Applications of Machine Learning and Determinants of Dividend Decision : Evidence from Indian Firms

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Abstract

Purpose : The theories of dividend decision have disentangled the firms' critical drivers of the dividend announcement, and their performances are empirically evaluated by employing ordinary least squares (OLS). However, after more than half a century of research, the debate over the determinants of dividend policy in firms is inconclusive. Therefore, the current study attempted to contribute to the literature by exploring new insights into the dividend decisions of Indian firms by employing machine learning.

Methodology : This study is based on secondary data, and empirical analysis has used a novel dataset of 919 listed Indian nonfinancial firms from 1999–2019. The study utilized the least absolute shrinkage and selection operator and logistic regression methodologies.

Findings : The findings revealed that the idiosyncratic variables are critically significant for dividend announcements by Indian firms. The results demonstrated that large, profitable, liquid, and firms with high market share were more likely to announce dividends in India than small, loss-making, illiquid, and low-market share firms. The direct relationship between Tobin's *Q* and the likelihood of paying dividends is a new insight into the dividend decision for Indian firms.

Practical Implications : The results will guide the dividend seeker investors to hold the shares of a high market share firm to receive the expected dividend.

Originality/Value : This current study extended the literature by studying the dividend decisions of Indian firms by employing the machine learning methodology.

Keywords : overfitting, machine learning, dividend decision

JEL Classification Codes : G20, G32

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Companies are the prime economic agents that channel investors' savings into profitable projects and generate excess returns over the owners' expectations. Investors seek a regular reward and acceleration in the value of assets over time for bearing the overall risk. When the firms decide about periodic payments (dividends) to shareholders, firms claim that the announcement of dividends does not harm the firms' value. Therefore, the payment and non-payment of dividends have always been critical questions for a company.

The utmost recognized relationship in this regard was established by Miller and Modigliani (1961), who advocated that the value of investors would remain unaffected by the firms' payment or non-payment of dividends

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under unrealistic assumptions. However, subsequent researchers challenged the irrelevance argument, and they concluded that the payment of dividends by the firms plays an essential role in determining the value of firms. For instance, the dividend decision may mitigate agency costs, send signals to the market, and provide tax benefits. Hence the firms maintain dividends at a fixed rate, which increases with the expected future earnings in the long run. Additionally, the announcement of dividends facilitates investors by increasing utility and reducing risk and uncertainty (Fama & Babiak, 1968; Lintner, 1956; Shefrin & Statman, 1984).

Though scholars have devoted significant efforts to dismantling the determinants of dividend policy, however, no consensus has been reached on the factors affecting dividend policy firms. The prominent drivers for disagreements among scholars are concerned with the methodologies adopted for selecting the variables affecting the dividend policy and the inferences deduced from these variables. For instance, the previous studies have contemplated maximum proxies linked to the market imperfections, idiosyncratic variables, and institutional variables irrespective of their redundancy and employed the ordinary least squares (OLS) for the significance of the variables.

Since the goodness of fit of the OLS is directly proportionate to the number of explanatory variables, it may induce the problem of overfitting. Furthermore, the OLS derives a linear relationship among the variables and approximates the coefficients using smoothing spline transformation of response and explanatory variables by assigning equal weights. However, the independent variables change significantly, and the fluctuations in response variables (dividend decisions) are diminutive. Therefore, the relationship between dividend decisions and idiosyncratic features is non-linear (Acharya et al., 2012; Bhat & Pandey, 1994; Lintner, 1956; Pettit, 1977; Reddy & Rath, 2005). Thus, the OLS may not efficiently capture the true relationship when the dividend decision is significantly affected by many correlated factors that are more volatile than the firm's dividend decision (Belloni et al., 2014; Cochrane, 2011).

To address the problem of overfitting, the shrinkage methodology is proposed; whereas, the logistic regression branch of machine learning (ML) is anticipated to resolve the linearity issues. The shrinkage methodology considers many noisy and correlated explanatory variables with the assumption of 'sparsity' in the variable selection process. Additionally, the logistic regression captures the non-linear relationship between the variables and provides efficient estimates.

The past studies have addressed the overfitting and surplus factors and proposed ML for variable selection and forecasting in finance branches, such as factor selection, capital structure, credit risk analysis, event studies, and portfolio selection (Heaton et al., 2016). However, the research on dividend decisions and ML is very scant, and rudimentary research has been undertaken hitherto to dismantle the dynamics of ML algorithms and dividend decisions for Indian nonfinancial firms.

Hence, this paper attempts to fill the gap by exploring the role of institutional and idiosyncratic variables in the dividend decisions of Indian nonfinancial firms listed on the Bombay Stock Exchange (BSE) while accounting for the sparsity and non-linearity assumptions. Accordingly, the prime objectives of this study are to identify the crucial variables associated with the announcement of dividends by Indian firms using least absolute shrinkage and selection operator (LASSO) and establish the non-linear relationships using logistic regression.

