely compares multiple regression frameworks on the same dataset. Studies typically employ a single model or fail to benchmark traditional approaches (Linear, Polynomial, Log-Transformed) against more sophisticated techniques (GAM, NLS, ANN), resulting in limited insight into model superiority.
- **Underutilization of Diagnostic and Residual Analysis in Model Validation:** Many studies overlook rigorous diagnostic testing for key assumptions such as multicollinearity, normality, homoskedasticity, and autocorrelation. This omission compromises the reliability and interpretability of regression results and limits their generalizability.

4. Objectives of the Study

The primary objective of this research is to examine and compare the effectiveness of various parametric and nonparametric models in identifying the key determinants of Dividend Per Share (DPS) among selected listed Indian companies. Specifically, the study aims to:

1. Identify and assess the impact of financial performance indicators on DPS using traditional regression models (Linear, Log-Transformed, Polynomial).
2. Estimate and compare the performance of different statistical and machine learning models namely, Linear Regression, Log-Transformed Linear, Polynomial Regression, Generalized Additive Model (GAM), and Nonlinear Least Squares (NLS).
3. Evaluate model accuracy using statistical fit indicators such as Adjusted R^2 , RMSE, F-statistic, and residual diagnostics.

5. Methodology

5.1 Data Source and Period

This study is based on panel data from selected Indian firms, namely: Ashok Leyland Ltd., Atul Auto Ltd., Bajaj Auto Ltd., Eicher Motors Ltd., Force Motors Ltd., Hero MotoCorp Ltd., Mahindra & Mahindra Ltd., Maruti Suzuki India Ltd., SML Isuzu Ltd., TVS Motor Co. Ltd., MRF, Escorts, BKT, BOSCH, VST Tillers Tractors Ltd., and Tata Motors Ltd. The dataset covers an 11-year period from 2014 to 2024.

Data were collected from the official websites of the selected companies, the CMIE Prowess database, and NSE/BSE

official filings. The dependent variable is Dividend Per Share (DPS). Key independent variables include:

- EPS (Earnings Per Share),
- NPM (Net Profit Margin),
- RONW (Return on Net Worth),
- ROTA (Return on Total Assets),
- QR (Quick Ratio),
- DE (Debt-to-Equity Ratio),
- DTR (Debtor Turnover Ratio),
- PE (Price-to-Earnings Ratio),
- PB (Price-to-Book Ratio),
- CTR (Creditor Turnover Ratio),

- YR (Yield Ratio),
- ATR (Asset Turnover Ratio), and
- Size (Firm Size, measured by total assets).

The dataset was standardized to ensure comparability and minimize scaling bias. Selection of independent variables for regression modelling was based on goodness-of-fit measures.

5.2 Methodological Framework

This research adopts a comparative modelling approach using five techniques:

Model Type	Model Name	Nature
Parametric Linear	Linear Regression (OLS)	Linear
Parametric Transformed	Log-Transformed Regression	Semi-linear
Parametric Nonlinear	Polynomial Regression	Quadratic nonlinear
Nonparametric	Generalized Additive Model (GAM)	Spline-based nonlinear
Nonparametric	Nonlinear Least Squares (NLS)	Power-law based

5.3 Model Implementation

Linear and log-transformed regression models, including diagnostics such as R^2 , RMSE, and residual plots, were estimated using the `lm()` function in R. Polynomial regression incorporated second-degree terms via `poly()` to capture curvature in EPS. GAM was implemented using `mgcv::gam()` with smoothing splines (`s()`) to identify non-linear relationships. NLS estimation was performed using `nlm()` to test exponential and power-law relationships (e.g., $DPS \sim a*(EPS^b) + c*(Size^d)$).

5.4 Model Evaluation Metrics

To assess model performance, the following metrics were employed:

- **Adjusted R^2 :** Goodness-of-fit
- **Root Mean Square Error (RMSE):** Model accuracy
- **F-statistic and p-value:** Model significance
- **Shapiro-Wilk Test:** Normality of residuals

- **Breusch-Pagan Test:** Homoskedasticity
- **Durbin-Watson Test:** Autocorrelation

6. Hypotheses of the Study

Based on the study's objectives and literature review, the following hypotheses are proposed:

- **H1:** Earnings Per Share (EPS) has a significant positive effect on DPS.
- **H2:** Quick Ratio (QR) and Debt-to-Equity Ratio (DE) negatively affect DPS.
- **H3:** Firm Size has a significant positive relationship with DPS.
- **H4:** The performance of DPS prediction models differs significantly between parametric and nonparametric methods.

