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Sensitivity of credit ratings to elasticities of financial ratios with respect to macroeconomic variables: A classifier decision tree model for Mexican companies

Sensibilidad de las calificaciones crediticias a elasticidades de las razones financieras respecto a variables macroeconómicas: un modelo de árboles de decisión clasificadores para las empresas mexicanas

Ana Cecilia Parada Rojas, Jorge Omar Razo De Anda*, Salvador Cruz Aké

Instituto Politécnico Nacional, México

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Abstract

The factors that influence a change in credit rating are unknown because the allocation process depends on private companies, so identifying these factors in combination with certain macroeconomic situations is essential to manage the credit risk, beyond the private process of assigning grades. The objective of this paper is to determine a set of rules that allow to firm's management to anticipate the change in the credit rating of a Mexican firm, considering the levels of elasticity of its financial ratios to macroeconomic variables from a data mining approach, through an iterative logit regression fitting process and a classification decision tree model using public data.

JEL Code: C63, G32, C53
Keywords: credit risk; classification and regression trees; data mining

*Corresponding author.
E-mail address: jorgerazodeanda@gmail.com (J. O. Razo De Anda).
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Resumen

Los factores que influyen en un cambio de calificación crediticia se desconocen porque el proceso de asignación depende de empresas privadas, por lo que identificar estos factores en combinación con determinadas situaciones macroeconómicas es fundamental para gestionar el riesgo crediticio, más allá del proceso privado de asignación de calificaciones. El objetivo de este artículo es determinar un conjunto de reglas que permitan a la gerencia de la empresa anticipar el cambio en la calificación crediticia de una empresa mexicana, considerando los niveles de elasticidad de sus razones financieras a variables macroeconómicas desde un enfoque de minería de datos, a través de un proceso iterativo de ajuste de regresión logística y un modelo de árbol de decisión clasificador utilizando datos públicos.

Código JEL: C63, G32, C53
Palabras clave: riesgo crédito; árboles de regresión y clasificación; minería de datos

Introduction

Credit ratings are issued by credit rating agencies that evaluate the issuer's ability to pay, mitigate credit risk, and reduce information asymmetry between the debtor and the lender. Credit ratings are benchmarks not only for debt issuers but also for market signals about the company's financial stability. As shown in the work of Wojewodzki, Poon, and Shen (2018), and Kisgen (2019), credit rating adjustments affect stock price and capital structure.

Due to the changing environment, a company's ability to meet its obligations is not static, leading to a systematic credit evaluation process. Unfortunately, the methodology of the rating process is not publicly available, so it is impossible to identify and measure the variables used to ratify or change a company's rating.

A methodology is proposed to solve this information problem by identifying the factors that influence the change in credit rating from publicly available information, such as related financial ratios and macroeconomic data, which includes an iterative modeling process of logistic regressions and a classification tree. Therefore, this methodology can be classified as an essential credit rating methodology.

Beaber proposed one of the first fundamental credit rating models (1966). The author proposed using financial liquidity ratios to predict the probability of bankruptcy. A similar but more recent approach is the work of Le and Viviani (2018), which uses machine learning techniques on financial ratios to predict credit rating changes. It is also worth mentioning Acosta-González, Fernández-Rodríguez, and Ganga (2019), who also included macroeconomic data and financial ratios for the same purpose.

From the fundamental approach is the seminal work of Altman E. I. (1968), who uses multivariate discriminant analysis to predict bankruptcy. Examples of more recent work in that line are seen in the work of Almamy, Aston, and Ngwa (2016), in which Altman's Z and the cash flow index are used to predict corporate failure, and in the work of Kliestik, Vrbka, and Rowland (2018), who present a discriminant analysis based on financial ratios to reveal unhealthy company development[1].

Probably the most common fundamental model to address the issue of financial distress is Merton's (1974), which is a reference model even today, as shown in the papers by Anuwar and Jaffar (2017) and Lee and Yu (2020) since both papers use it as a basis.