Review of Literature

The financial management in a firm attempts to maximize the owner's wealth. The maximization of the wealth axiom is steered by decisions regarding the acquisition of assets (capital budgeting), minimizing the cost of borrowing (financing mix), and uninterrupted routine operations of the firm (working capital management). Additionally, the decision regarding the reinvestment or distribution of profit (dividend decision) amidst the shareholders is crucial. The dividend decisions include the answers to related questions, such as whether the firm should declare the dividend. If the dividend is to be paid, what should be the pay-out ratio, when should the firms pay dividends, and how the firm should pay a dividend? The initial attempt in this regard was made by Lintner (1956), who advocated that the US firms thrive to maintain fixed dividend pay-out ratios that increase in the long-run. However, the rise in the pay-out is decided based on current and future expected profitability, where the firms' investment decisions play a vital role. The findings of Lintner (1956) caught the attention of the researchers, and they conducted primary and secondary studies. The findings also supported the results and concluded that firms prefer a stable dividend policy in the US, UK, Japan, Germany, and Australia (Bhattacharya, 1979; Fama & Babiak, 1968; Pandey & Bhat, 2007; Poornima et al., 2019; Pruitt & Gitman, 1991).

The risk and return principle provides another justification in favor of dividend announcements. For instance, investors are expected to receive capital gains in the future that are highly volatile and depend upon the market conditions; whereas, the shareholders wish to receive the current dividend shortly, therefore, it contains a lower amount of risk. So, the shareholders prioritize current dividend payments over future capital gains (Gordon, 1959; Walter, 1963). Firms also utilize dividend decisions to lessen the agency costs between shareholders and managers and between the debtholders and shareholders. As the dividend payment reduces the available free cash flows, this ultimately lowers the discretion power of the management of the firms (Easterbrook, 1984; Jensen & Meckling, 1976; Rozeff, 1982). However, Miller and Modigliani (1961) refuted the dividend relevance for changing the market value of the firms. They advocated that in the absence of tax, transaction, and floatation costs, firms can raise funds whenever they need from the market easily; in such cases, the firms' dividend decisions will be irrelevant to alter the firms' value.

In addition to maximizing the firms' value, the corporates also practice the dividend policy to communicate their financial stability. For instance, when insiders have information that is not available to outsiders and capable of changing the market price of the firms, in such information asymmetries, investors closely monitor the activities of the firms. Therefore, when the firms announce dividends, outsiders treat the decision as a symbol of the good financial health of the firms. Furthermore, the tax regimes also significantly influence the dividend decisions of the firms. For example, when tax laws exempt dividend income, capital gains are heavily taxed in the hand of the receiver. Under such situations, the dividend declaration improves the value of the firms, and non-payment of dividends inversely affects the firms' value (Miller & Scholes, 1978, 1982). In favor of the dividend payment, the scholars provide a convincible explanation by Bajaj and Vijh (1990), who advocated that investors closely monitor the firms regarding the dividend announcement status. Investors may be further categorized as non-dividend seekers and divided seekers. The dividend seekers buy a firm's stock that regularly announces dividends, and non-dividend seekers abstain from investing in these firms. Therefore, firms tend to have precise types of shareholders and announce their dividend decision policy based on their shareholders' requirements. This phenomenon is termed 'clientele effects.'

The stages of the firms' life cycles also critically define the dividend policy of the firms. For instance, in the introduction and growth stages of the firms, companies are found to be financially constrained. Hence, they have insufficient funds to meet their financial obligations. Accordingly, firms may not allocate the profit to the shareholders. Therefore, they abstain from announcing the dividend. In contrast, when the future growth rates are lower during the maturity stage, and firms tend to carry more free cash flows in their financial statements, they are more likely to announce dividends (DeAngelo et al., 2006; Fama & French, 2001). Besides the theories of dividend decisions, the risk and return principle provides a convincible approach to dividend decisions. Since the firms' shareholders are the owners of the firms who provide finance for the operations and bear the risk that stems from operations, the managers must satisfy the requirements of the shareholders. Therefore, the managers of firms announce dividends when the shareholders expect dividends. Thus, the dividend decision of a firm is primarily driven by catering to the needs of the shareholders. However, when the market discounts the shares of the firms, then the managers tend to reward the existing shareholders with stock dividends. When the stock prices exhibit a premium, then the firms are inclined to issue cash dividends (Baker & Wurgler, 2004). Qualitative studies concluded that the shareholders and managers of the firms believe that the past dividend, current earnings, and expected future earnings of the firms are consistent determinants of the dividend decision of firms.

After the establishment of various theories of dividend decisions, the empirical studies on the determinants of dividend decisions by Indian firms are dominated by selecting the proxies for idiosyncratic and institutional variables from the firms' financial statements and data collected from regulatory bodies and then evaluating the importance of the variables (Anand, 2004; Labhane & Mahakud, 2016; Pandey & Bhat, 2007; Singhania, 2006; Sudhahar, 2010; Sur & Majumdar, 2012). The importance of each variable is evaluated based on the coefficients derived from OLS. The significant studies further assumed a linear relationship between the response and explanatory variables. The findings concluded the applicability of one or more theories of dividend decisions in India. However, it has been argued that the explanatory variables such as size, growth opportunities, and the probability of bankruptcy fluctuate at a high rate, and the response of dividend policies to these variables is minimum. Hence, the relationship between dividend pay-out and the dependent variables is non-linear (Graham & Leary, 2011). Consequently, applying OLS for forecasting and prediction would result in inaccurate and unstable forecasts. Furthermore, the avoidance of non-linearity and multicollinearity among the independent variables leads to the problems of overfitting, minimum bias, and higher variance in the model (Belloni et al., 2014; Cochrane, 2011).