7. Results and Discussion

Table 1: Descriptive Statistics

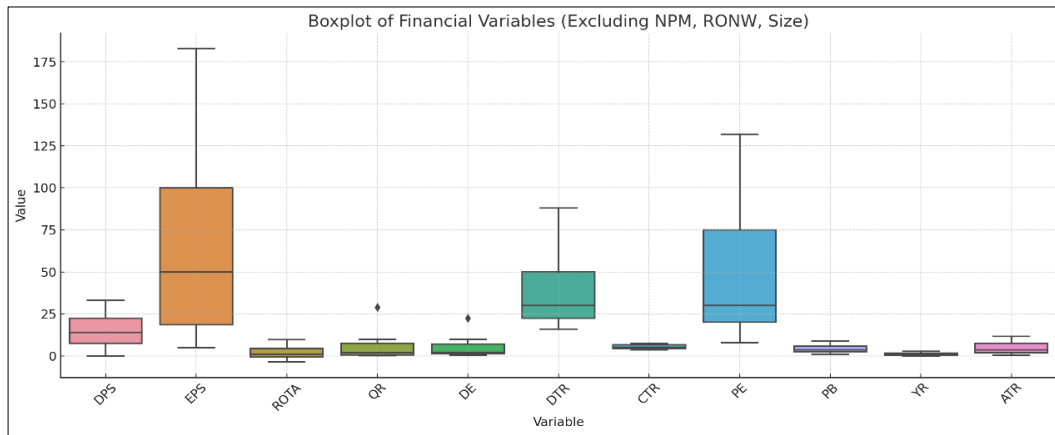
Variables	Mean	SD	Median	Trimmed Mean	MAD	Min	Max	Range	Skew	Kurtosis	SE
DPS	15.04	11.01	14.12	14.79	12.91	0	33.73	33.73	0.24	-1.41	2.2
EPS	52.6	57.81	27.2	45.67	23.07	4.53	183.82	179.29	1.08	-0.47	11.56
NPM	-95.75	322.4	-16.51	-32.77	25.92	-1609.72	117.36	1727.08	-4.12	16.46	64.48
RONW	-14.72	71.23	1.32	0.42	8.54	-342.62	22.79	365.41	-3.9	15	14.25
ROTA	1.33	3.57	0.62	1.11	3.22	-3.57	9.64	13.22	0.71	-0.6	0.71
QR	1.92	5.69	0.7	0.75	0.14	0.27	29.2	28.93	4.39	18.09	1.14
DE	2.23	4.37	0.97	1.26	0.31	0.57	22.56	21.99	4.02	15.75	0.87
DTR	33.57	19.51	27.58	30.16	8.72	16.03	88.39	72.35	1.81	2.09	3.9
CTR	5.22	1.05	5.12	5.14	0.91	3.76	7.54	3.78	0.78	-0.47	0.21
PE	30.82	23.58	23.52	26.96	7.72	7.89	132.59	124.7	3.17	10.98	4.72
PB	3.71	2.02	3.4	3.53	2.18	1.07	8.81	7.74	0.83	-0.14	0.4
YR	0.98	0.62	0.84	0.93	0.41	0.04	2.81	2.77	1.01	1.04	0.12
ATR	3.6	2.95	2.82	3.27	2.48	0.59	11.74	11.15	1.05	0.18	0.59
Size	196193.2	223307.9	148082	149266.6	157513.3	22345.67	925890.8	903545.2	2.06	3.8	44661.58

Variables such as NPM (Skew = -4.12, Kurtosis = 16.46), RONW (Skew = -3.90, Kurtosis = 15.00), QR (Skew = 4.39, Kurtosis = 18.09), DE (Skew = 4.02, Kurtosis = 15.75), PE (Skew = 3.17, Kurtosis = 10.98), and Size (Skew = 2.06, Kurtosis = 3.80) exhibit high skewness and leptokurtic behavior. These deviations from normality suggest the presence of outliers or extreme values.