With the evolution of computing power, econometric methods are becoming progressively more critical in the assessment of credit risk. Examples of this trend are works such as Schmid (2012) or Zamore, Djan, K., and Hobdari (2018). Econometric models have used two main methods: qualitative models such as Logit or Probit (Nehrebecka, 2018) and panel data models (Mpofu & Nikolaidou, 2018).

The most commonly used variables in credit risk analysis are financial ratios, according to Woo, Kwon, and Yuen (2020), Mishra and Bansal (2019) or Khemakhem and Boujelbene (2018), and certain macroeconomic variables, as in Dos Reis and Smith (2018) or Hassani and Zhao (2015). In the fundamental approach of the credit risk assessment literature, macroeconomic variables have an important influence on a company's health, but they do so differently depending on the company's characteristics, such as financial situation and structure and industry.

This paper proposes to consider the elasticity of key financial ratios for macroeconomic variables such as the spot exchange rate, Gross Domestic Product, employment, interbank interest rate, and country risk, based on a combination of econometric-computational search of significant variables. Specifically, a Logit fitting algorithm, as in Ramlall (2018), and decision trees, as in Bach, Zoroja, Jaković, and Šarlija (2017), are used to establish hierarchical interactions of risk factors inducing changes in credit rating.

The main objective of this paper is to identify a set of rules to forecast changes in the credit rating of a sample of Mexican companies. The paper's main argument is that if financial ratios are sensitive to macroeconomic variables, then a combination of the elasticities of financial ratios[2] for macroeconomic variables serves as a predictor of credit rating changes.

To identify the appropriate combination of elasticities (out of the 12 financial ratios related to the 10 proposed macroeconomic variables), a logistic fitting algorithm is used to select those that are statistically significant out of the 120 elasticities calculated. Once the screening process is completed, a classifier decision tree is used to find the set of rules that guide the credit rating process.

It is important to note that this method correctly classifies 90.6% of the data, and the results show that the industry to which the companies belong is the first and most important grouping criterion,

[1]The use of financial ratios such as assets ratio to current liabilities, net income ratio to total assets, non-current liability ratio and current liabilities to total assets, cash ratio and cash equivalents to total assets and return on equity.
[2]The financial ratios used are described in the following sections.

followed by the working capital to GDP elasticity, solvency to consumer default, debt to country risk ratio, and inventory turnover to financial market performance.

Section one of the paper reviews the academic literature on financial ratios as triggers for credit rating changes. It also reviews the most common macroeconomic interactions for credit ratings, creditworthiness and, in general, the company's ability to meet its financial commitments. Section two presents the proposed methodology that includes the Logit Delete Worse adjustment algorithm used to select the statistically significant elasticities in credit rating changes. These are used as inputs for the classifier tree model that provides the set of rules to forecast rating changes. Section three presents the analysis of the model results. Finally, the conclusions and future research agenda are presented.

Review of the literature

According to the Basel Committee—BCBS[3]—financial regulations have been strengthened due to recent defaults. A noteworthy regulation is the one requiring that at least two rating agencies must assess the payment capacity of those firms willing to sell debt instruments; for more details, see Hofbauer, Klimontowicz, & Nocoń (2016) and Sbârcea (2014).

As noted in Bonsall and Miller (2017), and Figlioli, Moreira Antonio, and Guasti Lima (2019), credit ratings are market signals capable of changing the cost of debt or the price of equity and, for that reason, are important. Unfortunately, they are not accessible to small companies because only three agencies monopolize this service (S&P, Moody's, and Fitch), which makes them more expensive.

On the other hand, CRAs came under academic and market scrutiny after the 2007 financial crisis (DeHaan, 2017) and (Hassani & Zhao, 2015). For this reason, academics develop models for credit risk assessment. Examples of such efforts are Duffie and Singleton (2012), in addition to a continuous-time approach with Markov chains, as in Koopman and Lucas (2008) and Dos Reis and Smith (2018).

As part of the academic research, the econometric modeling approach to default probability and credit risk assessment uses dichotomous or categorical variable models. Examples of this approach are Hernandez-Tinoco and Wilson (2013) and Hernandez-Tinoco, Holmes, and Wilson (2018).