One of the recognized solutions for these complexities is offered by the shrinkage methodology of the ML branch (Rai, 2019). The shrinkage methodology considers many noisy and correlated explanatory variables with the assumption of sparsity. It introduces some bias in the model to alleviate the variance in predictions. The ML methods select the predictors in a highly flexible setup and accommodate the non-linear relationships. This helps in producing the best forecast for the response variables by devising the data into training and testing the algorithm (Erel et al., 2018). As a result, the LASSO tools boast low bias and may accurately model the proper relationship with low variability by producing consistent predictions across different datasets.

Numerous research studies have advocated the superiority of ML techniques for variable selections and predictions in different branches of applied finance (Heaton et al., 2016). However, the research on dividend decisions and machine learning are very negligible. At the same time, no research study has applied ML to evaluate the dividend decision of Indian non-financial firms. This provides an opportunity to contribute to the literature with detailed research on the financing mix and application of ML methodology in the Indian context. Thus, the current study employs the LASSO and logistic regression, the branches of ML methodology, for selecting the vital determinants of the dividend decision of Indian firms with sparsity assumption. The study further estimates the forecasting capacity of ML techniques and considers non-linearity in dividend decisions, where the response variable is taken as a binary variable and explanatory variables as factors and numeric variables. Accordingly, the logit and probit regression models are used for inferences. The study exploited a novel dataset of 919 Indian nonfinancial firms to achieve these objectives. Thus, the novel dataset, advanced methodology, and consideration of market imperfection proxies are the study's main contributions to the existing literature.

Data Description and Descriptive Statistics

For the empirical analysis, the study uses idiosyncratic and macroeconomic variables. The data sources include information from annual financial statements of the companies and various economic surveys of the Government of India for the accounting period of 1999 – 2000 to 2018 – 19. The firm-specific data is compiled from Bloomberg, whereas the macro time-series data is extracted from the Reserve Bank of India (RBI) database. The financial and leasing firms are excluded from the analysis following standard practices. Moreover, only those

Table 1. ***Descriptive Statistics of the Sample Data***

Variable	Observations	Mean	Std. Dev.	Min	Max
PROFIT	8,154	0.116	0.091	–0.170	0.392
SIZE	8,154	8.210	1.922	3.197	12.974
LIQ	8,154	1.912	1.586	0.206	10.608
FCF	8,154	–0.017	0.118	–0.428	0.290
Tobin's Q	8,154	1.282	1.171	0.214	7.076
Z-Score	8,154	4.056	1.573	0.185	8.166
GDP	20	0.076	0.015	0.040	0.096
SMD	20	0.879	0.299	0.205	1.295
BD	20	0.559	0.138	0.177	0.746
FDIGDP	20	0.013	0.006	0.004	0.023
FPIGDP	20	0.012	0.013	–0.015	0.032

years included have no-missing value for each variable. This data validation process left an unbalanced panel dataset of 919 firms with 8,154 observations for further analysis. To remove the outliers from the sample, the idiosyncratic variables are further winsorized at 1% from both the tails. Based on the literature, the study employed the payment and non-payment of dividends by the firm as dependent variables, and potential firm-specific variables that may explain variation in the dividend are profitability *(PROFIT)*, size *(SIZE)*, free cash flows *(FCF)*, liquidity *(LIQ)*, Tobin's *Q (Tobin's Q)*, Altman's *Z* - score *(Z-Score)*, and minority interest *(MI)*. Also, five institutional variables, viz., the economic growth rate *(GDP)*, stock market development *(SMD)*, banking development *(BD)*, foreign direct investment *(FDIGDP)*, and foreign institutional investment *(FPIGDP)* are considered in the study as the potential explanatory variables. The study computed descriptive statistics, and the results are provided in Table 1.

Table 1 reports that Indian corporates generated 11.6% profit on average ; whereas, firms also fetched losses of up to 17% during the sample period. The firm's size varies from 3–12 (natural logarithmic value). The negative mean value of FCF signifies the hesitancy of Indian firms to maintain the FCF level. The spread of current assets to cover the current liabilities for the firms in the sample ranges from 20% of current liabilities to 10 times the current liabilities. The mean value of a firm's market share is 1.27; however, the sample also consists of firms whose Tobin's *Q* value ranges from 0.21–7.07. The average value of bankruptcy measured in terms of *Z*-score is 1.59, and it ranges from 0.18–8.16. The Indian economy has progressed on an average at the rate of 7.7% during the sample period. The country achieved the highest growth in 2006–2007; whereas, the lowest growth rate was reported during the period of 2003 – 04. In the financial markets, the nation accomplished average growth in BD and SMD of 49% and 76%, respectively. A higher mean value of SMD indicates that the Indian economy is an equity market development-oriented country. The country also experienced a sharp decline in SMD after the subprime crisis in 2008, which fell to 69% from 120% during this period. However, the banks in India have extended their credit, which increased to 62% from 55%. FDI and FPI are the yardsticks for foreign investment activities in India. In the study period, the Indian economy received 1.3% and 1.2 % of GDP as FDI and FPI, respectively. The maximum value of FPI has been 3.2% in contrast to 2.3% for FDI to GDP. To diagnose the possibility of any alarming correlation among the explanatory variables, the study reports the coefficient of correlation table as Table 2.

