BBR BRAZILIAN BUSINESS REVIEW

ARTICLE

Dividend distribution prediction for small- and medium-sized enterprises in an emerging economy

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ABSTRACT
The possibility of predicting dividends is a determining factor for shareholders, investors, and management, since dividends are an important variable for firm value creation. This study aims to predict small and medium-sized enterprises' (SMEs) dividend decisions in an emerging Latin American economy. Supported by a sample of 20,418 observations for the years 2016-2018, a boosting model is applied to establish the incidence of a set of financial indicators for dividend prediction. The findings reveal that none of the financial indicators alone can explain future dividend expectations, demonstrating the robustness of the boosting model applied, and confirming that companies that have distributed dividends in the past are consistent with their dividend policy. This work has methodological, academic, and practical contributions to the SME segment, to the context in which it is studied, and to other emerging economies. The empirical evidence provided opens the door to future research that will enhance and deepen the study of this financial decision.

KEYWORDS
Dividend policy, SMEs, Emerging economy, Dividend prediction

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Recebido: 05/01/2023.
Revisado: 08/17/2023.
Aceito: 09/21/2023.
DOI: https://doi.org/10.15728/bbr.2023.1578.en

Previsão de distribuição de dividendos para pequenas e médias empresas numa economia emergente

RESUMO
A possibilidade de prever dividendos é um fator determinante para acionistas, investidores e gestores, uma vez que os dividendos são uma variável importante para a criação de valor da empresa. Este estudo tem como objetivo prever as decisões sobre dividendos de pequenas e médias empresas (PMEs) em uma economia emergente da América Latina. Apoiado numa amostra de 20.418 observações para os anos 2016-2018, um modelo de boosting é aplicado para estabelecer a incidência de um conjunto de indicadores financeiros para previsão de dividendos. As conclusões revelam que nenhum dos indicadores financeiros por si só pode explicar as expectativas futuras de dividendos, demonstrando a robustez do modelo de boosting aplicado, e confirma-se que as empresas que distribuíram dividendos no passado são consistentes com a sua política de dividendos. Este trabalho tem contribuições metodológicas, acadêmicas e práticas para o segmento de PME, para o contexto em que é estudado, e para outras economias emergentes. A evidência empírica fornecida abre portas para pesquisas futuras que irão aprimorar e aprofundar o estudo dessa decisão financeira.

PALAVRAS-CHAVE
Política de dividendos, PME, Economia emergente, Previsão de dividendos

1. INTRODUCTION

Financial management of small and medium-sized enterprises, or SMEs, is instrumental, especially in emerging countries, given their significance in terms of contributing to the economy and job creation (Franco-Ángel & Urbano, 2019; Quintero, 2020). The main aim of corporate finances dealing with investment, financing, and dividend decisions is to create business value. Specifically, dividends have been studied through various theoretical foundations (Baker et al., 2019) in an attempt to understand their link with share prices (value creation) and the elements influencing dividend payout decisions.

Overall, dividend payout is related to legal matters, ownership structure, liquidity, and planned investment projects, among other factors (González & Moneta-Pizarro, 2017). In this connection, it is crucial to understand how organizations manage these variables by using their dividend policy to meet shareholders' expectations. This paper addresses a set of financial variables as predictors of dividend payout in SMEs in Colombia, an emerging economy. These determinants were clustered into three indicator categories, financial liquidity, profitability, and indebtedness– to understand the relationship between business performance and dividends, an essential input for investors. The proposed model treats the decision to pay dividends (dependent variable) as a dichotomous variable, as the prediction focus is on determining whether dividends will be declared or not, rather than the specific dividend amount.

Liquidity, measured through free cash flow, is studied as a predictor of dividends, considering that Jabbouri and El Attar (2017) and Budagaga (2020a) evidenced the correlation of these two variables. This is based on the fact that greater availability of cash flow after covering all operational commitments enables the firm to meet the obligations it has with financial creditors and shareholders; free cash flow is then a financial tool to respond to the commitments that managers acquire with capital creditors. The connection between profitability and dividends is also addressed. According to Renneboog and Szilagyi (2020), business efficiency, which translates into profitability, increases dividend possibilities due to greater revenue generation. Finally, high levels of leverage have an impact on dividends since the available resources are committed to paying the debt service (Benjamin et al., 2018), thereby reducing the resources available for dividends.

The results obtained for SMEs indicate that more efficient and therefore more profitable firms declare dividends. In line with Onali (2016), this finding shows that Colombian SMEs use profitability as an element to influence investors, given the possibility of greater dividend payout. In turn, firms with higher levels of indebtedness did not declare dividends in two of the three periods studied, confirming this relationship that results from high financial commitments, in line with Benjamin et al. (2018). In addition, it is concluded the largest firms declare dividends, supporting the notion of recurrence in dividend payout. That is, those SMEs with a history of dividend payments are more likely to do so in the future. The findings lead us to the conclusion that none of the indicators independently account for the dividend policy; rather, it relies on multiple factors.

This work presents several contributions to the scholarly and business community. In the academic field, empirical evidence is provided on the variables that help predict dividends in the context of an emerging economy given its institutional factors, which may serve as a reference for other studies in Latin America and for developing economies overall. In contrast, the studies by Singla and Samanta (2019) and Wahjudi (2019) align in demonstrating explanatory factors of dividend policy in emerging economies, albeit applied to specific industries. A large database of SMEs was used, unlike studies that have mainly explored listed firms. In this regard, this work is a reference for other researchers who want to understand the particularities of these firms. In the professional field, this study helps investors and analysts make investment decisions in small and medium-sized firms, mostly because these firms' financial information is not usually public, and the study findings serve to guide these decisions. This work is of special importance and value as it contributes to closing the gap in the existing literature on SMEs and opens the door to future research on dividends and financial decisions for these firms in emerging countries. This paper echoes the call by Ed-Dafali et al. (2023) in order to understand the determinants of dividend policies in emerging markets.