The econometric approach also has a branch of discriminant analysis (Altman E. I., 2013), (Zmijewski, 1984), or (Peres & Antão, 2017). The main difference between those papers is the explanatory variables they use (financial ratios or company characteristics), but there is no dominant approach for variable selection (Husein & Pambekti, 2015), (Mihalovic, 2016), or (Alifiaha & Tahir, 2018).

[3]Basel Committee on Banking Supervision (BCBS), 2004. Basel II: International convergence of capital measurement and capital standards: a revised framework. Report 107, Bank for International Settlements, Basel.

The variety of approaches and works that explain credit events (defaults and rating changes) can be attributed mainly to the fact that the variable selection criteria are not homogeneous due to the sources of information: internal or external to the company. Korol and Korodi (2010) show no single determinant for insolvency.

The academic literature has a theoretical division between internal and external causes. Internal causes include inefficiencies in resource allocation, capital structure, and company management (see Zhang, Bessler, & Leatham, 2013). Similarly, Altman E. I. (2013) and Brusov, Filatova, Orekhova, and Eskindarov (2018) point to the interest coverage and other debt service ratios and changes in the weighted average cost of capital—WACC—as the main reasons for marking a credit rating change.

On the other hand, authors such as Korol and Korodi (2010) or Hernandez-Tinoco and Wilson (2013) highlight external sources arguing that financial statements do not contain all the relevant information about the company. These authors include macroeconomic and market variables to complement them. Liou and Smith (2006), Alifiaha and Tahir (2018), and Hernandez Tinoco, Holmes, and Wilson (2018) also include market information to improve their predictions or analysis of credit events.

Lack of consensus on the determinants of credit events may occur due to non-normality in financial ratios (Alifiaha & Tahir, 2018) (Linares-Mustarós, Coenders, & Vives-Mestres, 2018) or due to collinearity issues and extreme values. Other authors, such as Fontaine Rezende et al. (2017), opt for a previous treatment for the data, such as: discarding variables through collinearity, regression, and correlation tests or censoring extreme values.

Authors such as West (2000), Li et al. (2017) and Tian, Yong, and Luo (2018) explore the use of new techniques such as machine learning and data mining for consumer credit allocation, risk assessment, or bankruptcy prediction. It is important to emphasize that these techniques make no assumptions about the variables' distributions, variance, or dependence because they eliminate redundancies through iterations or classification.

Among the most effective and popular machine learning and artificial intelligence techniques are artificial neural networks (ANNs). Schmidhuber (2015) and Angelini, di Tollo, and Roli (2008) proposed their use in the financial sector by assessing credit risk using financial ratios.

When the number of variables is cumbersome, or the complexities of the problem are not manageable with traditional methodologies—such as credit rating problems—techniques such as Support Vector Machine (SVM) are a reasonable option to achieve predictions. Lee Y. (2007), Wang (2017), and Prodan-Palade (2017) obtained the same conclusion when comparing supervised learning tools on the same credit risk assessment problem.

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In this paper, the classification and regression tree method, CART, was used. This methodology provides more information than other machine learning techniques, including relationships between explanatory variables, although they accept more significant errors than SVM or ANN (Rokach & Maimon, 2014).

Ruxanda, Zamfir and Muraru (2018) found that financial ratios used as inputs to the CART methodology show better performance in periods of financial distress than either SVM discriminant analysis or econometric techniques.

On the other hand, Barboza, Kimura, and Altman (2017) compare SVM, Random Forest, Bagging, and Boosting techniques with traditional econometric models and ANNs that predict bankruptcies one year in advance. The authors obtained a 10% increase in predictive power. These results were similar to those of Wang (2017) and Wagle, Yang, and Benslimane (2017). For a more detailed review of supervised learning algorithms on credit risk, see Devi & Radhika (2018).

It is important to emphasize that the CART methodology can establish a hierarchy and a set of rules for ranking, as in the rating process, which is the objective. Barboza, Kimura, and Altman (2017) showed that the CART methodology, enhanced by bagging or bootstrapping techniques, can achieve greater accuracy in the results. Most articles using these techniques consider proxy variables to measure credit risk (swaps). Nevertheless, one of the limitations of this research is that changes in the rating assigned directly by the rating agencies were considered, and given that these changes are sporadic, the amount of data is relatively small to apply this type of technique.