It reports the degree of relationship among the pairs of explanatory variables considered for the research. It is evident that the correlations among the variables vary from +0.80 to –0.25. Furthermore, the highest and lowest correlation is observed among the aggregate variables; whereas, the idiosyncratic variables are moderately

Table 2. ***Coefficient of Correlation Between the Pairs of Dependent Variables***

CORRELATIONS	*PROFIT*	*SIZE*	*LIQ*	*FCF*	*Tobin's Q*	*Z-Score*	*SMD*	*BD*	*FDIGDP*	*FPIGDP*
PROFIT	1									
SIZE	0.192	1								
LIQ	0.120	–0.169	1							
FCF	0.370	0.120	0.102	1						
Tobin's Q	0.382	0.179	0.117	0.192	1					
GDP	0.028	–0.126	0.064	–0.099	0.091	1				
Z-Score	0.289	0.130	0.046	0.143	0.096	1				
SMD	–0.007	0.063	0.010	–0.064	0.086	0.017	1			
BD	–0.030	0.213	–0.048	–0.003	0.054	0.010	0.797	1		
FDIGDP	–0.033	0.172	–0.023	0.051	0.018	0.001	0.395	0.707	1	
FPIGDP	0.0007	–0.069	0.008	–0.070	0.027	0.014	0.566	0.134	–0.253	1

correlated. The results further verify that the explanatory variables are highly correlated, which may create multicollinearity problems that cause overfitting of the model and reduce the bias; however, there is a higher variance. Moreover, it directs the study to adopt the shrinkage methodology to select the variables.

Research Methodology

Variable Selection Process

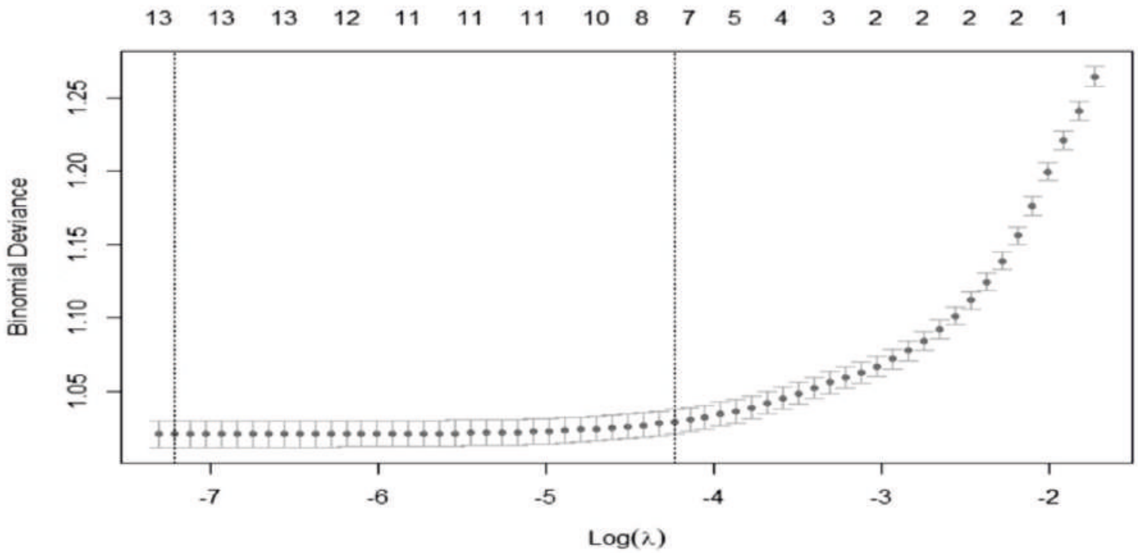
This section of the study is dedicated to establishing the model selection process using regularization[1] estimation. The shrinkage methodology advocates that a comparatively bad fit is chosen over the OLS to elevate the biases and reduce the variance. The major regularisation and shrinkage methods include RIDGE, LASSO, and Elastic Net Regression models. The functional equations of the shrinkage methods are provided in the Appendix to simplify the explanation.[2]

Equations 1 and 2 represent the linear panel regression model and indicate that the dividend decision in a firm '*i*' at the time '*t*' is possibly dependent upon 14 independent variables and a composite random error term 'ε_{it}.' The betas' estimates in equation 1 may be derived by minimizing the residual sum of the square's principle (Arellano, 2003) using OLS provided in equation 2. However, it is also provided that by adopting a bad fit, the estimates may be derived using equations 3, 4, and 5. Equation 3 is a classic example of the RIDGE regression. In contrast to the OLS, the RIDGE estimates are derived by minimizing the residual sum of square and the penalty times the slope square obtained from the OLS. The RIDGE regression estimates are computed by shrinking the coefficients by including all the explanatory variables of the study (Rai, 2019). Moreover, when the penalty is nil, the RIDGE estimates are equivalent to the OLS estimates.