Some distinct factors in Colombia that may influence the comparability of the results presented in this research with those of other emerging countries encompass the particular classification of business sizes, dividend taxes, interest rates on loans or borrowing costs, significant business informality, and a limited savings culture. As a result, this study is considered to offer valuable contextual insights for regional analysis and to contribute to the expansion of the literature on financial decisions within SMEs for countries of this nature.

In addition to this introduction, section 2 presents the reference framework with the SMEs Colombian context, dividend policies, and dividend prediction. Section 3 presents the sample and methodology. Results and the discussion are presented in section 4 and a robutsness analysis is presented in section 5. Section 6 contains conclusions, limitations, and lines of future research.

2. REFERENCE FRAMEWORK

This section addresses financial management in Colombia, presents theories on dividend policy, and discusses dividend prediction.

2.1. SMEs financial management and the Colombian context

Colombia is an emerging country with almost 99% of its business fabric made up of micro, small, and medium-sized organizations (MSMEs) (Franco-Ángel & Urbano, 2019). It has been a member of the Organization for Economic Co-operation and Development OECD since 2020 (OECD, 2020). As indicated by the Colombian Association of Small Businesses (Asociación Colombiana de Pequeñas Empresas - ACOPI), this business sector accounts for nearly 80 % of jobs in the country, despite a sizeable portion of this employment having concerns with informality (Quintero, 2020).

The size of an enterprise in Colombia is defined by Decree 957 of 2019. Within this decree, sizes are determined based on a company's revenues and economic activity, which can encompass commercial, industrial, or service sectors. Table 1 provides an approximation of revenues in dollars, which is utilized to classify companies into their respective size categories.

Table 1
Enterprise size classification in Colombia

Size	Services	Industrial	Commercial
Micro	USD 349.772	USD 249.838	USD 474.686
Small	USD 349.772 – USD 1.399.076	USD 249.838 to USD 2.173.562	USD 474.686 to USD 4.571.971
Medium	USD 1.399.076 – USD 4.644.475	USD 2.173.562 to USD 18.412.799	USD 22.909.817
Large	> USD 4.644.475	> USD 18.412.799	> USD 22.909.817

Source: elaborated by the authors from the Decree 957 of 2019.

Regarding financial information, all companies are required to maintain accounting records as established in the Commercial Code. However, there are two technical normative frameworks for financial information for MSMEs, outlined in Decree 2420 of 2015 as Annexes 2 and 3. Annex 2 is for small and medium-sized enterprises, which involves applying the IFRS for SMEs developed by the IASB. Annex 3 is a simplified local standard called the technical framework for financial information for microenterprises. Nevertheless, the supervision of the application of these standards, particularly for microenterprises, is very limited.

In terms of financial management, informality, and weaknesses in SMEs' financial processes constrain their growth potential. These include lack of strategic and financial planning; ongoing evaluation of organizational decisions and their effect on finances; weak administration of the working capital; absence of comprehensive accounting processes; and, therefore, lack of financial information for decision-making (Castaño, et al., 2021; Correa García & Jaramillo, 2007; Salazar et al., 2020).

Financial decisions concerning SME investment, financing, and dividend payout are a permanent source of study. The likelihood of these organizations remaining in the market depends on such decisions (Barros et al., 2020) as a large number of SMEs close their doors in their first years of existence (Correa García et al., 2009). By comparison, regarding research on firms' financial health, the relevance of liquidity, profitability, and indebtedness indicators are evident in establishing the paths that business decisions will follow (Correa García et al., 2010). Financial diagnoses that are performed using those indicators serve as the basis for informed decision-making and, therefore, represent a higher success probability as there are fewer informational asymmetries regarding the financial reality of the business. Similarly, difficulties obtaining financing are a recurrent subject of study (Ademosu & Morakinyo, 2021), a scenario worsened by the COVID-19 pandemic which has required state intervention to help organizations and prevent job losses (Ganlin et al., 2021).

2.2. Dividend Policies

Several theories help understand how dividend payment decisions are made in organizations. Although Baker et al. (2019) and Dewasiri et al. (2019) identified at least nine theories to explain this phenomenon, the present work is informed by Signaling Theory, Agency Theory and Free Cash Flow Theory.

According to Signaling Theory, administrators possess privileged information (information asymmetry), and the decision to declare dividends serves as a signal in the market to attract potential investors. In the same vein, Agency Theory proposes at least three types of costs resulting from the principal-agent relationship, such as bonding costs, monitoring costs and residual loss (Jensen & Meckling, 1976). Under the premises of this theory, organizations are expected to regularly deliver dividends as a means of minimizing costs between agent and principal; this particularly builds confidence in the positive performance of small firms' organizational management, which is validated through dividend payment (Anggoro & Yulianto, 2019; Tijjany & Bello, 2019). Moreover, this theory argues that keeping retained earnings is a way of reducing investment value to shareholders and that management must balance its decisions to propose dividend payouts while ensuring that the operation of the business entrusted to them is not jeopardized.

In this sense, to avoid jeopardizing the operation of the business, Free Cash Flow theory suggests the importance of paying dividends in the event the firm generates operating-free cash flows that are sufficient to pay both financial creditors and the declared dividend. As explained by Free Cash Flow Theory, it must be acknowledged that business profits do not represent the cash flow level produced by the firm's operation; hence, a firm that pays out all its profits in the form of dividends could be causing a future financial problem since it would be paying out cash it does not have. In consequence, firms must consider both business profits and free cash flow to determine the dividend value to be issued without risking financial stability.