Methodology

The proposed methodology consists of three stages. The first consists of calculating elasticities between financial ratios and macroeconomic factors (both are public information). These data provide a dynamic view of the companies' evolution and the macroeconomic environment. In the second stage, unrelated or redundant variables are discarded using a DW Logistic regression adjustment algorithm[4]. Finally, a classification tree of credit events (rating changes) is constructed based on statistically significant elasticities.

[4]Available upon request by e-mail

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Description of the data

This paper uses public macroeconomic information about the Mexican economy[5] and quarterly financial ratios calculated with information from Economática from 1998 - 2018. Apparently, rating agencies have access to the same information as that published[6], so the methodology would capture the same dynamics.

First, from the point of view of internal factors that can generate changes in the credit rating, Table 1 presents information related to the financial ratios, their calculation and description, as well as references to works that have used each of the ratios proposed in this article to describe the financial situation of the companies.

Table 1
Financial ratios description

Liquidity ratios			
Ratio	Name	Description	References
Liquidity ratio	LIQ	Current assets/Current liabilities	(Zmijewski, 1984), (Altman E. I., 2013), (Alifiaha & Tahir, 2018) (Ruxanda, Zamfir, & Muraru, 2018)
Acid test	PBACID	Current assets -Inventories / Current liabilities	(Fontaine Rezende, da Silva Montezano, Nascimento de Oliveira, & de Jesus Lameira, 2017)
Working capital to Assets	RCTA	Current Assets - Current Liabilities) / Total Assets	(Alifiaha & Tahir, 2018), (Altman E. I., 2013), (Fontaine Rezende et al. 2017)
Activity ratios			
Ratio	Name	Description	References
Inventory turnover	RINVT	Cost of sales /Inventory	(Bendig, Strese, & Brettel, 2017), (Elking et al., 2017), (Chuang, Oliva, & Heim, 2019)
Working capital turnover	RCT	Net sales/ Current assets - Current liabilities	(Bendig, Strese, & Brettel, 2017), (Elking et al., 2017), (Chuang, Oliva, & Heim, 2019)
Total assets turnover	RAT	Net sales/Total assets	(Fontaine Rezende et al., 2017), (Ruxanda, Zamfir, & Muraru, 2018)
Financial leverage ratios			
Ratio	Name	Description	References
Debt ratio	RDT	Total liabilities/Total assets	(Hernandez-Tinoco & Wilson, 2013), (Alifiaha & Tahir, 2018),

[5]Compiled from INEGI, the Mexican public entity responsible for the compilation and publication of Mexico's National Statistics https://www.inegi.org.mx/sistemas/bie/

[6]The work uses information from the financial statements published by the companies themselves; therefore, any errors or omissions (deliberate or not) that companies report to avoid downgrades or to improve their rating (creative accounting) are the responsibility of the companies.

Debt to equity ratio	RDTCC	Total liabilities/Total capital	(Hernandez Tinoco, Holmes, & Wilson, 2018), (Ruxanda, Zamfir, & Muraru, 2018), (Kemper, 2020) (Ruxanda, Zamfir, & Muraru, 2018)
		Coverage ratios	
Ratio	Name	Description	References
Interest coverage ratio	RINTD	EBIT/Interest expenses	(Hernandez-Tinoco & Wilson, 2013), (Hernandez Tinoco, Holmes, & Wilson, 2018), (Kemper, 2020)
		Profitability ratios	
Ratio	Name	Description	References
Net income margin	MUT	Net income/Total operating income	(Altman E. I., 2013)
Return on assets	ROA	Net income / Total assets	(Altman E. I., 2013), (Alifiaha & Tahir, 2018), (Ruxanda, Zamfir, & Muraru, 2018)
Return on equity	ROE	Net income / Equity	(Ruxanda, Zamfir, & Muraru, 2018)

Source: created by the authors

Regarding external factors, Hussain et al. (2005) find that Gross Domestic Product has predictive power for estimating financial stress. In this context, the works of Zhang, Bessler, and Leatham (2013), Hernandez-Tinoco and Wilson (2013), Hernandez-Tinoco, Holmes, and Wilson (2018), and Rezende et al. (2017) coincide with the previous one; however, they also incorporate variables referring to interest rates and stock and inflationary indexes.