Equation 4 shows the LASSO estimation process. The LASSO also follows the RIDGE procedure to compute the estimates; however, it minimizes the sum of squares of residuals and the absolute value of slope coefficients times the penalty term. When the penalty is zero, the LASSO estimators are also equivalent to the OLS estimates.

[1] Regularization and shrinkage are used interchangeably.
[2] All equations for the research methodology and models are provided in the Appendix.

Figure 1. ***Deportment of Penalty Terms Computed Using the Tenfold Cross-Validation for Dividend Decisions of Indian Firms***



When the penalty increases, the magnitudes of the slope of the least significant coefficients of explanatory variables shrink to zero.

In a nutshell, the RIDGE regression includes all the variables in the study; whereas, the LASSO attempts to pick up the most critical drivers that may explain the variation in the response variables. The equation 5 explains the elastic net regression, a combination of RIDGE and LASSO regressions. Since the current study considers the maximum potential variables proposed in the literature with their different proxies, the LASSO can exclude the redundant variables from the model. Hence, the current study utilizes LASSO, a better methodology than the RIDGE regression, for reducing the variance and selecting the variables (Amini et al., 2021). The optimum penalty term, that is, lambda (λ), is computed using the tenfold cross-validation method. Figure 1 explains the behavior of the penalty term.

Figure 1 depicts that all variables shrink to zero at the maximum penalty ; whereas, the model includes all variables in the study at the minimum penalty. Additionally, the number of variables selected tends to increase when the penalty is relaxed. To select the optimum penalty, the study applied the assumption of sparsity and cross-validation methodology and considered the lambda value at a 99 % significance level. The study noticed that with these restrictions, only eight variables among the 14 selected variables are sufficient to explain the variation in the dividend decision of Indian non-financial firms. Therefore, the study provides the status of all variables at a 99 % level of significance in Table 3.

Table 3 indicates that the long-term debt ratio, profit, size, liquidity, Tobins'*Q*, *Z*-Score, and minority interest in the firms determine the dividend decision of Indian firms. At the same time, the development of the stock market at the macro level influences the payment of dividends by Indian firms. With these chosen variables, the confusion matrix is derived for training and testing data and is reported in Table 4.

To evaluate the efficiency of the selected variables, for dividend decision, Table 4 is provided. The effectiveness of the ML algorithm is evaluated using the confusion matrix. The primary diagonals of the confusion matrix present the 'true positives;' whereas, the secondary diagonals show 'true negatives.' For example, the training or actual data algorithm for dividend decision correctly classifies 1,055 not dividend-paying and 3,895

Table 3. *Sparse Coefficient Matrix for Dividend Decisions of Indian Firms*

Dividend Decision	Coefficients
(Intercept)	–3.235959384
Long term leverage	–0.051070735
Short term debts	Shrink to zero
PROFIT	6.252476217
SIZE	0.411696691
LIQ	0.089735569
FCF	Shrink to zero
Tobins' Q	0.005201358
Z-Score	0.008420435
Minority Interest	0.174543641
GDP	Shrink to zero
SMD	–0.235394401
BD	Shrink to zero
FDIGDP	Shrink to zero
FPIGDP	Shrink to zero

Table 4. *Confusion Matrix for Testing and Training the Algorithm*

Confusion Matrix for Predicting the Dividend Decision of Indian Firms							
(Training the algorithm)				(Testing the algorithm)			
Predicted		Actual		Predicted		Actual	
		0	1			0	1
	0	1055	475		0	220	117
	1	1109	3895		1	274	1009
Classification Error		0.2424		Classification Error		0.2413	
Joint significance of all variables		*p*-value	0.0000	Joint significance of all variables		*p*-value	0.0000

dividend-paying firms' observations. Whereas, for testing the data algorithm, the model correctly classifies the 220 firms not paying dividend and 1,009 dividend-paying firms' observations.

It is also given in Table 4 that the model's efficiency depends on the training data and testing of the algorithm. In the training data, the model correctly classifies 75.76% of dividend decisions of the firms; whereas, for testing data, the model correctly classifies 75.87% of the total dependent variables. Furthermore, the confusion matrix reports that the variables selected by the LASSO are jointly significant to explain the variation in the dividend decision of Indian firms. The significance of the variables is supported by the *p*-value, as it rejects the null hypothesis of the non-significance of the variables for dividend decisions of Indian firms. In the following subsection, the study presents the estimation process of coefficients of the regression model selected using logistic regression.

Estimation of the Coefficient of the Regression Equation

In this subsection of the paper, the study examines the dividend decisions of Indian firms. The LASSO suggests that the payment of dividends in any year is a function of leverage, profitability, size, liquidity, market share, bankruptcy, minority interests of the firm, and stock market development in the country. The relationship may be written in the regression equation, given as Equation 6 (see Appendix).

