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Evaluando el modelo de *Puntuación Z''* de Altman para determinar su nivel de precisión en empresas mexicanas
Testing Altman's *Z''-Score* to assess the level of accuracy of the model in Mexican companies

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Resumen

Introducción: en 1968, Altman desarrolló un modelo multivariado predictivo denominado *Puntuación Z* para evaluar la posibilidad de quiebra en empresas públicas manufactureras. Posteriormente, Altman (1983) rediseñó el modelo de *Puntuación Z''*, mejorándolo para su aplicación en empresas públicas y privadas, manufactureras o no manufactureras, incluso en países emergentes. El nivel de predicción del nuevo modelo demostró ser altamente eficiente. Esta investigación evaluó el nivel de precisión del modelo aplicado en empresas listadas en la Bolsa Mexicana de Valores, ya que la investigación en este tema es muy escasa.

Método: la presente investigación fue realizada mediante un enfoque cuantitativo a través de un censo de alcance situacional con un corte longitudinal. El periodo cubierto fue 2012-2019, pues en este intervalo se tuvo cierta estabilidad económica sin altibajos significativos. El estudio incluyó la integración de una amplia base de datos y el diseño de una tipología para clasificar y analizar 155 empresas, basándose en la desviación estándar y el promedio de resultados de 837 puntuaciones Z''. Un segundo análisis fue conducido para probar si la predicción de la situación (área asignada) por la *Puntuación Z''* correspondía con la situación real del mercado de cada empresa.

Resultados: los resultados obtenidos mostraron que el nivel de precisión del modelo disminuyó cuando se aplicó al censo de empresas mexicanas. El error del modelo aplicado a empresas mexicanas, y que fueron ubicadas en la zona de predicción de bancarrota, fue del 75 % de casos de error en su clasificación. El error total del modelo, incluyendo todos los casos y todas las zonas, fue del 18 % basado en la incorrecta clasificación de empresas. Se espera que el modelo sea efectivo dentro de un margen de tiempo de dos años previos a la posible bancarrota. Aun considerando un periodo más largo, las compañías ubicadas en la zona de predicción de bancarrota continuaron manteniendo un 57 % de error en su clasificación. El error total del modelo, incluyendo todas las empresas y todas las zonas clasificadas, siguió manteniendo un 14 % de error en sus clasificaciones. Esto representó un alto nivel de ineficiencia del modelo aplicado a países emergentes, en este caso México.

Discusión o Conclusión: el modelo es ciertamente efectivo al predecir la ubicación de empresas en las zonas de no-bancarrota o gris, pero resultó ser ineficiente al predecir la posibilidad de bancarrota. También fue demostrado que el periodo de dos años ya no es efectivo al aplicar el modelo a empresas mexicanas. Se evidencia que se requieren más casos de investigación para poder calibrar de nueva cuenta el modelo, a fin de que pueda ejecutarse eficientemente en países emergentes, tomando en cuenta condiciones específicas del país y considerando un periodo de diferente para predecir la bancarrota.

Abstract

Introduction: in 1968, Altman developed a multivariable predictive Z-score model to assess the probability of a public manufacturing company going to bankruptcy based on financial ratios. Later, Altman (1983) re-stated a more improved *Z''-Score* model designed to apply in public or private, manufacturing, or non-manufacturing firms, but also in emerging countries. Prediction of the updated model proved to be highly efficient. This research was conducted to prove the level of accuracy of the *Z''-Score* model applied to firms listed in the Mexican Stock Exchange (MSE) since there is little relevant research on this subject.

Method: this research was conducted under a quantitative approach as a census and its scope was situational with a non-experimental and longitudinal research design. The period covered by this research was 2012-2019 since the data was available for those years under a somehow stable economic situation without significant economic ups and downs. This research considered the integration of a large financial database and the design of a typology to classify and analyze 155 firms based on a standard deviation and average results of 837 Z''-scores. A second analysis was conducted to prove if the predicted situation (area) by the *Z''-Score* corresponded to the real situation in the marketplace for every company.

Results: the results showed that the accuracy level of the Altman model decreased when applied to Mexican firms. The error of the model applied to Mexican companies related to those classified in the bankruptcy prediction area was 75 % of misclassification cases. The total error of the model included all areas, or cases, was 18 % of misclassification cases. This model is supposed to be effective within a time frame of two years before a possible bankruptcy. Even considering a longer time frame, the companies located in the bankruptcy prediction area continued having misclassifications representing 57 % of error. The error for the model considering all cases and all areas, was 14 % of misclassification cases. This represented a high level of inefficiency of the model applied to an emerging country companies, such as Mexico.