Among the papers that relate financial ratios of debt, economic activity, and market activity to credit quality are the works of Keenan and Sobehart (1999) and Duffie and Singleton (2012), which show a negative relationship with respect to default rate and GDP growth in the United States up to 1983. In the same respect, Koopman et al. (2012) include the market effect through principal components, and Tang, D. Y. and Yan, H. (2010) use Credit Default Swap (CDS) spreads as a proxy for delinquency in the market.

The above review identifies a consensus in the literature concerning the following variables: Economic Activity Indicator, Stock Market Indicator, Benchmark Interest Rates, Inflationary Indicator, and Delinquency Rate[7]. In order to incorporate the effect of these variables, Table 2 shows the description, source, and periodicity of the variables used for the Mexican case.

[7]The default rates are constructed as the ratio of non-performing loans to total loans in consumer and mortgage loans, respectively.

Table 2
Description of macroeconomic variables

Variable	Description	Source
PIB (GDP)	Gross Domestic Product (Millions of Mexican pesos, 2008)	(National Institute of Statistics and Geography, INEGI, 2020)
INPC (NCPI)	National Consumer Price Index	(National Institute of Statistics and Geography, INEGI, 2020)
TC	Exchange rate, end of quarter (Mexican peso per U.S. dollar)	(Bank of Mexico, BANXICO, 2020)
TIIE	Interbank interest rate, 28 days	(Bank of Mexico, BANXICO, 2020)
PIBI	Economic indicator of secondary activities	(National Institute of Statistics and Geography, INEGI, 2020)
PIBS	Economic indicator of tertiary activities	(National Institute of Statistics and Geography, INEGI, 2020)
MC	Commercial bank delinquency rate, consumption	(Bank of Mexico, BANXICO, 2020)
MV	Commercial bank delinquency rate, housing	(Bank of Mexico, BANXICO, 2020)
IPC (CPI)	Price and Quotations Index, Mexican market, BMV	INVESTING
RP	CETES (28-day) and U.S. T-Bills rate differential	(Bank of Mexico, BANXICO, 2020), (Federal Reserve Bank of Saint Louis, 2020)

Source: created by the authors; quarterly data from 1998 to 2018

Long-term corporate ratings published by Fitch Ratings and Standard & Poors are used. The long-term rating correspondence table in Annex 1-B[8] is used to homogenize them. Information is available for 28 debt issuing companies[9]; 23 rated by Fitch, 17 by S&P, and 12 by both companies, throughout each quarter of the 1998 Q1 - 2018 Q2 period. A value of "0" is assigned to each period with no change in the credit rating and "1" in case of change (better or worse rating). 120 elasticities[10] are calculated, and all periods are filtered out (companies with no credit ratings assigned) so that 224 quarterly observations are available.

Discrimination of elasticities: Delete Worse (DW) algorithm

A Delete Worse (DW) algorithm based on logistic regression models is used to discard non-statistically significant elasticities. The DW methodology consists of iteratively discarding non-statistically significant

[8]Resolution amending the general provisions applicable to credit institutions: http://dof.gob.mx/nota_detalle_popup.php?codigo=5186974

[9] ARCA CONTINENTAL, ALSEA, AMERICA MÓVIL, TV AZTECA, BACHOCO, BIMBO, CEMEX, CHEDRAUI, CREAL, CULTIBA, ELEKTRA, ELEMENTIA, FEMSA, GRUPO AEROPORTUARIO DEL PACÍFICO, GRUPO CARSO, HERDEZ, ICA, IENOVA, INMUEBLES CARSO, KIMBERLY CLARK, COCA COLA, GENNOMA LAB, LIVERPOOL, MEXICHEM, PEÑOLES, RADIO CENTRO, SORIANA, TELEVISA