Research has been conducted in emerging countries to establish the relationship between dividend policies and different financial variables, for example, in Sri Lanka (Baker et al., 2019), Malaysia (Benjamin et al., 2018), countries in North Africa and the Middle East (Budagaga, 2020a, 2020b; Jabbouri, 2016), India (Ranajee et al., 2018; Singla & Samanta, 2019) and Indonesia (Kosala, 2017). These studies have focused on SMEs as they are the most prominent organizations in those contexts, which mirrors the Colombian situation. As Gamez et al. (2018) explain, accessing financing is difficult for Colombian SMEs because, in many cases, most financial institutions impose unreasonable requirements or charge exorbitant interest rates to grant them loans (Galindo & Micco, 2016). Ademosu and Morakinyo (2021) have also highlighted how important it is for SMEs to acquire financing from investors since, as their shares are not listed on the stock market, the profitability offered to investors would mainly take the form of dividends.

2.3. Dividend prediction

Dividend prediction is a topic of interest because of its relevance in making financial decisions and its impact on firm value (Onali, 2016). There is a significant trend in SMEs not declaring dividends when liquidity is not high (Dewasiri et al., 2019; Tanyi et al., 2021), when they face high indebtedness levels (Benjamin et al., 2018; Adamu et al., 2019), or when their returns are low (Ranajee et al., 2018). The influence of financial indicators regarding the decision to pay or not pay dividends is hence significant. Besides, as Chen and Zhang (2018) point out, organizations that had issued dividend payments in previous periods are more likely to continue doing so since it becomes a firm's established policy. Therefore, it is important to consider this variable in dividend prediction models.

Dividend prediction entails several problems, such as predicting dividend growth (Ang, 2012; Chen, 2009; Møller & Sander, 2017), cuts in dividend payout (Onali, 2016), predicting exact dividend value, and predicting whether or not there will be a dividend payout. The present study seeks to predict the decision of whether dividends will be paid or not, regardless of their declared value. As such, the dividend decision becomes a classification problem, so the use of the booting algorithm developed by Roumani et al. (2019) is proposed over regression models that have been employed in other works to address dividend prediction (Bae, 2010; Won et al., 2012). Additionally, even though the study by Kosala (2017) also approached the decision on dividends as a classification problem, the present study differs in that regression and classification models are compared to establish which of the models classifies the companies most accurately. In this vein, by comparing the different models, a broader panorama emerges which allows us to assess each prediction's performance and determine the most suitable model to predict a firm's decision to declare dividends.

From a statistical perspective, there are several models to perform decision predictions, such as the boosting algorithm (Correa-Mejía & Lopera-Castaño, 2019; Roumani et al., 2019), logistic regression, and support vector machines (Kosala, 2017). However, these last two models are problematic either due to the lack of dividend information asymmetry, since a considerable percentage of SMEs do not declare dividends, or the volume of data that the sample under analysis may contain, as highlighted by Correa-Mejía and Lopera-Castaño (2019). Accordingly, this study expects to prove how the boosting algorithm may be a more accurate tool for predicting dividend payouts in SMEs.

3. METHODOLOGY

This chapter discusses the sample studied and describes the prediction model and the financial indicators used as parameters.

3.1. Sample

The research sample included Colombian SMEs from nine different economic sectors that reported information to the Colombian Superintendence of Corporations between 2016 and 2019. Financial information from the years 2016, 2017, and 2018 was used to forecast dividend payout for 2017, 2018, and 2019 respectively as this study predicts the dividend payout decision one year in advance. The years 2020 and 2021 were not considered since firms' financial performance was significantly altered during this time due to the quarantines and other social and economic restrictions caused by COVID-19, which may have biased the results. Table 2 displays the sample of companies that declared and did not declare dividends, broken down by industry and year.

Table 2
Sample composition

Panel A: Dividends declared by industry 2017					
Industry	**Do not declare**	**Frequency**	**Declare**	**Frequency**	**Total**
Trading	1,302	0.64	718	0.36	2,020
Construction	1,309	0.81	309	0.19	1,618
Manufacture	763	0.61	498	0.39	1,261
Services	640	0.65	347	0.35	987
Agricultural	376	0.75	124	0.25	500
Financial	134	0.65	71	0.35	205
Communications	93	0.55	77	0.45	170
Transport	70	0.67	34	0.33	104
Mines and Energy	45	0.80	11	0.20	56
Total	**4,732**	**0.68**	**2,189**	**0.32**	**6,921**
Panel B: Dividends declared by industry 2018					
Industry	**Do not declare**	**Frequency**	**Declare**	**Frequency**	**Total**
Trading	1,162	0.64	640	0.36	1,802
Construction	1,338	0.80	328	0.20	1,666
Manufacture	718	0.59	500	0.41	1,218
Services	567	0.63	330	0.37	897
Agricultural	367	0.75	125	0.25	492
Financial	124	0.62	77	0.38	201
Communications	88	0.59	62	0.41	150
Transport	73	0.73	27	0.27	100
Mines and Energy	52	0.81	12	0.19	64
Total	**4,489**	**0.68**	**2,101**	**0.32**	**6,590**
Panel C: Dividends declared by industry 2019					
Industry	**Do not declare**	**Frequency**	**Declare**	**Frequency**	**Total**
Trading	1,360	0.67	656	0.33	2,016
Construction	1,469	0.85	261	0.15	1,730
Manufacture	821	0.66	427	0.34	1,248
Services	569	0.65	305	0.35	874
Agricultural	405	0.78	113	0.22	518
financial	139	0.76	45	0.24	184
Communications	99	0.62	61	0.38	160
Transport	75	0.77	22	0.23	97
Mines and Energy	66	0.83	14	0.18	80
Total	**5,003**	**0.72**	**1,904**	**0.28**	**6,907**

Source: elaborated by the authors.

It can be observed in Table 2 that SMEs tend not to declare dividends (68%, 69%, and 72% for the years 2017, 2018 and 2019, respectively) rather than declaring dividends (32%, 32%, and 28% for the years 2017, 2018 and 2019, respectively. This structure demonstrates an asymmetric distribution (Calabrese & Osmetti, 2015). According to Correa-Mejía and Lopera-Castaño (2020), the prediction model should take into consideration this data structure to prevent biases in the results, since the asymmetry in the dependent variable of this study is consistent throughout the industries.