Equation 6 represents the linear probability model (LPM) with the composite error term, where:

$$DIV_{it} = \begin{Bmatrix} 1 \; \textit{if the firm pays dividend} \\ 0 \; \textit{if the firm does not pay dividend} \end{Bmatrix} \text{ and } i = 1 \text{ to } 919 \text{ and } t = 1999-2000 \text{ to } 2018-2019.$$

The response variable is a binary variable, and the explanatory variables are dichotomous and continuous, and the objective is to find the conditional probability of a firm for the payment of dividends based on the variables selected by LASSO. Hence, equation 6 may be rewritten in a compact form using the matrix.

In Equation 7, Y_{it} denotes the decision on payment of dividend by the firms over time. The representations, such as β represents a $K \times 1$ (column vector), and X_{it} is the T_{in}observation on explanatory variables, and v_{it} represents the composite error term. Since the dependent variable is binary, the relationship between response and explanatory variables will be parallel lines to the *x*-axis, i.e., non-linear. To model this non-linear relationship, applying OLS will create some serious issues. For instance, OLS assumes that the probability of paying dividends by the firm moves linearly with the values of explanatory variables, irrespective of the intensity of the coefficients.

Furthermore, the values of response variables are restricted to 0 and 1, and the OLS does not consider such restrictions. As a result, the dependent variables' axis range is $-\infty$ to $+\infty$; whereas, the response variable is confined to 0 and 1.

Further, the assumptions of normality and homoscedasticity are violated when the response variable follows a binomial distribution. To resolve these problems, the study employs alternative models, such as logit and probit, that accounts for the restricted values 0–1 and non-linearity. The logit models for the analysis are derived.

Equation 8 represents the logistic regression model, which is capable of classifying the dividend-paid and not paid firms in a given year by transformation. The log of odds transformation will provide all ranges of possible values. This transformation has two important properties: the explanatory variables will not lie out of this range, and the distribution of the dependent variables will also be symmetrical to zero (Do Prado et al., 2019). Equation 7 may also be called the random effect binomial logistic model (REBLF) because the response variable can have only two possible outcomes. To compute the estimates of equation (7), the study has applied the fixed effect (FEM) and random effect model (REM). The study has applied these models to account for endogeneity. The study notices a significant fixed effect present in the model as the Hausman test signifies the presence of the fixed effect in the model. In the next section of the study, the results derived from FEM and REM are reported with discussion.

Results and Discussion

The findings presented in this section exhibit the behavior of dividend decisions to idiosyncratic and institutional variables during the study period. Table 5 reports the logit and probit estimates of coefficients by employing the LPM methodology. An examination of the *t*-statistics and *p*-value for testing the significance of the individual and joint variables depicts that the explanatory variables selected by LASSO are statistically insignificant to determine the dividend decision of Indian firms.

Table 5. ***Estimation Results of Logit and Probit Models Developed for Dividend Decisions***

Methods	Logit	Probit
Intercept	NA	–4.136***
	NA	(0.000)
Long term leverage	0.329*	0.123
	(0.086)	(0.218)
Profit	5.276***	3.862***
	(0.000)	(0.000)
Size	0.789***	0.515***
	(0.000)	(0.000)
Liquidity	0.211***	0.132***
	(0.000)	(0.000)
Tobins' *Q*	0.102*	0.055*
	(0.096)	(0.080)
Z-Score	–0.055	0.003
	(0.359)	(0.885)
MI	–0.049	0.097
	(0.770)	(0.253)
SMD	–0.222	–0.260***
	(0.130)	(0.001)
Significance of variables	LR χ^2 (8) = 271.01	Wald χ^2 (8) = 556.87
	Prob > χ^2 = 0.0000	Prob > χ^2 = 0.0000
Observations	4,009	8,154
No. of Companies	413	919
Hausman Test	χ^2 (8) = 291.57	NA
	Prob > χ^2 = 0.0000	

Since the logit and probit coefficients are incapable of measuring the marginal effects of the explanatory variables on the dependent variables, it is hard to interpret the coefficients of the models (Koop, 2008). However, the current study has used the coefficients to interpret the sign of the determinants of dividend decisions of Indian firms. It is observed in the estimation output that the variations in the dividend decision of Indian firms are significantly explained by leverage, profit, size, liquidity, and market share of the firm. For instance, a highly levered firm is likely to pay a dividend to its shareholders. Moreover, the large, profitable, liquid, and high market share firms tend to pay dividends than the small, loss-making, illiquid, and low market share firms. It indicates that the idiosyncratic factors are statistically significant in determining the likelihood of a firm paying dividends. The relationships of idiosyncratic variables with dividend decisions are consistent with the previous studies conducted in this field in India and abroad.