[10]The elasticities between financial ratios and macroeconomic variables are obtained from the division between the rates of change of each of the 12 ratios in combination with the rates of each of the 10 macroeconomic variables $\varepsilon_{x_i,y_j} = \frac{v\_x_{it}}{v\_y_{jt}} = \frac{(x_{it}-x_{it-1})/x_{it-1}}{(y_{jt}-y_{jt-1})/y_{jt}}\ \forall i,j$, where x_{it} is the i-th financial ratio for the quarter

elasticities until the algorithm reaches a Logit model with all significant variables at a 95% confidence level. To avoid the problem of collinearity and consider the collective explanatory capacity of the variables in a model, the algorithm was run with different initial sets of variables, and the statistically significant variables were kept in each run. In the first instance, 60 regressions are performed on sets with pairs of elasticities, followed by 40 regressions on triplets and finally, 24 regressions on quintets. From the significant elasticities resulting from these processes, a list of 28 different elasticities is constructed, from which the DW algorithm consisting of 13 additional regressions is run, concluding with a list of 15 elasticities. Table 3 describes the logistic model using the 15 statistically significant variables.

Table 3
Statistically significant elasticities after running the DW algorithm

(Intercept)***	E_RDT_RP*	E_MUT_TIE*	E_RINVT_IPC*
E_RCTA_PIB*	E_RDTCC_RP*	E_PBACID_MC.	E_RDTCC_IPC*
E_ROA_INPC*	E_RDT_TIE.	E_RINTD_MC*	E_LIQ_MC*
E_ROE_INPC*	E_RINVT_MC.	E_LIQ_IPC*	E_ROA_IPC*

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$ Mac Faden's pseudo R2 = 0.31, 62.94% model accuracy. Source: created by the authors using (R Core Team, 2020). The variable code is created as: E_financial ratio_macro variable.

Table 4
Classification of companies on the Mexican Stock Exchange (BMV)

Sector	Subsector
1) Energy	Energy
2) Industry	Capital assets
	Construction*
	Transportation
3) Materials	Materials*
4) Frequent consumption goods	Food, beverages, and tobacco
	Personal or household products
	Sale of frequent consumption products*.
5) Health	Pharmaceuticals, biotechnology, and health sciences
6) Telecommunication services	Communications and media
	Telecommunication services
8) Non-core assets and services	Consumer Services
	Retail sales

Source: created by the authors with information from the Mexican Stock Exchange.
*Sectors identified as discriminants of group 2 of the model (see Table 7).

Decision trees: CART model

Decision trees are flexible, non-parametric models that capture the interactions between variables conditioning decisions. In the literature, this is called rules: constructing combinations of input values to obtain an output (Faraway, 2016). In these models, the results depend on the individual decisions made at

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each tree node. A CART model classifies values into a set of defined classes based on sample characteristics.

To prevent the classification and regression tree—CART—from overfitting the model, the tree must be "pruned." The pruning process consists of eliminating the final nodes that do not greatly diminish the model's explanatory power (deviation error)[11]. In this model, the 15 elasticities taken from the previous steps plus two categorical variables (sector and subsector of the company) were used according to the classification of the BMV, which are shown in Table 4, following the works of Liou and Smith (2011) and Karkinen and Laitinen, (2015) who mention that the sector or industry are discriminants that can affect the financial operations of a company.

Using the "tree" library (Ripley, 2019) in R, a tree with 17 end nodes was found that classifies 90.6% of the observations. A pruning value, α = 7.01 (corresponding to the median), is used to minimize the complexity cost[12]. As a result, a classification tree with 13 nodes (7 end nodes) was obtained. Figure 1 shows the decision tree in which the rules that indicate a change or no change of rating are displayed.