Variables with high variability and range include NPM (Range = 1727.08, SD = 322.40), RONW (Range = 365.41,

SD = 71.23), and Size (Range = 903,545.16, SD = 223,307.91), indicating potential outliers or unstable variance that may affect regression estimates.

Relatively stable and approximately normal variables include DPS, CTR, PB, and ROTA. For instance, DPS (Skew = 0.24, Kurtosis = -1.41), CTR (Skew = 0.78, Kurtosis = -0.47), and PB (Skew = 0.83, Kurtosis = -0.14) display moderate skewness and are likely to perform well under linear modelling assumptions.

**Chart 1:** Box plots of Selected Variables

EPS and PE display wide interquartile ranges and notable outliers, indicating high variability and right skewness. QR and DE exhibit extreme values, suggesting potential heteroskedasticity. Conversely, CTR, YR, and PB show

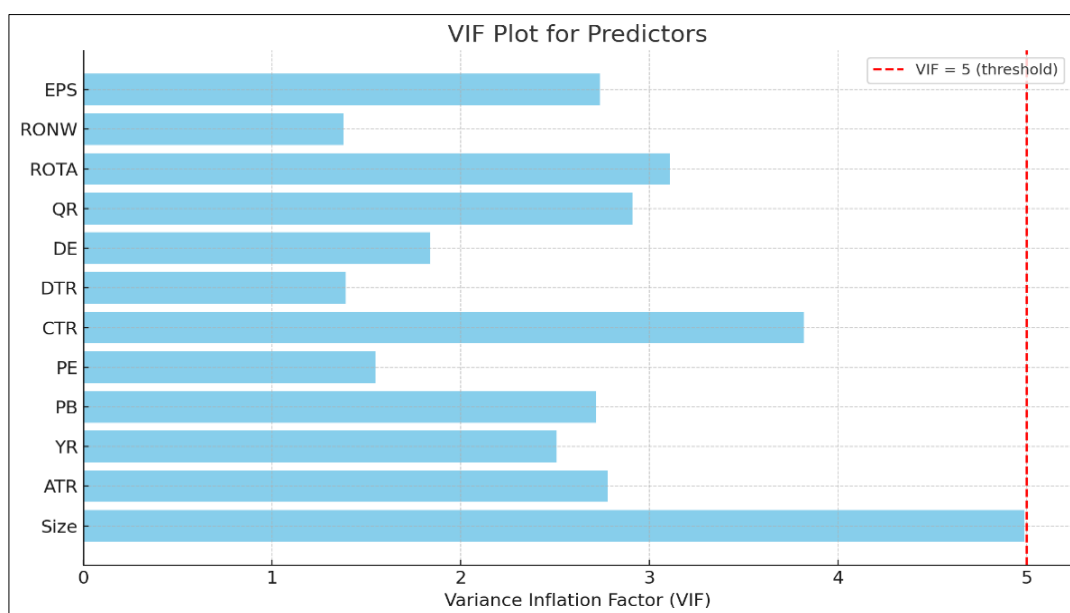
narrower distributions, implying greater consistency. DTR and ATR demonstrate moderate spread, with some potential for outliers.

Table 2: Multicollinearity of Selected Independent variables

Term	VIF	VIF 95% CI	Increased SE
EPS (Earning Per Share)	2.74	[2.14, 3.64]	1.65
RONW (Return on Net worth)	1.38	[1.18, 1.81]	1.17
ROTA (return on Total Assets)	3.11	[2.41, 4.16]	1.76
QR (Quick Ratio)	2.91	[2.27, 3.89]	1.71
DE (Debt Equity Ratio)	1.84	[1.50, 2.42]	1.36
DTR (Debtor Turnover Ratio)	1.39	[1.19, 1.82]	1.18
CTR (Creditor Turnover Ratio)	3.82	[2.92, 5.14]	1.95
PE (Price to Earnings Ratio)	1.55	[1.30, 2.03]	1.25
PB (Price to Book Ratio)	2.72	[2.13, 3.62]	1.65
YR (Yield Ratio)	2.51	[1.98, 3.33]	1.58
ATR (Asset Turnover Ratio)	2.78	[2.17, 3.70]	1.67
Size	4.99	[3.76, 6.76]	2.23

The variance inflation factor (VIF) analysis indicates no severe multicollinearity (all VIFs < 5). However, moderate multicollinearity is observed for **Size** (VIF = 4.99). While all

predictors are acceptable for inclusion, variables with higher VIFs may require attention during sensitivity analysis or stepwise regression.