Discussion or conclusion: the model is certainly effective while predicting companies in the areas of non-bankrupt sector and grey, but it was inefficient when predicting the possibility of bankruptcy. It was also demonstrated that the time frame of two years is no longer effective when applying the model to Mexican companies. As a result, more research cases are needed to update the model to perform efficiently in emerging countries including country-specific conditions and considering a different time frame to predict bankruptcy.

Introduction

The history of financial evaluation of a firm using financial ratios is already more than a century old. Beaver (1966) points out that "At the turn of the [XX] century, ratio analysis was in its embryonic state. It began with the development of a single ratio, the current ratio, for a single purpose—the evaluation of creditworthiness" (p. 71). In 1969, Beaver mentioned that ratio analysis involved the use of several ratios by several users including credit lenders, credit-rating agencies, investors, and management. Today, "contemporary tools of financial analysis which always focus on the future and whose emerging is based on the criticism of traditional financial analysis indicators, particularly the profit indicator, measure either the company's potential to produce value for the owners (EVA) [Economic Value Added], cash flow return on investment (CFROI) or the value at risk (VaR); or assess a company as an investment opportunity" (Vimrova, 2015, p. 170).

The use of financial ratios analysis to predict or estimate the possibility that a firm may go into bankruptcy has been developed since the first decades of the 20th century until today. The interest regarding this subject has led to classify the consequences that the situation of probability of bankruptcy of a company may have in four categories. Those categories include: "(i) financial reporting and auditing consequences, (ii) firm-level operational consequences, (iii) capital market consequences and (iv) corporate governance consequences" (Habib *et al*., 2020, p. 1023). According to Horrigan (1968), the need to carry out a financial analysis grew in the last half of the 19th century when companies had industrial maturity and the banks needed to conduct more credit analysis. Among the main authors for bankruptcy prediction, Altman (1968) is well known for developing a Z-score model designed to predict bankruptcy in public manufacturing firms. Later, in 1983, Altman improved the model to also be applicable in private, non-manufacturing and emerging countries' firms. Altman's *Z''-Score* model has been widely disseminated but also tested by a various number of authors (Balcaen & Ooghe, 2006; Bauer & Agarval, 2014; Grice & Ingram, 2001; Jackson & Wood, 2013; Kumar & Ravi, 2007; Xu & Zhang, 2009) implementing different types of analysis. Nevertheless, the recent updated research that Altman *et al.* (2017) have conducted shows that the *Z''-Score* model has still been highly efficient in all samples applied around the world, including firms in emerging countries.

This research provides significant evidence to evaluate the level of accuracy of the *Z''-Score* model based on the performance of Mexican firms listed in the Mexican Stock Exchange (Bolsa Mexicana de Valores, BMV) during the period of 2012-2019. This period was selected based on information availability and because this period showed to be economically stable without any significant upturns or downturns. The present study provides a literature review that builds a framework of bankruptcy prediction history based on Altman's model. The findings demonstrate what the actual level of accuracy is of the model applied in the context of Mexican firms in an emerging country. Thus, this study makes a significant contribution to the limited research on the bankruptcy prediction in emerging countries, specifically in Mexico, to assess the model's accuracy that could allow managers, investors, and creditors to make the best decisions.

This paper is organized in four sections. The first section provides a literature review regarding the origin of bankruptcy prediction until the actual situation of the *Z''-Score* model. The second describes the research design of the study: Methodological analysis and typology of firms.

The third section examines the results of the testing on accuracy of the *Z''-Score* model applied to Mexican firms. Finally, the last section presents the conclusions of the paper.

Literature review

The research studies conducted during the first two decades of the 20th century related to financial ratios included, among others, the one from Wall (1912). Wall compiled seven ratios of 981 firms for an unspecified period and stratified them by industry and geographic location. Another study carried out by the Du Pont Company in 1919 included the triangle system of profit, assets, and sales as a foundation for ratio analysis. These two studies did not focus directly on ratios as predictors of business failure, but they set the basis for a new explosion of ratio analysis during the 1920s (Horrigan, 1968). This would become the starting point for later research studies related to bankruptcy conducted by Beaver and Altman in late 1960s.