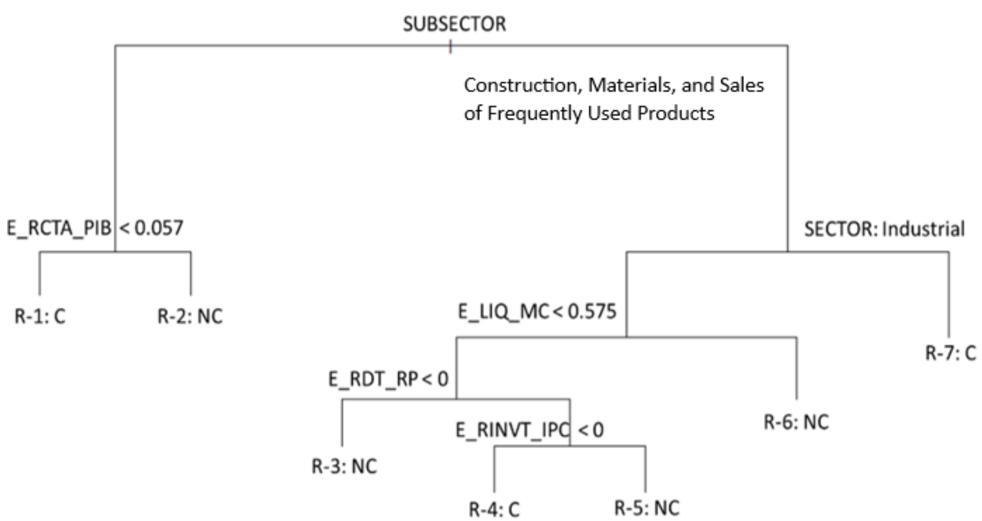

Figure 1 .Classification tree, α = 7.01 Tree impurity, $\mathrm{D} = 119.5$, with mean residual error, $\mathrm{E} = \mathrm{D}/(\mathrm{n}-7) = 0.55$
Source: created by the authors using "tree" (Ripley, 2019) in R Project (R Core Team, 2020)

[11]The deviation is defined as: $D = \sum_k D_k = \sum_k -2n_k[n_k^C \ln(n_k^C) + n_k^{NC} \ln(n_k^{NC})]$

Table 5
Significant variables in the pruned tree

Variable	Financial ratio	Macroeconomic Variable
E_RCTA_PIB	Working capital to assets	Gross Domestic Product
E_LIQ_MC	Liquidity ratio	Commercial bank default ratio, consumer
E_RDT_RP	Debt ratio	Spread between Mexican CETES (28 days) and U.S. T-Bills
E_RINVT_IPC	Inventory turnover	Price and Quotations Index

Source: created by the authors with the "tree" package (Ripley, 2019).

The model shows that the main classification criteria are the economic sector and sub-sector, revealing different sensitivities to macroeconomic values depending on the industry[13]. The model establishes greater sensitivity in the construction, materials (both highly procyclical), and consumer staples sectors. Table 5 shows the elasticities that make up the pruned tree classification rules.

The misclassification rate (MC) is calculated to evaluate the classification tree, which measures the model's ability to generalize an example with a confidence level (Rokach & Maimon, 2014). A cross-validation test is also performed by generating four mutually exclusive random subsamples with an average MC of 8.5%.

Table 6
Precision and accuracy of the model

Confusion matrix			Rule/Exception			Accuracy	
	Estimate (C)	Estimate (NC)		C	NC	C	NC
Examples (C)	18	19	C	0.49	0.51	0.9	0.09
Examples (NC)	2	185	NC	0.01	0.99	0.1	0.91

Source: created by the authors based on (Rokach & Maimon, 2014)

As a final check of the model, a confusion matrix is calculated (see Table 6) as in Chapra (2012) or Rokach and Maimon (2014). The pruned model has an accuracy rate of 90.62%.

Analysis of results

Once the classification tree and confusion matrix are obtained, the credit rating change rules from the model are presented in Table 7.

[13]Main argument of the CAPM model

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The right branch of the tree (Figure 1) represents the second group of companies (6) belonging to the subsector: Construction, Materials or Frequent Consumption, see Table 4. In group 1, the probability that one of these companies will receive a rating change is only 8%; however, the model identifies the elasticity between the working capital ratio and the growth of Gross Domestic Product (E_RCTA/GDP) as the main criterion to explain possible rating changes.

