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Judicial recovery and forecasting models; A study on the determining indicators of the recovery of Brazilian companies

Recuperación judicial y modelos de previsión; un estudio sobre los indicadores determinantes de la recuperación de las empresas brasileñas

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Abstract

The aim of this study is to identify forecasting models that relate the main financial, value, an environmental, social, and governance (ESG) indicators to the periods during which Brazilian companies were in judicial reorganization or went bankrupt between 2010 and 2020. A database comprising 73 open capital companies was constructed, with 34 undergoing judicial recovery (JR) or bankruptcy during the analyzed period, and 39 selected for the control base. A total of 2,954 observations were obtained. Logistic regression, the most utilized methodology in surveyed studies, was employed to assess the significance of each variable group in the model. A total of 73 variables were calculated, including capital structure, profitability, liquidity, investment, value, and ESG indicators. Analysis revealed that, in cases of companies in JR, significant variables were bank debt, working capital, and spread. For companies that went bankrupt, the most significant variables were bank debt and working capital. This proposed model is anticipated to contribute notably to academia and the market by incorporating various variables and indicators not previously analyzed together. It aims to enhance the understanding of corporate insolvency. In conclusion, these findings may inform strategic decision-making and risk management practices within the corporate sector.

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Keywords: judicial reorganization; bankruptcy; financial indicators; value variables; environmental; social and governance indicators (ESG)

Resumen

El objetivo de este estudio es identificar modelos de predicción que relacionen los principales indicadores financieros, de valor y de medio ambiente, sociales y de gobernanza (ESG) con los períodos en los que las empresas brasileñas estuvieron en proceso de recuperación judicial o quebraron entre 2010 y 2020. Se construyó una base de datos compuesta por 73 empresas de capital abierto, de las cuales 34 pasaron por recuperación judicial (RJ) o quiebra durante el período analizado, y 39 fueron seleccionadas para la base de control. Se obtuvieron un total de 2.954 observaciones. Se utilizó la regresión logística, la metodología más empleada en los estudios revisados, para evaluar la significancia de cada grupo de variables en el modelo. Se calcularon un total de 73 variables, incluyendo estructura de capital, rentabilidad, liquidez, inversión, valor e indicadores ESG. El análisis reveló que, en los casos de empresas en RJ, las variables significativas fueron deuda bancaria, capital de trabajo y spread. Para las empresas que quebraron, las variables más significativas fueron deuda bancaria y capital de trabajo. Se espera que el modelo propuesto contribuya de manera relevante a la academia y al mercado, al incorporar diversas variables e indicadores que no habían sido analizados en conjunto anteriormente. Su objetivo es mejorar la comprensión de la insolvencia corporativa. En conclusión, estos hallazgos pueden orientar la toma de decisiones estratégicas y las prácticas de gestión de riesgos dentro del sector corporativo.

Código JEL: G33, G32, C25, M14
Palabras clave: reorganización judicial; quiebra de empresas; indicadores financieros; variables de valor; indicadores ambientales; sociales y de gobernanza (ESG)

Introduction

In recent years, Brazil has faced a significant economic crisis, leading to a considerable increase in the number of companies resorting to financial recovery. According to Serasa Experian, requests for judicial recovery (JR) increased by 105.2% in May 2023 compared to the same month of the previous year (Serasa, 2023). Bill No. 1,397/2020, introduced in May 2020, implemented temporary regulations for JR requests during the crisis period, simplifying procedures and enhancing credit availability to stimulate economic recovery. Similarly, Law No. 14,112/2020, enacted on December 24, 2020, significantly reformed Law No. 11,101/2005, which regulates judicial recovery, extrajudicial recovery, and bankruptcy. These reforms prioritized conciliation processes, extended suspension periods, and improved protections for asset sales, providing critical support to financially distressed companies.

This study examines the financial, value-based, and environmental, social, and governance (ESG) indicators that influence judicial recovery and bankruptcy outcomes for Brazilian companies between 2010 and 2020. The dual focus on ESG and financial predictors aims to deepen the understanding of corporate insolvency and to contribute to literature on predictive models by incorporating contemporary

sustainability practices. The study also explores how variables like transparency, governance, and sustainability correlate with judicial recovery requests, advancing both theoretical and practical knowledge in this domain.