**Chart 2:** Variance Inflation Factors of Selected Independent Variables

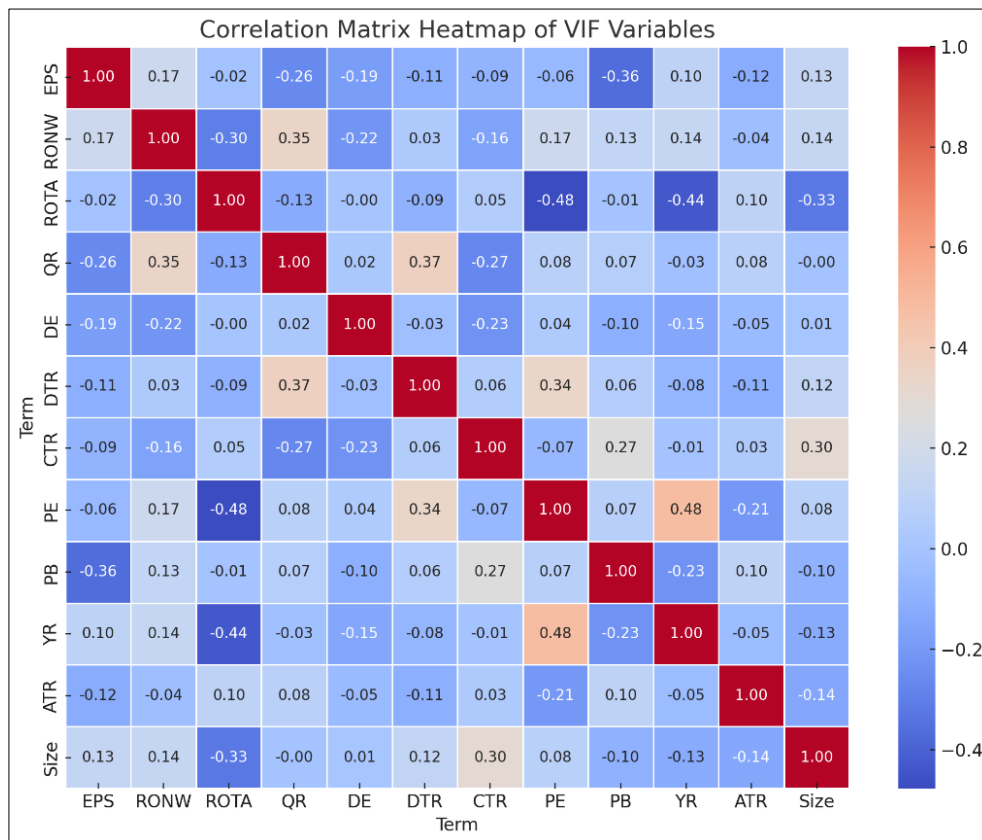
Variables close to or exceeding the red threshold line (VIF = 5) may indicate multicollinearity concerns notably, Size appears the most collinear

Table 3: Correlation Matrix

Term	EPS	RONW	ROTA	QR	DE	DTR	CTR	PE	PB	YR	ATR	Size
EPS	1	0.17	-0.02	-0.26	-0.19	-0.11	-0.09	-0.06	-0.36	0.1	-0.12	0.13
RONW	0.17	1	-0.3	0.35	-0.22	0.03	-0.16	0.17	0.13	0.14	-0.04	0.14
ROTA	-0.02	-0.3	1	-0.13	0	-0.09	0.05	-0.48	-0.01	-0.44	0.1	-0.33
QR	-0.26	0.35	-0.13	1	0.02	0.37	-0.27	0.08	0.07	-0.03	0.08	0
DE	-0.19	-0.22	0	0.02	1	-0.03	-0.23	0.04	-0.1	-0.15	-0.05	0.01
DTR	-0.11	0.03	-0.09	0.37	-0.03	1	0.06	0.34	0.06	-0.08	-0.11	0.12
CTR	-0.09	-0.16	0.05	-0.27	-0.23	0.06	1	-0.07	0.27	-0.01	0.03	0.3
PE	-0.06	0.17	-0.48	0.08	0.04	0.34	-0.07	1	0.07	0.48	-0.21	0.08
PB	-0.36	0.13	-0.01	0.07	-0.1	0.06	0.27	0.07	1	-0.23	0.1	-0.1
YR	0.1	0.14	-0.44	-0.03	-0.15	-0.08	-0.01	0.48	-0.23	1	-0.05	-0.13
ATR	-0.12	-0.04	0.1	0.08	-0.05	-0.11	0.03	-0.21	0.1	-0.05	1	-0.14
Size	0.13	0.14	-0.33	0	0.01	0.12	0.3	0.08	-0.1	-0.13	-0.14	1