For instance, the positive sign on the coefficients of leverage indicates that highly levered firms tend to announce dividends compared to the unlevered firms. For instance, the positive sign on the coefficients of leverage indicates that highly levered firms tend to announce dividends compared to unlevered firms. The possible explanation may be that the share of debtholders in the ownership structure creates agency costs; therefore, the high debt restricts firms from investing in new projects, and further issues in the market require tightened conditions. Therefore, the levered firms in India pay a higher dividend to equity shareholders to alleviate the agency costs and reward the shareholders for bearing the additional financial risks stemming from the leverage. Moreover, Indian firms generate more returns than the interest rate on debt, and then the firms may utilize the additional returns to declare the dividend to equity shareholders. The dividend policy, in this case, facilitates establishing a healthy relationship with equity shareholders so that the firms may not face any complexity in raising further funds for financing. Hence, the positive relationship between leverage and dividend is convincible (Kapoor et al., 2010). It is also noticeable that large Indian firms tend to announce dividends compared to small firms. This is in line with the studies by Grullon et al. (2002) and Roy (2015) in India and abroad. It is advocated that generally, large Indian firms have nominal growth opportunities, have substantial free cash flows, and operate in diversified business activities. Under such situations, large firms tend to utilize the existing free cash flows to announce dividends instead of increasing the existing free cash flows. Additionally, these firms tend to carry more fixed assets on their balance sheets which are acquired over a long period, generating more cashflows. Thus, large firms in India tend to pay a dividend to their shareholders.

The study has noticed that the likelihood of paying dividends by Indian firms tends to rise when these firms' profit increases. This is in line with many studies conducted in India and abroad (Bajaj & Vijh, 1990; Bhat & Pandey, 1994; Baker & Jabbouri, 2016; Nissim & Ziv, 2001; Reddy & Rath, 2005). The direct relation indicates that the Indian firms may pay dividends when they can sustain the payment in the long run. The rise in the profit or available profit increases the ability of the firm to pay a dividend. Therefore, the positive relation is pronounced. The direct relationship between profit and the likelihood of dividend payment indicates that the dividend payment follows the earnings capacity of Indian firms.

A direct relationship is also observed between liquidity and dividend payment. It indicates that liquidity in the firms is an essential factor in determining the likelihood of paying a dividend. This finding contrasts with the conclusion of Bhat and Pandey (1994), who advocated in survey research that Indian firms' managers tend to give importance to firms' profitability ; whereas, liquidity seems to be the indifferent determinant of dividend payment.

Tobin's *Q* is a direct measure of the product market competition of a firm and is directly linked with the payment of dividends by Indian firms. The positive relationship indicates that a high product market share firms are more likely to announce dividend than a low market share firm. This behavior is observed because a high market share firm with lower leverage can engage in predatory practices to eliminate rivals (Guney et al., 2011). Further, the firms with a larger market share are mature, having substantial profits, free cash flows, and internally generated funds. Hence, they have more free funds to declare dividends. Thus, the positive relationship between firms' market share and dividend announcements is apparent for Indian firms. In the next section, the study is summarized and concluded.

Conclusion and Implications

Exploring the determinants of dividend announcement by a firm is always a burning question among academicians and practitioners. However, this field's empirical evidence is dominated by utilizing the agency, signalling, and clientele theories of dividend decisions. A significant amount of literature in this field is also confined to testing the hypothesis based on the variables selected in the theories. The current study extends the literature by investigating the institutional and idiosyncratic determinants of dividend decisions using LASSO for Indian nonfinancial firms. The shrinkage methodology is chosen to select the variables because it allows data to speak about the underlying relationships between the variables without prejudice. The study exploits macroeconomy data and an unbalanced panel dataset of 919 Indian companies listed on the BSE from 1999–2019 and employed logit regression to estimate the coefficients. The findings reveal that the idiosyncratic variables are highly significant in determining the dividend announcement in India. Furthermore, the results demonstrate that large, profitable, liquid, and high market share firms are more likely to announce in India than small, loss-making, illiquid, and low market share firms.

The current research study is valuable for financial institutions, shareholders, and academicians. For financial institutions, it is observed that the large, profitable, liquid, and high market share firms tend to announce dividends; therefore, the financial institutions expecting recurring income on their investment should invest in these firms. For shareholders, this study advises that the firms with leverage tend to bear agency costs between shareholders and debtholders; consequently, they may mitigate the agency costs by compelling firms to pay a dividend. Lastly, this study unites the two branches of literature, the ML and dividend decision of Indian corporates, that opens a new paradigm in this field.

Limitations of the Study and Scope for Further Research

The current study has great value for various stakeholders, though it has some limitations. For instance, the study excludes financial firms, therefore, a separate study should also be carried out to analyze the factors affecting the dividend policy of financial firms. The study has divided all firms into two categories, i.e., dividend-paying, and not paying firms; however, studies should also be undertaken to study the firms' paying between zero to one. The study also leaves a gap for analyzing the impact of less than 95% confidence level penalty terms on the number of explanatory variables.

Authors' Contribution

Dr. Sandeep Vodwal designed the study and the data analysis. Dr. Vipin Negi gathered the related literature and data for the study. Both authors jointly wrote the paper.

Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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Appendix (Development of Methodology and Model)

$$DIV_{it} = \beta_0 + \beta_1 LTL_{it} + \beta_2 STL_{it} + \beta_3 Profit_{it} + \beta_4 Size_{it} + \beta_5 LIQ_{it} + \beta_6 FCF_{it} + \beta_7 \text{Tobins'} Q_{it} + \beta_8 Z\text{-Score}_{it} + \beta_9 MI_{it} + \beta_{10} GDP_t + \beta_{11} SMD_t + \beta_{12} BD_t + \beta_{13} FDI_t + \beta_{14} FPI_t + \varepsilon_{it} \quad \text{........... (1)}$$

$$\underset{\hat\beta_0, \hat\beta_1, \hat\beta_2, \ldots\ldots\hat\beta_{14}}{minimize} \Sigma_{i=0}^{14} \Sigma_{t=1999}^{2019} ESS\ (OLS) = \underset{\hat\beta_0, \hat\beta_1, \hat\beta_2, \ldots\ldots\hat\beta_{14}}{minimize} \Sigma_{i=0}^{14} \Sigma_{t=1999}^{2019} \hat\varepsilon_{it}^2 \Rightarrow \underset{\hat\beta_0, \hat\beta_1, \hat\beta_2, \ldots\ldots\hat\beta_{14}}{minimize}$$

$$\Sigma_{i=0}^{14} \Sigma_{t=1999}^{2019} (DIV_{it} - \widehat{DIV}_{it})^2 \quad \text{........... (2)}$$

$$\underset{\hat\beta_0, \hat\beta_1, \hat\beta_2, \ldots\ldots\hat\beta_{14}}{minimize} \Sigma_{i=0}^{14} \Sigma_{t=1999}^{2019} ESS\ (RIDGE) = \underset{\hat\beta_0, \hat\beta_1, \hat\beta_2, \ldots\ldots\hat\beta_{14}}{minimize} \Sigma_{i=0}^{14} \Sigma_{t=1999}^{2019} \hat\varepsilon_{it}^2 \Rightarrow \underset{\hat\beta_0, \hat\beta_1, \hat\beta_2, \ldots\ldots\hat\beta_{14}}{minimize}$$

$$\Sigma_{i=0}^{14} \Sigma_{t=1999}^{2019} (DIV_{it} - \widehat{DIV}_{it})^2 + \lambda \Sigma_1^{14} \beta_i^2 \quad \text{........... (3)}$$

$$\underset{\hat\beta_0, \hat\beta_1, \hat\beta_2, \ldots\ldots\hat\beta_{14}}{minimize} \Sigma_{i=0}^{14} \Sigma_{t=1999}^{2019} ESS\ (LASSO) = \underset{\hat\beta_0, \hat\beta_1, \hat\beta_2, \ldots\ldots\hat\beta_{14}}{minimize} \Sigma_{i=0}^{14} \Sigma_{t=1999}^{2019} \hat\varepsilon_{it}^2 \Rightarrow \underset{\hat\beta_0, \hat\beta_1, \hat\beta_2, \ldots\ldots\hat\beta_{14}}{minimize}$$

$$\Sigma_{i=0}^{14} \Sigma_{t=1999}^{2019} (DIV_{it} - \widehat{DIV}_{it})^2 + \lambda \Sigma_1^{14} |\beta_i| \quad \text{........... (4)}$$

$$\underset{\hat\beta_0, \hat\beta_1, \hat\beta_2, \ldots\ldots\hat\beta_{20}}{minimize} \Sigma_{i=0}^{14} \Sigma_{t=1999}^{2019} ESS\ (ELASTIC\ NET) = \underset{\hat\beta_0, \hat\beta_1, \hat\beta_2, \ldots\ldots\hat\beta_{14}}{minimize} \Sigma_{i=0}^{14} \Sigma_{t=1999}^{2019} \hat\varepsilon_{it}^2 = \underset{\hat\beta_0, \hat\beta_1, \hat\beta_2, \ldots\ldots\hat\beta_{20}}{minimize}$$

$$\Sigma_{i=0}^{14} \Sigma_{t=1999}^{2019} (DIV_{it} - \widehat{DIV}_{it})^2 + \lambda \Sigma_1^{14} ((1-\alpha)\beta_i^2 + \alpha |\beta_i| \quad \text{........... (5)}$$

$$DIV_{it} = \beta_0 + \beta_1 LTL_{it} + \beta_2 Profit_{it} + \beta_3 Size_{it} + \beta_4 LIQ_{it} + \beta_5 Tobin's\ Q_{it} + \beta_6\ Z\text{-}Score_{it} + \beta_7 MI_{it} + \beta_8 SMD_{it} + \varepsilon_{it} \quad \text{.....(6)}$$

$$Y_{it} = \alpha + X_{k,it}\, \beta_K + v_{it} \quad \text{.......(7)}$$

$$(P_{it\ (DIV)})^1 = \frac{1}{1+e^{-(\alpha + X_{k,it}\beta_K)}} \text{ then } (1 - P_{it\ (DIV)}) = \frac{1}{1+e^{(\alpha + X_{k,it}\beta_K)}}$$

$$\frac{(P_{it\ (DIV)})}{(1 - P_{it\ (DIV)})} = \frac{\dfrac{1}{1+e^{-(\alpha + X_{k,it}\beta_K)}}}{\dfrac{1}{1+e^{(\alpha + X_{k,it}\beta_K)}}} = e^{(\alpha + X_{k,it}\beta_K)}$$

$$\ln (\text{odds of } DIV)^2 = c + X_{k,it}\beta_K \quad \text{........ (8)}$$

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[1] Where, $P_{it} = 1$ when firm is declaring dividend and $1 - P_{it} = 0$ or Q in case not paying dividend.
[2] Because the $Pr/1 - Pr$ is the odd ratio.

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