Traditional models, such as Altman's Z-score (1968), remain widely used in predicting bankruptcy, despite their lack of updates to incorporate modern financial dynamics (Stasko, Birzniece, & Kebers, 2021; Buele, Mora, & Santiago, 2021). Recent research has shifted toward integrating value drivers, such as capital structure and profitability, as indicators for insolvency evaluation (La Font et al., 2020). Advanced models like Merton's (1974) and machine learning approaches (Scabora, 2019; Vargas & Miñano, 2012) have been explored, leveraging methodologies like neural networks and decision trees to enhance predictive accuracy.

ESG considerations are increasingly integrated into insolvency models due to their influence on company stability and investor behavior. Studies such as Amel-Zadeh and Serafeim (2017) demonstrate that ESG data is critical for evaluating financial performance and risk. Similarly, governance mechanisms, as highlighted by Ashbaugh-Skaife et al. (2006), address agency conflicts and asymmetry issues, fostering better financial decision-making.

This research builds on these advancements by combining logistic regression techniques with ESG and value-based indicators to examine their combined effect on judicial recovery and bankruptcy outcomes. By adopting this approach, the study provides a more holistic and nuanced analysis of corporate financial health and insolvency risk in Brazil.

This introduction sets the foundation for further exploration in subsequent sections, including a detailed methodology, results, and conclusion, which collectively address the research question: Which variables are relevant in determining the judicial recovery of Brazilian companies from 2010 to 2020?

In addition to this introduction, the paper includes a literature review section that provides an overview of judicial recovery, previous works on predicting judicial recovery and bankruptcies in Brazil, and the ESG theme. Subsequently, the study sample and research methodology are presented, followed by the results section, conclusion, and bibliography.

Literature review

Judicial recovery is a legal procedure that allows financially distressed companies to reorganize their debts and avoid bankruptcy. In Brazil, the legal framework regulating judicial recovery until 2020 was primarily defined by Law No. 11,101/2005, which introduced a comprehensive set of rules for judicial recovery, extrajudicial recovery, and bankruptcy. This law aimed to provide mechanisms for debt reorganization and business continuity while safeguarding creditors' interests.

In 2020, Law No. 14,112/2020 was sanctioned, significantly amending Law No. 11,101/2005. These amendments introduced key procedural changes designed to enhance the efficiency of judicial recovery. For instance, the law extended the suspension periods of debt execution proceedings against the debtor, incentivized conciliation and mediation before initiating judicial recovery, and allowed the sale of company assets with greater legal certainty for buyers. These measures were intended to balance the interests of debtors and creditors while promoting faster resolution of insolvency cases.

Additionally, during the COVID-19 pandemic, Bill No. 1,397/2020 was proposed to address the economic challenges faced by businesses during this period. The bill provided temporary relief by streamlining judicial recovery processes and implementing measures such as debt renegotiation and credit protection to support financially struggling companies. Although these provisions were time-bound, they marked a significant response to an unprecedented economic crisis.

These legislative frameworks provide context for understanding the evolving landscape of judicial recovery in Brazil. They reflect the interplay between traditional recovery mechanisms and contemporary challenges, such as economic shocks and the growing importance of environmental, social, and governance (ESG) factors in evaluating a company's financial health and sustainability. Together, these laws and amendments set the stage for a more adaptive and inclusive approach to addressing corporate distress.

According to the Foundation Institute of Administration (FIA) Business School (2021), financial indicators are numerical metrics that provide insights into a company's financial condition based on its accounting records. Understanding and assessing these financial indicators is crucial because companies seeking judicial recovery or facing bankruptcy face financial difficulties.

Studies adopting a machine-learning approach include the works of Scabora (2019) and Vargas and Miñano (2012). Scabora (2019) uses artificial neural networks methodology combined with information from Brazilian companies' Cash Flow Statements (DFS) to analyze the impact of DFS indicators on judicial recovery filings. Vargas and Miñano (2012) employ a decision tree methodology to analyze how accounting and control variables are relevant for predicting companies' solvency.