Most pairwise correlations among independent variables are weak to moderate, indicating minimal multicollinearity. Strongest negative associations include EPS and PB: -0.36,

ROTA and PE: -0.48 and ROTA and YR: -0.44. Moderate positive correlations include PE and YR: 0.48, CTR and Size: 0.30 and QR and DTR: 0.37

**Chart 3:** Correlation matrix of Selected Variables

Most correlations fall below $|r| = 0.4$, indicating weak linear relationships. The strongest negative correlations are between ROTA and PE (-0.48), ROTA and YR (-0.44), and EPS and PB (-0.36). Moderate positive correlations are observed between PE and YR (0.48), CTR and Size (0.30), and QR and DTR (0.37).

Regression Models: Dividend Per Share (DPS) is used as the dependent variable in five different regression models Linear, Log-Transformed, Polynomial, Generalized Additive Model (GAM), and Nonlinear Least Squares (NLS).

Table 4: Models Regression Coefficients Summary

Model	Intercept	EPS	log(EPS + 1)	poly(EPS,2) [1]	poly(EPS,2) [2]	QR	DE	CTR	Size	Log (Size)	Size^d
Linear	17.91	0.10		-	-	-0.4	-0.3	-2.35	2.97E-	-	-
Log-Transformed	-99.15	-	2.65044	-	-	-0.05	-0.19	1.49		8.398	-
Polynomial	22.79	-	-	28.93	-1.809	-0.50	-0.33	-2.25	2.93E-	-	-
GAM	15.038	s(EPS)	-	-	-	s(QR)	s(DE)	s(CTR)	s(Size)	-	-
Nonlinear (NLS)	-	-48.0	-	-	-	-	1	1	-	-	10.1

Table 5: Mathematical Equations of All Models

Model	Mathematical Equation
Linear Model	$DPS = 17.91 + 0.1008 \times EPS - 0.4976 \times QR - 0.3428 \times DE - 2.353 \times CTR + 0.00002973 \times Size + \epsilon_t$
Log-Transformed Model	$DPS = -99.15891 + 2.65044 \times \log(EPS+1) - 0.05533 \times QR - 0.19057 \times DE + 1.49237 \times CTR + 8.39851 \times \log(Size) + \epsilon_t$
Polynomial Model	$DPS = 22.79 + 28.93 \times \text{poly}(EPS,2)[,1] - 1.809 \times \text{poly}(EPS,2)[,2] - 0.5024 \times QR - 0.3362 \times DE - 2.256 \times CTR + 0.00002928 \times Size + \epsilon_t$
GAM Model	$DPS = 13.5273 + s(EPS) + s(QR) + s(DE) + s(CTR) + s(Size) + \epsilon_t$
Nonlinear Model (NLS)	$DPS = -48.0DPS - 48.03885 \times (EPS^{-0.09162}) + 10.10258 \times (Size^{0.13715})$

Intercepts vary significantly across models, ranging from -99.16 (Log-Transformed) to 22.79 (Polynomial), reflecting model-specific baseline shifts.

Earnings Per Share (EPS) is a consistent and strong predictor across all models:

- In the Linear model, EPS has a positive and significant coefficient (0.1008).
- In the GAM, EPS exhibits a smoothed, nonlinear effect, confirming its central role.
- In the Log-Transformed model, $\log(EPS + 1)$ has a strong positive effect (2.65044), suggesting that transforming EPS improves model fit.
- In the Polynomial model, the first-order term is strongly positive (28.93), while the second-order term is negative (-1.809), indicating a nonlinear (concave) relationship. EPS emerges as the most influential determinant of DPS, displaying both linear and nonlinear predictive power.