3.2. Variables

3.2.1. Dependent variable

The decision to pay dividends is the dependent variable, a dichotomous variable that takes the value of 1 when a SME declares dividends and the value of 0 when it does not (Kosala, 2017). Since the response variable is in a 0-1 interval, the result that will be achieved through the estimation of different models will correspond to the classification that an SME declares dividends one year in advance.

3.2.2. Interest variables

The models were developed with ten financial indicators categorized into liquidity, profitability, and indebtedness. Some financial variables, considered by Jabbouri (2016) as control variables, were also included to obtain more accurate forecast results. The Free Cash Flow to Assets variable was employed following Correa-Mejía et al. (2021) and Benavides et al. (2016). This indicator enables us to determine a company's ability to generate free cash flow in relation to its assets (Terreno et al., 2020). Companies with excess cash flows tend to declare dividends, according to prior studies by Jabbouri and El Attar (2017) and Budagaga (2020a).

On the other hand, according to Renneboog and Szilagyi (2020), profitability is a fundamental aspect that directly influences dividend decisions. Following Pinto et al. (2019), Brédart and Correa-Mejía (2022) and Sreejith and Ananth (2017), EBITDA margin, net profit margin, return on assets (ROA), and return on equity (ROE), were considered profitability measures in our study. Sreejith and Ananth (2017) explain that the EBITDA margin is a special measure that reveals the proportion of cash-based operating profit that a company obtains for each sale it makes. According to Sreejith and Ananth (2017), net profit margin shows the proportion of profit that remains available to shareholders with respect to the sales made by a company. Benjamin et al. (2018) define ROA as an indicator of overall profitability that shows the efficiency in the use of corporate assets. According to Renneboog and Szilagyi (2020), when organizational resources are utilized to their full potential, cash flows and dividend payouts tend to increase. Finally, ROE was also considered in this study since this indicator shows the efficiency in the use of shareholder resources (Baker et al., 2019); if ROE is higher than the profitability expected by shareholders, there will be a favorable scenario for declaring dividends.

Pinto and Rastogi (2019) found that the level of indebtedness has a direct impact on the decision to declare dividends. Companies with high levels of indebtedness prefer to allocate surplus cash flows to service debt rather than distribute dividends (Tran, 2019; Benjamin et al., 2018). Finally, authors such as Pinto and Rastogi (2019), Dewasiri et al. (2019) and Singla and Samanta (2019) believe that financial factors including company size, growth prospects, the dividend rate paid out by the company, and the amount of dividends declared in the previous period may affect the decision to declare dividends.

According to Barros et al. (2020), businesses are more likely to pay dividends to their shareholders as they expand and gain market share. Additionally, the amount of dividends declared in the current period, and the dividend payout indicator serve as a measure of firms' dividend policy and largely determine the dividend that will be declared in the following period (Baker et al., 2019). Finally, Anwer et al. (2020) argue that the decision to pay dividends is directly influenced by growth potential. Huang and Paul (2017) claim that businesses with growth possibilities prefer to allocate their cash flows to growth rather than declaring dividends. The variables utilized in this study and the methods employed to measure them are listed in Table 3.

Table 3
Summary of variables

Category	Variable	Abbreviation	Measurement	Authors
	Distribute dividends	Dividend_dist	1: Declare dividends 0: Otherwise	(Kosala, 2017)
Liquidity	Free cash flow to assets	FCF_assets	Free cash flow/total asset	(Dewasiri et al., 2019), (Benavides et al., 2016)
Profitability	EBTIDA margin	EBITDA_margin	EBITDA/Sales	(Pinto et al., 2019), (Brédart & Correa-Mejía, 2022), (Sreejith & Ananth, 2017)
Profitability	Net profit margin	Net_margin	Net profit/Sales	
Profitability	Return on assets	ROA	Net profit/Asset	
Profitability	Return on equity	ROE	Net profit/Equity	
Indebtedness	Debt level	Debt_level	Liabilities/(Liabilities + Equity)	(Benjamin et al., 2018), (Pinto & Rastogi, 2019)
Control	Size	Size	Natural logarithm of assets	(Pinto & Rastogi, 2019), (Dewasiri et al., 2019), (Singla & Samanta, 2019)
Control	Current dividends	Current dividend	Natural logarithm of current year's dividend	
Control	dividend payout ratio	Payout_div	Dividends/Net profit	
Control	Growth opportunities	Growth_op	Change in assets	

Source: elaborated by the authors.

3.3. Model

The boosting algorithm worked by Roumani et al. (2019) served as the basis for the model used to forecast the dividend distribution decision. Correa-Mejía and Lopera-Castaño (2019) explain that this algorithm is an efficient classification tool that performs well even with an asymmetric sample. This study used the AdaBoost.M1 algorithm proposed by Freund and Schapire (1997), which is useful for solving binary classification problems such as predicting the dividend distribution decision. The steps of the process through the boosting algorithm are described below.

1. Make $w_i = 1/N$ for $i = 1,2,\ldots,N$.
2. For $m = 1,2,\ldots,M$
   a. Adjust the weak classifier $G_m(x_i)$ to the training data using weights w_i.
   b. Calculate the error rate from step m,
   $$\bar{e}_m = \frac{\sum_{i=1}^{N} w_i I\big(y_i \neq G(x_i)\big)}{\sum_{i=1}^{N} w_i}$$
   c. Calculate $\alpha_m = \log\big((1-\bar{e}_m)/\bar{e}_m\big)$
   d. Make $w_{i,m} = w_{i,m-1} e^{\alpha_m I(y_i \neq G(x_i))}$
3. Calculate the prediction given by $G(x_i) = sign(\sum_{m=1}^{M} \alpha_m G_m(x_i))$

The boosting algorithm can be applied to any classifier. As noted by Hastie et al. (2008), it yields more accurate results when the model is a classification tree, as in the present study. According to Zhang and Ma (2012) boosting algorithms models are less susceptible to multicollinearity issues compared to other linear models, such as linear regression. This is because boosting algorithms use decision trees to model the nonlinear relationships between variables, which can mitigate the effects of multicollinearity.