Focusing on variables rather than methods, Bezerra (2018), Ferreira (2017), and Wijaya and Anantadjaya (2014) also incorporated macroeconomic variables into accounting variables to develop forecasting models that determine the relationship between these variables and JR. Despite using different indicators, both studies concluded that macroeconomic scenarios influence company insolvency. Bezerra (2018) also incorporates governance variables such as corporate governance levels and delays in financial statements, which were significant in the analysis.

Finally, some studies are primarily based on quantitative information for analysis, such as Belli's (2020) study. By utilizing information such as sector, whether the company is publicly or privately held,

the company's age at the time of the JR request, total debt listed on the creditors' list, and total creditors listed, it was possible to develop an empirical model for predicting the bankruptcy of companies undergoing JR.

This research employs Value-Based Management (VBM) indicators because organizations seek to maximize wealth creation and generate shareholder value. In this context, companies have realized the potential use of value drivers to measure whether they are capable of creating or destroying value and anticipating results to create shareholder value (Guimarães Junior et al., 2009). For companies in JR, a long-term perspective is essential as the company undergoes reorganization, necessitating the monitoring of value metrics (Rappaport, 2001).

According to Escuin (2010), the prominence of VBM models arises from companies' perception that creating mechanisms to monitor business financial performance can maximize shareholder wealth. VBM aims to identify what creates and destroys value within a company. Caselani and Caselani (2006) developed the concept of value drivers to analyze resource allocation. Value drivers are measures intended to anticipate results and create value for shareholders.

Krauter (2006) analyzed financial performance measures and value creation in industrial companies. He selected 79 companies and examined which performance measures were used, including return on investment (ROI), return on equity (ROE), ROA, economic value added (EVA®), price/earnings ratio, earnings per share, return on net assets (RONA), added value margin (MVA®), or none of these measures. The research concludes that the most commonly used indicators are ROI and ROE.

Moreover, this study relates the theme to the ESG framework. Bouma et al. (2001) link environmental concerns with the banking ecosystem. The second chapter of the book focuses on sustainability issues according to the UBS Group, a Swiss-based financial service company. The group reveals that, from an environmental perspective, they can contribute by helping reduce emissions and waste, benefiting from reduced financial risks.

Regarding the usefulness of ESG indicators for investors, Amel-Zadeh and Serafeim (2017) highlight that most respondents use ESG data to assess investments, considering these aspects relevant to companies' financial performance. Additionally, there is a distinction between North American and European citizens: while North Americans focus more on financial aspects, Europeans place greater importance on the ethical aspects associated with ESG practices, although the study suggests that the real motivation is financial. The research also indicates that the second reason investors use ESG data is to assess company risk.

In the context of agency conflict and governance, Ashbaugh-Skaife et al. (2006) emphasized that governance is a response to agency conflicts, especially those related to informational asymmetry

between management and external agents. Governance mechanisms are implemented to reduce such conflicts, promoting more informed managerial decision-making and limiting opportunistic behaviors.

Methodology

To examine the performance of insolvent companies during the analysis period, both traditional and value-based metrics were used. The latter were derived from previous studies, such as those by Caselani and Caselani (2006), Corrêa (2012), Segovia and Camacho (2012), and Correa, Assaf Neto (2014), with most of them utilizing indicators proposed by conventional literature.

Regarding the financial variables, the analysis encompasses indicators of operational performance, activity, cash generation, financial balance, capital structure, leverage, profitability, lucrativeness, and spread. The multiple-indicator approach aims to construct a comprehensive model that differentiates itself from previous models focusing on a specific group of variables (Fabozzi & Grant, 2000; Rappaport, 2001; Copeland, Koller, & Murin, 2002; Martin & Petty, 2004; Caselani & Caselani, 2006; Martins, 2009; Botazzi, Grazzi, Secchi, & Tamagni, 2011; Segovia & Camacho, 2012; Firk, Richter, & Wolff, 2020; Belli, 2020, Jaki & Cwiek, 2021).

After analyzing the 33 indicators, the indicators were grouped, and one variable from each group was chosen to reduce multicollinearity. The variables selected by the group were determined based on their significance in a stepwise logistic regression to enhance information quality. The financial variables used for the analyses were bank indebtedness, gross margin, working capital, and spread.