Quick Ratio (QR) has a negative association with DPS:

- Negative coefficients in the Linear (-0.4976) and Polynomial (-0.5024) models.
- Not statistically significant in the Log-Transformed model.
- Smoothed in the GAM, indicating potential nonlinear effects.

Debt-to-Equity Ratio (DE) also shows a negative effect on DPS in Linear and Polynomial models, suggesting that higher leverage is associated with reduced dividend payments.

Creditor Turnover Ratio (CTR) is consistently negative:

- **Linear:** -2.353
 - **Polynomial:** -2.256
- This may indicate that liquidity constraints reduce a firm's capacity to pay dividends.

Firm Size is positively associated with DPS in all models:

- Linear and Polynomial models show a small but significant positive coefficient (Size in scientific notation).
- Log-transformed model reveals a strong positive influence of $\log(Size)$ (8.39851), suggesting exponential scaling.
- GAM and NLS models confirm this with smoothed and exponential terms, respectively.
- In NLS, $Size^{0.13715}$ contributes positively, though not independently significant.

Overall, firm size consistently enhances dividend capacity, likely due to economies of scale and cash flow stability in larger firms.

Role of Nonlinear Models

- GAM effectively captures smoothed, nonparametric relationships, making it ideal for modeling complex dividend dynamics.
- NLS is useful for testing power-law behavior. However, it exhibits estimation instability in this dataset, possibly due to sensitivity to outliers or local minima.

Model-Specific Insights

- **Log-Transformed Model:** Best suited when variables (like EPS and Size) span wide numerical ranges. Transformation improves interpretability and fit.
- **Polynomial Model:** Captures curvilinear patterns in EPS, illustrating diminishing returns or threshold effects.
- **GAM:** Offers flexibility in modeling nonlinear effects without specifying a functional form. Best performer in capturing subtleties.
- **NLS:** Useful for theoretical models (e.g., power-law distributions) but less robust under real-world data noise or variance.

Model Fit Comparison

Table 6: Models Fit Comparison

Models	Adjusted R ²	RMSE	F-statistic	p-value (F)
Linear	0.9286	2.943	63.4	3.44e-11 ***
Log-Transformed	0.9381	2.739	73.74	8.94e-12 ***
Polynomial	0.9258	3	50.89	2.55e-10 ***
GAM	0.979	1.579		
NLS	0.933	3.048		

A comparative assessment of model fit was conducted using Adjusted R², RMSE, and F-statistics. Among all models, the Generalized Additive Model (GAM) outperformed the others, achieving the highest Adjusted R² (0.979) and the lowest RMSE (1.579), indicating superior explanatory power and predictive accuracy. The Log-Transformed and Linear models also demonstrated satisfactory performance, whereas the Polynomial and Nonlinear Least Squares (NLS) models exhibited slightly higher error metrics.

Residual Diagnostics

To validate the assumptions of linear regression, diagnostic tests were conducted for normality, homoscedasticity, and autocorrelation. The key results are summarized below:

Table 7: Residual Diagnostics

Model	Linear	Log-Transformed	Polynomial
Shapiro-Wilk (p)	0.02927		
Breusch-Pagan (p)	0.6426		
Durbin-Watson	2.1197	1.852	2.1731
RESET Test (p)	0.0066		
Harvey-Collier Linearity Test (p)	0.1002		

The Shapiro-Wilk test for the Linear model indicated a statistically significant deviation from normality ($p = 0.029$), though the Q-Q plots suggest only mild deviation, implying that the violation is not severe. The Breusch-Pagan test ($p = 0.6426$) suggests no evidence of heteroskedasticity.

The Durbin-Watson statistics across all models were close to 2, indicating the absence of autocorrelation in the residuals. Cook's Distance plots did not reveal any influential outliers that unduly affected the regression estimates.

However, the RESET test ($p = 0.0066$) indicated functional form misspecification, suggesting that the relationship between predictors and DPS may not be purely linear. In contrast, the Harvey-Collier linearity test ($p = 0.1002$) failed to reject the null hypothesis of linearity, indicating an overall acceptable linear fit. These diagnostics underscore the relevance of incorporating nonlinear modelling techniques to better capture the complexities in dividend behaviour.