Boosting algorithms can handle highly correlated features and do not require predictor variables to be uncorrelated to obtain accurate results. In fact, one of the benefits of using tree-based models like boosting algorithms is that there is no need to perform a multicollinearity test or apply variable transformations to deal with multicollinearity.

4. RESULTS AND DISCUSSION

This section presents the descriptive results of the financial indicators chosen to make the prediction, followed by an analysis of the forecasts made. The dividend distribution decision for the years 2017, 2018, and 2019 was predicted using financial information for each previous year; that is, financial indicators for 2016, 2017, and 2018. Table 4 shows the descriptive statistics of the financial indicators in each year, as well as the difference in medians. According to Charitou et al. (2013), analyzing the difference in medians is the proper way to compare companies that declare dividends and companies that do not declare dividends, considering the presence of outliers in each financial ratio.

According to the information in Table 4, companies declaring dividends perform better financially than non-declaring companies, in line with the findings of Tanyi et al. (2021). Firms that declare dividends have higher levels of cash flows than SMEs that do not declare dividends and this is a determinant of making such decision since the former have greater liquidity (Dewasiri et al., 2019). Similarly, SMEs that declare dividends have higher levels of profitability, which is consistent with Ranajee et al. (2018) findings. Since profitability is linked to profit generation and the efficient use of resources, companies with high levels of profitability will be more likely to distribute dividends among their shareholders (Onali, 2016).

In two of the three years analyzed, companies that do not declare dividends exhibit a higher level of indebtedness. Firms with large levels of debt are less likely to declare dividends for their shareholders since their resources are allocated to commercial and financial creditors (Adamu et al., 2019; Benjamin et al., 2018). In terms of size, SMEs that declare dividends are larger than those that do not declare dividends across the three years examined. Singla and Samanta (2019) explain that dividend payment is a strategy of larger companies whose shareholding structure is divided among various shareholders to send positive signals to the market about their treatment towards the owners.

It is unclear from Table 4 whether businesses that declare dividends have greater or lesser growth opportunities than non-declaring firms. This is because SMEs are constantly growing; hence, when examining this variable, there may be instances where businesses with growth potential also pay dividends to shareholders to meet their requirements (Barros et al., 2020). Finally, the variables related to dividend policy (dividend payout and current dividend) clearly show that companies that declare dividends in one period had also done it in the previous period. According to Chen and Zhang's (2018) research, there is a strong likelihood that a firm will pay dividends if it did so in the immediately preceding period.

Table 5 contains the confusion matrices for the three prediction years studied. The accuracy of the classification model for companies declaring and not declaring dividends can be assessed through the confusion matrix. The sample of dividend-declaring and non-declaring SMEs was split into two random groups for the forecasting procedure: one group for training the algorithm and the other for testing. The sample was randomly divided into 80% for training the model and 20% for the testing procedure.

Table 5 shows the percentage of both correctly and wrongly categorized firms in each forecasted year. For the years 2017, 2018, and 2019, respectively, 79%, 80%, and 88% of the companies that declared dividends were appropriately classified. This classification is known as true positives. On the other hand, for the years 2017, 2018, and 2019, respectively, 89%, 91%, and 91% of SMEs that do not declare dividends were correctly classified. This classification is known as true negatives.

Type I error, Type II error, and the model's overall accuracy were used for measuring the performance of the prediction model. Type I error consists of classifying a company that declares a dividend as if it did not declare a dividend, while Type II error consists of classifying a company that does not declare a dividend as if it did. Both errors affect information users differently (Brown et al., 2008). Making a type I error would imply that shareholders interested in receiving dividends would not invest in this type of shares, negatively affecting firm value (Budagaga, 2020b). Meanwhile, making a Type II error would increase the price of a firm that does not declare dividends since current investors and buyers would expect the company to pay out dividends (Hauser & Thornton, 2017).

Table 4
Descriptive statistics and differences in medians

Panel D: 2016 descriptive statistics

Variable	Declare				Do not declare				Difference in medians
	Mean	Median	Sd	Obs	Mean	Median	Sd	Obs	(Declare – Do not declare)
FCF_assets	0.041	0.032	0.086	2,189	0.010	0.007	0.078	4,732	[0.023 ; 0.029]
EBITDA_margin	0.880	0.072	11.745	2,189	-336.852	0.061	17,412.610	4,732	[0.006 ; 0.016]
Net_margin	0.624	0.051	9.949	2,189	-360.001	0.037	17,339.810	4,732	[0.011 ; 0.0175]
ROA	0.071	0.059	0.060	2,189	0.037	0.026	0.052	4,732	[0.029 ; 0.035]
ROE	0.134	0.109	0.112	2,189	0.075	0.053	0.102	4,732	[0.047 ; 0.059]
Debt_level	0.403	0.415	0.212	2,189	0.440	0.451	0.235	4,732	[-0.053 ; -0.024]
Size	16.302	16.226	0.943	2,189	16.217	16.156	0.876	4,732	[0.018 ; 0.120]
Growth_op	0.039	0.020	0.121	2,189	0.045	0.030	0.130	4,732	[-0.012 ; -0.001]
Payout_div_UN	0.575	0.279	4.003	2,189	0.090	-	10.164	4,732	[0.304 ; 0.352]
Current dividend	8.294	12.101	6.281	2,189	1.502	-	4.155	4,732	[12.196 ; 12.308]