Table 1
Selected financial variables

Variable	Code
Debt composition	Debt
Gross Margin	Margin
Working Capital	Wcapital
Company Spread (ROA-ki)	Spread

Source: Prepared by the author

As a distinctive feature, this study aimed to identify the relevance of value variables in determining companies' insolvency. The analyzed value variables include Economic Value Added, Cash-based Value Added, Aggregate Market Value, Shareholder Value Created, Company Return Above Cost of Capital, Risk-Adjusted Cost of Capital, and Future Economic Value (Correa, Assaf Neto, 2014; Fernandez, 2002; Corrêa, 2012). Each variable will be detailed in Table 2.

Table 2
Value variables

Variable	Code
Economic Value Added	EVA
Market Value Added	MVA
Shareholder value created	CSV
Return on Equity Above Cost of Capital	Spread do EVA
Future Economic Value	EFV

Source: Prepared by the author.

A highlighted aspect among the analyzed studies is the use of control variables, such as time in judicial recovery, company sector, whether the recovery is voluntary or mandatory, among others (Jaki & Cwiek, 2021; Firk, Richer, & Wolff, 2020; Belli, 2020; Vargas & Miñano, 2012; Segovia & Camacho, 2012).

Furthermore, this study aims to assess whether companies' adoption of ESG practices contributes to their solvency. To achieve this, dummy variables were employed to identify the presence of ESG practices in companies, such as i) publication of sustainability reports, ii) prominence in transparency practices according to National Association of Finance, Administration and Accounting Executives (NAFAAE) data, and iii) a governance index from B3. If a company adopts one or more of these practices, the ESG variable is defined as 1; otherwise, it is defined as 0.

The high number of chosen indicators is attributed to assessments from previous research, including Fabozzi and Grant (2000), Rappaport (2001), Copeland, Koller, and Murin (2002), Martin and Petty (2004), Martins (2009), and Assaf Neto (2014). These studies revealed deficiencies in one or more indicators and not all drivers were applied across all sectors used in the sample. This study analyzed companies between 2010 and 2020 to identify the most significant indicators in each of the following situations:

i) When companies are in Judicial Recovery (JR)

ii) When companies go bankrupt.

To conduct the proposed analysis, researchers performed logistic regressions to assess how independent variables, including those related to values and ESG practices, affect the prediction of outcomes for companies in JR and bankruptcy. The sample consists of 2,954 observations and 73 variables. The descriptive statistics of the sample are presented below to examine the behavior of the observations and variables. Based on the analysis and selection of variables, logistic regression was first conducted with only financial variables, followed by the inclusion of value variables, and finally with the inclusion of the ESG variable to assess their contribution to the explanatory power and predictive capability of the model.

The first analysis focuses on the prediction of the judicial recovery period. An ordered logistic

model was applied considering whether the company was undergoing JR in each quarter during the analysis period. The dependent variable, denoted as JRit, indicates whether the company was in judicial recovery for each observation, whereas VI represents the set of independent variables.

$$RJit = \beta \times VIit + \varepsilon t \quad (1)$$

The second analysis aims to predict bankruptcy. Similarly, a logistic model was used, where the dependent variable FALit indicates whether the company went bankrupt for each observation and VI continues to represent the set of independent variables.

$$\text{FAL}it = \beta \times VIit + \varepsilon t \quad (2)$$

To determine which independent variables were statistically significant, researchers used the stepwise logistic regression technique, gradually including and excluding variables, to find the most relevant set with a significant impact on predictions. Additionally, the predictive ability of each model was assessed to understand the contribution of the independent variables to the accuracy of the predictions.

Results and analysis

After the necessary analyses were conducted, the data underwent logistic regression using Stata/SE 14.0, with the period in JR as the dependent variable and bank indebtedness, gross margin, working capital, spread, EVA, and ESG as independent variables. Regressions were performed in three ways to identify the contributions of the value and ESG variables in the model:

Model A: Bank indebtedness, gross margin, working capital, and spread. Model B: Bank indebtedness, gross margin, working capital, spread, and EVA.

Model C: Bank indebtedness, gross margin, working capital, spread, EVA, and ESG.