Table 7
Classification tree rule set

RULES					
Rule #		Condition			Likelihood
Group 1					
1	IF	E_RCTA_PIB < 0.0564335	→	C	0.08
2	IF	E_RCTA_PIB > 0.0564335	→	NC	0.96
Group 2					
3	IF	E_LIQ_MC < 0.57 & E_RDT_RP < 0	→	NC	0.81
4	IF	E_LIQ_MC < 0.57 & E_RDT_RP > 0 & E_RINVT_IPC < 0	→	C	0.98
5	IF	E_LIQ_MC < 0.57 & E_RDT_RP > 0 & E_RINVT_IPC > 0	→	NC	0.56
6	IF	E_LIQ_MC > 0.57	→	NC	0.92
7	IF	Sector = 'Industry' & Subsector='Construction'	→	C	0.84

Source: created by the authors based on the classification tree

The interpretation of the model is that the order of the rule implies hierarchy. For example, Rule 4 states that, in group 2, if the elasticity of the current ratio of liquidity to default, E_LIQ_MC, is less than 0.57 (step 1), and the elasticity of the debt to country risk ratio, E_RDT_RP, is greater than zero (step 2), and, in addition, the elasticity of inventory turnover to the Price and Quotations Index, E_RINVT_IPC, is less than zero (step 3), then there is a 0.98 probability of having a change in the credit rating.

The article's results are not surprising, as they relate the asset working capital to GDP ratio, E_RCTA_GDP, as the main source of credit rating changes due to its relationship with the company's short-term ability to meet its financial commitments without external money.

The model also relates the current ratio to delinquency, E_LIQ_MC, meaning that if there is widespread difficulty in collecting debts, companies will have fewer liquid resources and accounts receivable will be less valuable. The next significant elasticity is the borrowing rate spread over short-term interest rates between Mexico and the United States, E_RDT_RP; this implies that companies that are transnational or strongly related to the U.S. market make financing decisions considering the country risk induced by the rate differential. The increase in the relative cost of money between currencies (exchange rate depreciation) directly demands more liquid resources.

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Conclusions

The results of this work show the dynamic nature of a company's ability to meet its financial commitments, in addition to identifying the effect of the macroeconomic environment on the company's rating. Moreover, the set of rules obtained from the classification tree analyzes the closed credit rating process.

The structure of the model (set of rules) reflects the traditional and empirical knowledge about the behavior of the company's ability to pay its debts related to the internal process of the company, such as inventory turnover, liquidity, or working capital to macroeconomic variables, considering the sector to which the company belongs.

The CART model identifies a set of 7 rules (described in Table 7) based on a combination of criteria representing a company's financial situation and its sensitivity to the macroeconomic environment to forecast possible rating changes.

Rating changes for Mexican companies belonging to the materials and sales of frequent consumption products subsectors (group 2) are susceptible to financial ratios related to liquidity, indebtedness, and activity ratios, as well as their sensitivity to country risk, consumer default, and capital market. In contrast, for most of the companies in the sample (group 1), the rating depends on the sensitivity of the working capital ratio to economic activity as measured by domestic production. It is important to mention that the significant elasticities indicate a relationship between the company's corporate governance and different types of risk: market, credit, and liquidity.

The proposed methodology combines the best of the two branches of credit rating analysis: the power of computational analysis (step 1, obtain the 10 macroeconomic variables * 12 financial ratios * companies * number of quarterly observations) with the traditional econometric approach (step 2, performed based on the logistic regression model through the DW fitting algorithm that estimates 137 regressions) with the use of a supervised learning technique (step 3, classifier tree and pruning).

The CART model allows company financial managers to identify risk factors and macroeconomic environments that jeopardize the company's ability to meet its financial commitments. It also allows them to manage these credit, market, and liquidity risks within the margins provided by each company's respective elasticities.

Future research includes applying the methodology to companies in other countries and comparing whether the rules are maintained. Another possible line of research is to implement the methodology to other types of risk or rating changes; for example, that issued for short-term debt. This methodology can also be improved by including bagging or bootstrapping techniques as long as more observations are incorporated.

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