Panel E: 2017 descriptive statistics

Variable	Declare				Do not declare				Confidence interval α=0.05
	Mean	Median	Sd	Obs	Mean	Median	Sd	Obs	(Declare – Do not declare)
FCF_assets	0.030	0.023	0.078	2,101	0.007	0.004	0.066	4,489	[0.017 ; 0.023]
EBITDA_margin	0.270	0.079	3.958	2,101	-12.143	0.066	656.344	4,489	[0.006 ; 0.017]
Net_margin	0.525	0.049	5.816	2,101	-141.256	0.035	6,339.462	4,489	[0.008 ; 0.015]
ROA	0.060	0.049	0.050	2,101	0.029	0.021	0.046	4,489	[0.024 ; 0.031]
ROE	0.109	0.090	0.092	2,101	0.059	0.041	0.086	4,489	[0.041 ; 0.051]
Debt_level	0.274	0.251	0.197	2,101	0.256	0.211	0.217	4,489	[0.014 ; 0.045]
Size	16.479	16.399	0.890	2,101	16.394	16.327	0.856	4,489	[0.012 ; 0.110]
Growth_op	0.041	0.024	0.122	2,101	0.045	0.029	0.112	4,489	[-0.006 ; 0.004]
Payout_div_UN	0.590	0.257	4.336	2,101	0.126	-	2.663	4,489	[0.311 ; 0.387]
Current dividend	8.117	12.002	6.377	2,101	1.061	-	3.544	4,489	[12.138 ; 12.272]

Panel F: 2018 descriptive statistics

Variable	Declare				Do not declare				Difference in medians
	Mean	Median	Sd	Obs	Mean	Median	Sd	Obs	(Declare – Do not declare)
FCF_assets	0.037	0.029	0.078	1,904	0.012	0.006	0.063	5,003	[0.021 ; 0.028]
EBITDA_margin	0.305	0.080	2.732	1,904	0.310	0.060	39.847	5,003	[0.014 ; 0.025]
Net_margin	0.270	0.048	2.680	1,904	0.962	0.033	60.209	5,003	[0.012 ; 0.018]
ROA	0.060	0.051	0.053	1,904	0.029	0.020	0.045	5,003	[0.027 ; 0.033]
ROE	0.109	0.094	0.092	1,904	0.056	0.040	0.082	5,003	[0.047 ; 0.057]
Debt_level	0.391	0.394	0.209	1,904	0.419	0.426	0.233	5,003	[-0.046 ; -0.013]
Size	16.497	16.439	0.926	1,904	16.374	16.313	0.921	5,003	[0.067 ; 0.164]
Growth_op	0.049	0.031	0.114	1,904	0.043	0.027	0.110	5,003	[0.001 ; 0.009]
Payout_div_UN	1.375	0.213	22.532	1,904	0.093	-	3.939	5,003	[0.245 ; 0.310]
Current dividend	7.845	11.878	6.411	1,904	1.267	-	3.844	5,003	[12.076 ; 12.223]

Source: elaborated by the authors.

Table 5
Confusion matrix

Classification	2017		2018		2019	
	Declare	**Do not declare**	**Declare**	**Do not declare**	**Declare**	**Do not declare**
Training	1,751	3,786	1,681	3,591	1,523	4,002
Testing	438	946	420	898	381	1,001
Total sample	**2189**	**4732**	**2101**	**4489**	**1904**	**5003**
Declare	0.79	0.11	0.80	0.09	0.88	0.09
Do not declare	0.21	0.89	0.20	0.91	0.12	0.91
Type I error	0.21		0.20		0.12	
Type II error	0.11		0.09		0.09	
Overall Accuracy	0.86		0.88		0.90	

Source: elaborated by the authors.

As an organization's cash flows are used to cover its debt service and dividends, according to Higgins' (1972) residual theory of dividends—making Type I and Type II errors affects not only investors but also financial creditors. In this regard, a financial institution will be exposed to potential losses if it extends credit to a business whose cash flows are only sufficient to cover its debt service and if the financial entity categorizes the business as one that does not declare dividends, according to Jabbouri and El Attar (2017). Therefore, financial creditors should refrain from making a Type II error, particularly regarding SMEs with limited cash flows.

The overall accuracy of the three forecasts performed is 86%, 88%, and 90% for 2017, 2018, and 2019 respectively. These results show a good performance of the prediction model as compared to Kosala's (2017) work, whose best predictive model had an 82% accuracy. Additionally, graphical analyses were carried out using the ROC curve shown in Figure 1 to assess the effectiveness of the model created.

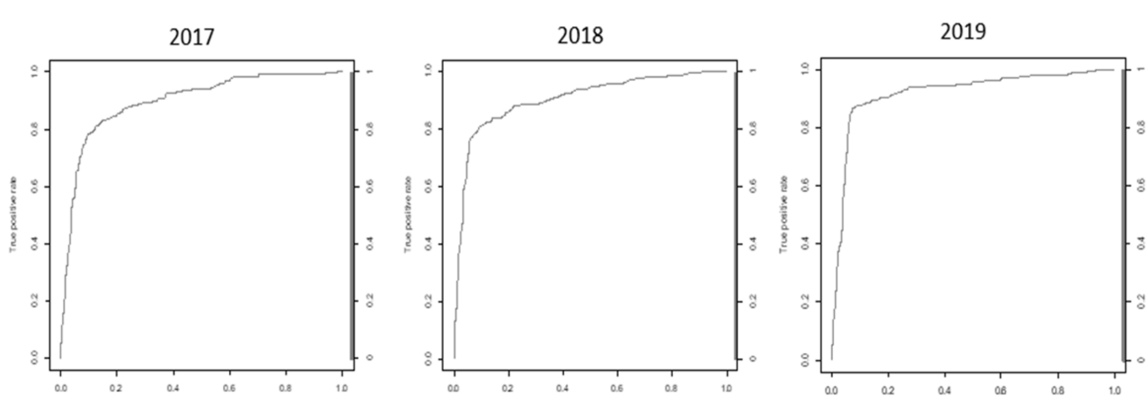

Figure 1. ROC curves
Source: elaborated by the authors.