The results are shown below:

Table 3
Results of logistic regression model A:

Variable	Coefficient	Standard Deviation	P-valor
Debt	0.75	0.174	0.000
Spreadem	4.79e-6	5.98e-7	0.000
Wcapital	-7.90e-8	1.09e-8	0.000
_cons	-1.46	0.113	0.000

Source: Prepared by the author.

Model A's results indicate that the variables significant at the 95% confidence level are bank indebtedness, spread, and working capital. There is a positive relationship between bank indebtedness and spread, and a negative relationship with working capital. Thus, an increase in the independent variable of whether the company is in JR is mainly associated with its bank indebtedness. An increase in bank indebtedness increases the chances of the company being in JR by 75%.

It was also observed that variables with negative coefficients indicated that an increase in the independent variable was associated with a decrease in the indicator. However, the coefficient of the working capital variable suggests that changes in this variable have a relatively small impact on the variations in the dependent variable.

Table 4
Confusion Matrix Model A

Classification	Real positives	False negatives	Total
Real Negatives	31	15	46
False Positives	449	2177	2626
Total	480	2192	2672

Source: Prepared by the author.

Table 4 contains the confusion matrix for Model A, and analyzing the classification of true positives, true negatives, false positives, and false negatives indicates that this model correctly classified 82.63% of the cases.

In Model B, EVA was included as a value variable. With the regression, it can be observed that the EVA is not significant, but it makes the gross margin significant. In this case, an increase in bank indebtedness and a decrease in gross margin indicates an increase in the chances of judicial recovery. Bank indebtedness remains the variable with the highest explanatory power regarding whether the company is in judicial recovery or not.

Table 5
Logistic regression results model b

Variable	Coefficient	Standar deviation	P-valor
Debt	1.09	0.211	0.000
Margin	-0.02	0.008	0.003
Spreadem	3.78e-6	5.57e-7	0.000
Wcapital	-6.47e-8	1.08e-8	0.000
cons	-1.51	0.145	0.000

Source: Prepared by the author.

Model B correctly classifies 82.06% of the cases, revealing that the inclusion of value variables does not significantly alter the model's predictive capacity, but makes more variables significant in the analysis of JR companies.

Table 6
Confusion Matrix Model B

Classification	Real positives	False negatives	Total
Real Negatives	62	18	80
False Positives	298	1383	1681
Total	360	1401	1761

Source: Prepared by the author.

Finally, Model C includes an ESG variable, which is a dummy variable. If the company has any governance index on B3, publishes a sustainability report, and/or has been nominated for Transparency Trophy by the ANEFAC, it receives a value of 1; otherwise, it receives a value of 0. The inclusion of this variable resulted in the exclusion of only EVA, while the other analyzed variables remained significant.

Table 7
Results of logistic regression model c

Variable	Coefficient	Standard Deviation	P-valor
Debt	1.15	0.216	0.000
Margin	-0.02	0.008	0.001
Spreadem	3.69e-6	5.61e-7	0.000
Wcapital	-5.94e-8	1.11e-8	0.000
ESG	-0.48	0.13	0.000
_cons	-1.25	0.145	0.000

Source: Prepared by the author.

In Model C, an increase in bank indebtedness, decrease in gross margin, and decrease in the ESG index indicate an increase in the chances of judicial recovery. Bank indebtedness remains the variable with the highest explanatory power, but the ESG variable gains prominence in the analysis of whether a company is in judicial recovery. In this model, the classification was correct in 81.68% of the cases, indicating that there was no significant improvement in explanatory power with the inclusion of ESG variables in this model. However, similar to Model B, the inclusion of new variables contributes to the significance of other variables in the analysis.

Table 8
Confusion matrix model c

Classification	Real positives	False negatives	Total
Real Negatives	61	20	81
False Positives	299	1361	1660
Total	360	1381	1741

Source: Prepared by the author

To analyze the companies that went bankrupt in the studied sample, the three models were rerun for cases where the bankruptcy dummy variable was equal to 1. To differentiate between them, they are referred to as Models D, E, and F:

Model D: Bank indebtedness, gross margin, working capital, and spread. Model E: Bank indebtedness, gross margin, working capital, spread, and EVA.