8. Policy Implications

- **Investor Decision-Making:** Investors should prioritize Earnings Per Share (EPS) and firm size when forming dividend expectations. Large and consistently profitable firms are more likely to provide stable and regular dividend payouts.
- **Corporate Financial Planning:** Chief Financial Officers (CFOs) and financial strategists should monitor leverage and liquidity closely, as both exert significant influence on dividend policy. Reducing debt and maintaining healthy liquidity levels can enhance a firm's capacity to issue sustainable dividends.
- **Dividend Forecasting Models:** Regulatory bodies and credit rating agencies could benefit from integrating nonparametric models such as Generalized Additive Models (GAM) into their forecasting frameworks. These models provide more accurate assessments of dividend sustainability under changing financial conditions.
- **Modelling Dividend Behaviour in Policy Formulation:** The evidence supports the formulation of hybrid dividend policy frameworks that combine traditional linear predictors with advanced nonlinear techniques. Such an approach enables adaptive regulation in increasingly volatile financial markets.

9. Conclusion

This study offers a comprehensive empirical assessment of the determinants of Dividend Per Share (DPS) by applying both parametric (Linear, Log-Transformed, Polynomial, Nonlinear Least Squares) and nonparametric (GAM) modelling approaches.

Across all models, Earnings Per Share (EPS) and firm size consistently emerged as significant positive determinants of dividend policy, while Debt-to-Equity Ratio (DE) and Creditor Turnover Ratio (CTR) exhibited negative associations, suggesting that firms with higher debt or liquidity constraints tend to reduce dividend payouts.

The Generalized Additive Model (GAM) demonstrated the highest explanatory power (Adjusted $R^2 = 0.979$), affirming the effectiveness of nonparametric methods in capturing nonlinear patterns. Residual diagnostics confirmed the robustness of the models, showing no major violations of assumptions related to homoskedasticity or autocorrelation, although the Linear model exhibited mild non-normality.

These findings reinforce the importance of integrating flexible, data-driven approaches in modelling dividend

behaviour, with practical implications for investors, corporate managers, and policymakers alike.

10. Limitations and Future Research

Limitations

1. **Sample Size Constraints:** This study is based on a relatively limited dataset, which may inflate performance metrics such as R-squared and accuracy. Small sample sizes increase the risk of overfitting, thereby reducing the generalizability of the findings to broader populations or market contexts.
2. **Scope of Variables:** While key financial indicators such as EPS, QR, DE, CTR, and firm size were included, other important determinants such as governance practices, industry-specific effects, and tax policies were excluded. These omitted variables may significantly influence dividend policy.
3. **Static Model Design:** The current modelling framework does not incorporate time dynamics or lagged effects. Given that dividend policies often evolve with firm performance, the use of static or cross-sectional models may limit the ability to capture temporal trends and causality.
4. **Transformation Sensitivity:** The performance and interpretability of the log-transformed and nonlinear models were sensitive to the choice and range of transformations applied. This sensitivity may affect model comparability and the consistency of coefficient interpretation across models.

Future Research Directions

1. **Incorporation of Dynamic Time-Series Models:** Future studies may incorporate panel data or dynamic time-series frameworks (e.g., VAR, LSTM networks) to capture the evolving nature of dividend decisions across years.
2. **Inclusion of Macroeconomic and Behavioural Variables:** Broadening the scope by integrating market volatility, investor sentiment, inflation, and policy shifts could improve explanatory power and deepen insight into dividend dynamics.
3. **Model Robustness through Cross-Validation:** Employing k-fold cross-validation or bootstrapping techniques, especially in GAMs, can ensure the generalizability and stability of model results.
4. **Comparative Industry-Based Analysis:** Extending the study to specific sectors (e.g., FMCG, IT, Manufacturing) could reveal sectoral patterns in dividend policy determinants, allowing for more targeted insights.
5. **Hybrid and Ensemble Learning Approaches:** Future research may explore stacking or blending models (e.g., combining ANN with decision trees or SVMs) to leverage the strengths of multiple techniques for robust dividend forecasting.

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