According to Kovacova and Kliestik (2017), the ROC curve is a graphical technique that enables a graphical analysis of the model's prediction accuracy. Wide areas under the curve (AUC) of 89.8% (2017), 90.3% (2018), and 91.9% (2019) are observed for the three forecasted years, demonstrating prediction accuracy. In addition, the significance of each variable in the forecasting process can be determined with the boosting algorithm, as shown in Table 6.

Table 6
Relative relevance

Variable	2017	2018	2019	Mean
Payout_div_UN	0.126	0.154	0.170	0.150
Pastdividend	0.145	0.128	0.101	0.124
FCF_assets	0.110	0.101	0.109	0.107
Growth_op	0.102	0.117	0.101	0.107
ROA	0.109	0.100	0.105	0.105
Size	0.090	0.085	0.107	0.094
Debt_level	0.086	0.081	0.084	0.083
Net_margin	0.085	0.077	0.077	0.080
ROE	0.074	0.080	0.076	0.076
EBITDA_margin	0.074	0.078	0.071	0.074
Total	**1.00**	**1.00**	**1.00**	**1.00**

Source: elaborated by the authors.

On average, the relevance of the variables is not highly concentrated in a specific financial indicator, which suggests that the indicators chosen are determinants in SMEs' decisions to distribute dividends (Bessembinder & Zhang, 2015). However, as an important finding, the indicators related to dividend policy (dividend payout and current dividend) are the ones that contribute the most to the forecast. This result is consistent with Chen and Zhang's (2018) findings since businesses tend to maintain their dividend distribution policies over time. Another relevant finding derived from this study is that EBITDA_margin is the indicator that contributes the least to the forecasting process. Previous studies by Jiraporn and Chintrakarn (2009), Allen et al. (2012) and Huang and Paul (2017) indicated that firms from developed markets consider the EBITDA margin when deciding whether to pay dividends. The low relevance of this variable is explained by the fact that Latin American SMEs use information from the income statement to define their dividends, but the majority do not take this measure into account since EBITDA is not explicitly shown in this financial statement.

On the other hand, it is noteworthy that the sample for the study is significant, as the database from the Colombian Superintendence of Corporations is the primary source of public information with the largest volume of financial data related to SMEs. This is particularly important in a context where obtaining information directly from the financial statements and dividend decisions of these organizations is complex.

In addition, it should be noted that there are specific characteristics of the Colombian case that result in differences from the results in other emerging countries. These include dividend taxes, interest rates on loans or borrowing costs, high business informality, low savings culture, and the classification of business size, which varies across most countries due to region-specific regulations.

5. ROBUSTNESS TEST

To compare the outcomes of the boosting algorithm, predictions were made for the three years, studied through logistic regression and support vector machines as used by Kosala (2017). However, Correa-Mejía and Lopera-Castaño (2020) have questioned the validity of these two models because, in the case of logistic regression, symmetry in the dependent variable is required to ensure high forecast accuracies and, in the case of support vector machines, model efficiency is lost when the data analyzed are large (more than a thousand) and when there is asymmetry in the dependent variable (García & Lozano, 2006). Table 7 shows the confusion matrix for the estimated models.

Table 7
Confusion matrices, boosting algorithm, logistic regression and support vector machines.

Classification	2017		2018		2019	
	Declare	Do not declare	Declare	Do not declare	Declare	Do not declare
Training	1,751	3,786	1,681	3,591	1,523	4,002
Testing	438	946	420	898	381	1,001
Total sample	**2189**	**4732**	**2101**	**4489**	**1904**	**5003**
Panel G: Boosting algorithm results						
Declare	0.79	0.11	0.80	0.09	0.88	0.09
Do not declare	0.21	0.89	0.20	0.91	0.12	0.91
Type I error	0.21	0.20	0.12			
Type II error	0.11	0.09	0.09			
Overall accuracy	0.86	0.88	0.90			
Panel H: Logistic regression results						
Declare	0.63	0.12	0.66	0.08	0.70	0.10
Do not declare	0.37	0.88	0.34	0.92	0.30	0.90
Type I error	0.37	0.34	0.30			
Type II error	0.12	0.08	0.10			
Overall accuracy	0.80	0.84	0.85			
Panel I: Support vector machines results						
Declare	0.42	0.23	0.60	0.20	0.64	0.15
Do not declare	0.58	0.77	0.40	0.80	0.36	0.85
Type I error	0.58	0.40	0.36			
Type II error	0.23	0.20	0.15			
Overall accuracy	0.66	0.74	0.79			

Source: elaborated by the authors.

According to Table 7, the boosting algorithm is the model that most accurately forecasts the decision to distribute dividends in the SMEs under study. These results are presented due to the disadvantages of logistic regression and support vector machines for this type of information, which increases the probability of incurring type I and type II errors when making forecasts using these models. ROC curves were also examined as shown in Figure 2 in order to compare the AUC for each year.