Model F: Bank indebtedness, gross margin, working capital, spread, EVA, and ESG.

These models were used to assess bankruptcy within the studied sample. If you require further information or have other questions, they feel free to ask.

Table 9
Results of logistic regression model d

Variable	Coefficient	Standard deviation	P-valor
Debt	2.42	0.558	0.000
Wcapital	-7.53e-7	2.17e-7	0.001
_cons	-2.47	0.418	0.000

Source: Prepared by the author

The analysis indicates that the significant variables in Model D at the 95% confidence level are bank indebtedness and working capital. Compared with the JR model, the positive relationship between bank indebtedness and the negative relationship with working capital is maintained. In the bankruptcy model, bank indebtedness is even more relevant than in Model

A. Assessing the classification, this model correctly classified 78.38% of cases.

Table 10
Confusion matrix model d

Classification	Real positives	False negatives	Total
Real negatives	19	6	25
False positives	26	97	123
Total	45	103	148

Source: Prepared by the author.

When model E is checked, the inclusion of value variables does not alter the model. Despite considering EVA, the significant variables and coefficients remain the same as in model D.

Table 11
Results of logistic regression model e

Variable	Coefficient	Standard deviation	P-valor
Debt	2.42	0.558	0.000
Wcapital	-7.53e-7	2.17e-7	0.001
cons	-2.46	0.418	0.000

Source: Prepared by the author.

Model E correctly classifies 78.38% of cases, revealing that the inclusion of value variables does not significantly alter the model's predictive capacity.

Table 12
Confusion matrix model d

Classification	Real positives	False negatives	Total
Real negatives	19	6	25
False positives	26	97	123
Total	45	103	148

Source: Prepared by the author.

Finally, model F includes an ESG variable. The inclusion of this variable results in the exclusion of the spread, EVA, ESG and gross margin variables, at a 95% significance level.

Table 13
Results of logistic regression model f

Variable	Coefficient	Standard deviation	P-valor
Debt	2.42	0.558	0.000
Wcapital	-7.53e-7	2.17e-7	0.001
_cons	-2.46	0.418	0.000

Source: Prepared by the author.

In this model, the classification is correct in 78.38% of cases, indicating that there is no significant improvement in explanatory power with the inclusion of ESG variables in this model.

Table 14
Confusion Matrix Model F

Classification	Real positives	False negatives	Total
Real negatives	19	6	25
False positives	26	97	123
Total	45	103	148

Source: Prepared by the author.

The results are shown in Tables 15 and 16.

Table 15
Summary of bankruptcy analysis model

Model	Variables used	Significant variables	Percentage of correct classify
A	Debt, Margin, Wcapital e spread	Debt, Wcapital e spread	82.63%
B	Debt, Margin, Wcapital, spread e EVA	Debt, Margin, Wcapital e spread	82.06%
C	Debt, Margin, Wcapital, spread, EVA e ESG	Debt, Margin, Wcapital, spread e ESG	81.68%

Source: Prepared by the author.

In the case of the judicial reorganization analysis, the variables bank debt, working capital and spread were significant in all the models. As new variables were added to models B and C, more variables became significant, but the percentage of correct classifications decreased.

Table 16
Summary of bankruptcy analysis results

Model	Variables used	Significant variables	Percentage of correct classify
D	Debt, Margin, Wcapital e spread	Debt e Wcapital	78.38%
E	Debt, Margin, Wcapital, spread e EVA	Debt e Wcapital	78.38%
F	Debt, Margin, Wcapital, spread, EVA e ESG	Debt e Wcapital	78.38%

Source: Prepared by the author.

Regarding the analysis of bankrupt companies, all three models yielded the same results. The significant variables were bank debt and working capital, and the classification was correct in 78.38% of cases. Ferreira (2017) used both accounting and macroeconomic variables to compare these results with those of previous studies.

Logistic regression was employed, and the statistically significant variables were net worth, net profit, working capital interest, and the selic rate. In this context, the importance of working capital for the analysis of companies' judicial recovery is evident, as, despite different samples and indicators, this variable remains significant. Bezerra (2018) also analyzed financial, macroeconomic, and governance indicators using a logistic regression.

The significant logistic analysis indicators are third-party capital participation, total indebtedness, return on assets, general liquidity, debt composition, asset turnover, equity immobilization, onerous indebtedness, financial cycle, gross domestic product (GDP), corporate governance level, and

delay in financial statement disclosure.

The results also reinforce the variables found in this research, as both debt and corporate governance levels are significant in both cases. In this study, the corporate governance level does not have an explicit contribution but is part of the ESG variable. In the works of Schio and Sampaio (2022), Onofrei and Laupu (2014), and Voda, Dobrotã, Tîrcã, Dumitrascu, and Dobrotã (2021), the degree of indebtedness appears as a significant variable, emphasizing the importance of this variable for the analysis of companies in judicial recovery.

Despite the varying results of the analyzed studies, the variables of debt and working capital are common to the vast majority, revealing their importance. Similarly, this study observes the contribution of the value and ESG variables, and in all models, these variables are significant. The use of value variables, ESG variables, and the structuring of different models for judicial recovery and bankruptcy were differentiating factors that filled a gap in the literature. It is expected that the proposed model will contribute mainly to academia and the market by using various variables and indicators that have not been previously analyzed in the same model to analyze corporate insolvency. This has improved the predictive ability of judicial recovery and bankruptcy for companies and has contributed to predicting and maintaining the financial health of businesses.

Conclusions

In recent years, the economic and political scenario in Brazil has led to an increase in the number of requests for judicial recovery. With the COVID-19 pandemic and government decrees closing non-essential activities, many companies suspended their operations, causing difficulties in meeting financial obligations. To support these companies, Bill No. 1,397/2020 established reformulated guidelines for judicial recovery requests during the crises. This initiative marked a substantial step toward increasing credit availability, a crucial element in encouraging job creation, income growth, and economic revitalization in the country.

In this context, this research aimed to identify significant financial indicators for predicting a company entering judicial recovery or bankruptcy and to assess whether value and ESG indicators contribute to improving the model's predictive ability. A sample of 36 Brazilian companies undergoing judicial recovery, using data from the Securities Commission Portal, was employed. Additionally, a control sample of 39 companies was used to examine similarities and differences between the analyzed groups. The sample size was limited owing to data availability, with some studies opting for a single-case approach owing to similar limitations.

The analysis covers 2010 to 2020, with quarterly data collection. This timeframe was chosen

considering the implementation of the International Financial Reporting Standards (IFRS) in Brazil and providing a comprehensive sample of companies undergoing different situations: bankruptcy, judicial recovery, and successful exits from the judicial recovery process.

After constructing the database, which included information from Securities Commission Portal, ANEFAC and investor relations portal, statistical analyses were conducted using Stata 14.0. Logistic regression, suitable for exploring the relationships between independent variables and a binary outcome, was applied to evaluate events related to judicial recovery and bankruptcy.

The results identified Model A as having the best classification power, correctly classifying 82.63% of cases with significant variables being bank debt, working capital, and spread. An increase in bank debt or spread and decrease in working capital indicate an increased likelihood of judicial recovery, with bank debt being the most explanatory variable.

Although the inclusion of value and ESG variables in Models B and C did not significantly improve the explanatory power, introducing these variables made others significant in the analysis.

The same three models were executed in the second analysis group with different nomenclatures for differentiation. Model D continued to exhibit the best classification power, correctly classifying 78.38% of the cases, with bank debt and working capital as significant variables. As in the analysis of companies in judicial recovery, an increase in bank debt and/or a decrease in working capital indicates an increased likelihood of bankruptcy.

Identifying drivers impacting a company's financial health benefits society primarily by maintaining employment stability. Companies undergoing judicial recovery may need reorganization, potentially leading to job cuts; if a company goes bankrupt, jobs will be lost. This study also aids investors and creditors in understanding which indicators are relevant for analyzing and predicting a company's financial health. By using financial data disclosed by companies to identify new indicators, stakeholders can conduct more informed analyses, leading to more judicious investments.

As a suggestion for future research, these indicators could be applied to other periods to confirm whether the conclusions can be generalized. Additionally, comparing laws to determine if there are differences in significant variables during each law's validity period could be explored. Furthermore, future studies should focus on methods that show the highest explanatory power.

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