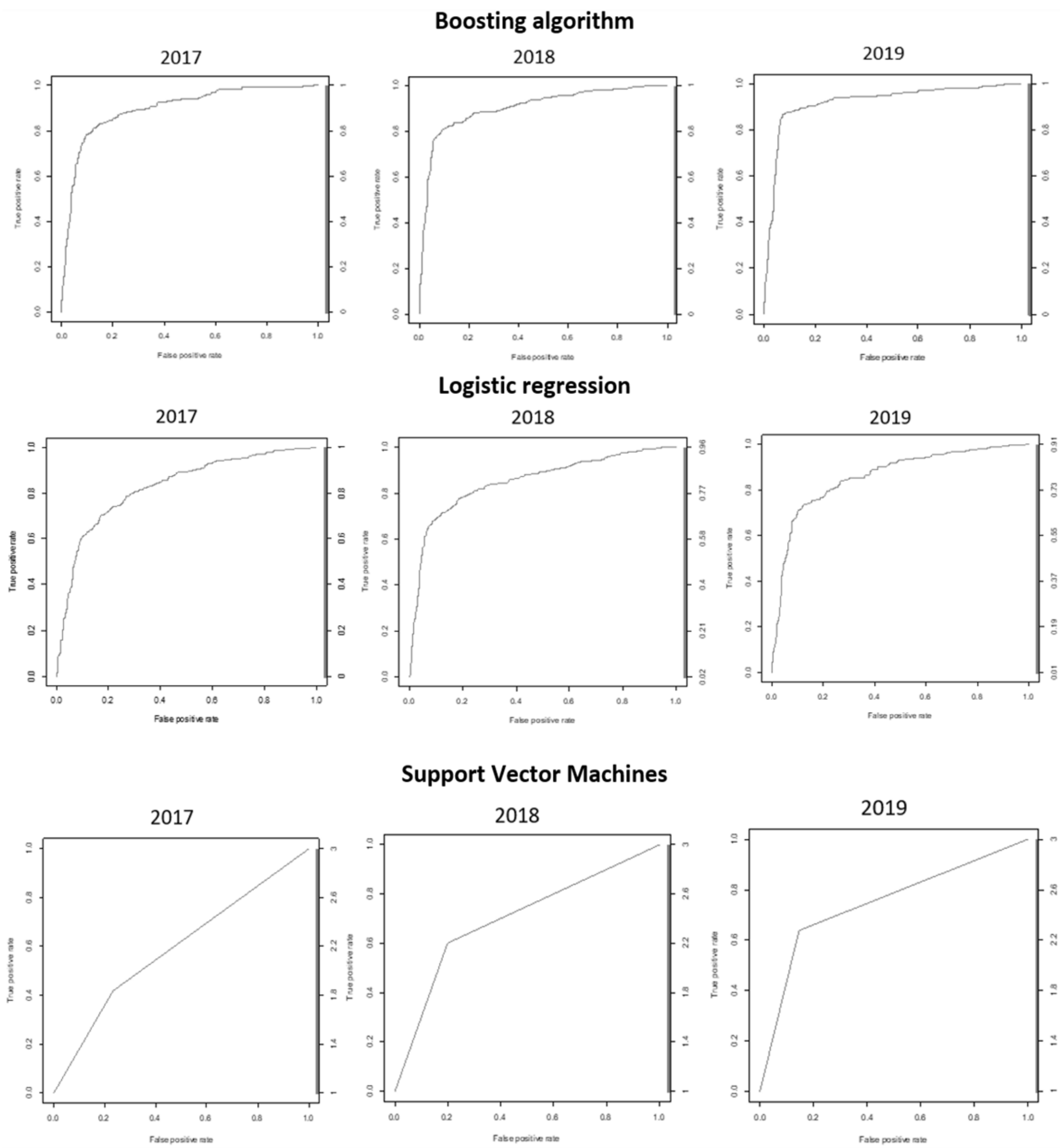

Figure 2. ROC curves, boosting algorithm, logistic regression and support vector machines
Source: elaborated by the authors.

This model is not optimal for forecasting the decision to distribute dividends because the area under the curve is larger in the boosting algorithm and the support vector machine's curve tends to 45°. In addition, the performance of the logistic regression prediction is negatively affected by information asymmetry since SMEs have a strong tendency not to declare dividends.

The results obtained in this study have allowed for predicting the decision to declare dividends in SMEs in an emerging economy with an average accuracy of 88%. This result reduces the risk of investors, potential investors, and financial creditors making Type I and Type II errors that may harm them financially and may affect the price of a company's shares.

6. CONCLUDING REMARKS

This study aimed to predict dividend decisions for small and medium-sized enterprises (SMEs) in an emerging Latin American economy. To this end, the boosting algorithm was applied for dividend prediction, following the approach of Roumani et al. (2019). The results obtained confirm the efficiency of this methodology to understand the determining factors of dividend policy. It was found that no financial indicator explains profit sharing to a large extent. However, financial indicators associated with dividend policy (dividend payout and current dividend) contributed the most to the prediction model, as also found by Chen and Zhang (2018). The overall results of the applied prediction algorithms suggest an average adjustment level of 88 %, which is sufficiently robust compared to previous studies.

To the best of our knowledge, this work is novel and provides relevant, empirical evidence for different reasons. In the first place, it examines the SMEs segment, whose financial decision analysis is difficult due to the availability of information, as most studies are focused on listed firms. Second, its application in Colombia, an emerging Latin American economy, serves as a reference not only at the regional level but also for other developing economies that may view the Colombian case as an ideal reference for financial management and, specifically, dividend payout. Lastly, the application of prediction models with a significant sample of firms yields satisfactory results as described in the existing literature. Those models become an additional reference given their high prediction rate.

The information source from the Colombian Superintendence of Corporations is the most extensive database in the country, comprising financial information about Colombian companies. This underscores the importance of the chosen sample, which is considered the most representative for this type of study. Furthermore, it should be highlighted that the Colombian case exhibits specific traits that necessitate analysis when contrasting these findings with those of other emerging nations. These characteristics include the classification of business size as per local regulations, dividend taxes, interest rates on loans or borrowing expenses, elevated business informality, and a limited savings culture.

This study has several practical implications. It provides empirical evidence for shareholders and investors to understand the financial factors that may determine SMEs' future dividends and therefore take concrete investment actions to create value. For managers and analysts, this work can serve as a reference to understand the importance of financial management and how to better guide potential investors who see dividends as a stimulus to purchase shares in SMEs. In the academic field, this work contributes to the existing literature on SMEs dividends in developing economies, thus offering support to scholars and researchers, particularly concerning the results obtained and the prediction methodology used.

Lastly, it should be noted that, although this study focuses on an emerging economy, it has been conducted using a significant sample of firms, so it opens the door to future research seeking to delve into other financial or non-financial variables as tools for predicting dividends, hence expanding the existing literature as well as contributing to different decision makers at the working level.

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AUTHOR'S CONTRIBUTION

All authors contributed equally to the development of the research.

CONFLICTS OF INTEREST

There is no conflict of interest to report in this submission.