According to Swart (1936) and Beaver (1968), the first study on failing firms to appear was in 1932, when Fitz Patrick examined a sample of thirty-eight companies including failed and non-failed companies. The study determined that there were significant changes in ratios for at least three years prior to failure. This result was the foundation for later authors to explore the time prediction variable. Horrigan (1968) mentions that:

> Winakor and Smith (1935) began their analysis on a sample of firms which had experienced financial difficulties during the 1923-1931 period. They analyzed the prior ten years' trends of the means of 21 ratios and concluded that the ratio of net working capital to total assets was the most accurate and steady indicator of failure, with its decline beginning ten years before the occurrence of financial difficulty. By this research they added the concept of impact of the cash measures to the actual models of bankruptcy. However, their study suffered the shortcoming of lacking a contrasting control group of successful firms; this was a serious shortcoming (p. 288).

The first serious and sophisticated ratio analysis study as a predictive and statistic credible business failure predictor was by Mervin (1942). Mervin conducted a statistic method during a period of eleven years on five different types of industries to analyze failure and non-failure businesses. The author found that "a comparison of selected credit ratios for continuing and discontinuing companies reveals signs of comparative weakness in the latter as early as four or five years before the date of discontinuance" (Mervin, 1942, p. 3). Mervin's research was indeed one of the major contributions for future research on bankruptcy of businesses. Later, Beaver (1966) conducted a study to develop a mechanism for financial analysis applied to prediction of a firm's failure. Beaver's (1966) research included five years prior to failure financial data of 79 failed firms and five years prior according to the years that were assigned to their failed paired samples of 79 non-failed firms within the period of 1954-1964. Firms were selected from the Moody´s Industrial Manual that were only industrial publicly owned. The selected failed firms were bankrupt, involved non-payment of preferred stock dividends, and had bond defaults or had an overdrawn bank account. Firms were also selected according to industry classification (38) and asset size using a pair-sample design. Beaver (1966) recognized that the study's results applied only to this kind of firms and that there was a major need to also study non-publicly owned and non-industrial firms. As well, the paired-sample design that Beaver used was not able to predict the failure of a firm under a single observation. In his study, the author (1966) selected all the firms with 30 ratios divided into six groups. The analysis was carried out by using a comparison of means (profile), a dichotomous classification (failed/non-failed) test, and an analysis of likelihood ratios (histogram). The results identified six financial ratios that were most likely predictive based on the highest percentage of failure prediction in each group: 1) cash flow/total debt; 2) net income/total assets; 3) total debt/total assets; 4) working capital/total assets; 5) current ratio; and 6) no-credit interval. This prediction was based on a bivariate normality, with some limitations, but Beaver's study demonstrated that asset size was not a directly correlated variable that would affect the prediction power of the proposed study. Recognizing the limitations of his study, Beaver (1966) also demonstrated that not all selected ratios have the same impact on prediction of a firm's failure, but each ratio has a different level of impact on it. This finding set up the basis for other authors to conduct further research on a weighted analysis of ratios. Beaver (1968) conducted another study related to alternative accounting measures as predictors of failure. He used the very same number of firms, period, and source of information that was used in his 1966 study. The new study included the selection of 14 ratios placed into three groups, one group of non-current assets including three ratios, and two more groups of current assets including 11 ratios. The research was based on the initial premise that current assets-based ratios were better predictors in the previous years of failure. Beaver (1968) also found that contrary to the initial premise, the error in predicting a failure classification for a firm through non-current assets was much lower than the ratios calculated on current assets, cash flow or net income. In addition, he found that many of the traditional assumptions for selecting the main or popular ratios for failure prediction were not a reliable criterion. For example, in his study he found “that the two less frequently advocated measures, net working capital and cash, outperformed current assets and quick assets, the two more frequently advocated measures” (Beaver, 1968, p. 119).

Since Beaver’s (1968) study was conducted under a univariate analysis, Altman decided to conduct a multivariate analysis. Altman’s work was preceded by Beaver’s research carried out in 1966 and 1968.The last study was published in January of that year while Altman’s first paper was published in September of 1968, a difference of 9 months. Nevertheless, Altman makes no mention of Beaver’s name but Altman´s work provides a strong critique of the nature of a univariate analysis. Altman (1968) researched the prediction of bankruptcy under a more rigorous statistical technique named multiple discriminant analysis (MDA). He used a sample of 66 manufacturing companies and grouped them into 33 bankrupt companies and 33 non-bankrupt companies. The results obtained by Altman (1968) identified “which ratios are the most important in detecting bankruptcy potential, what weights should be attached to those selected ratios, and how should the weights be objectively established” (p. 591). For all the sample firms selected, a total of 22 financial ratios were compiled for evaluation and they were classified in five categories: liquidity, profitability, leverage, solvency, and activity. The discriminant function was transformed to a single discriminant score, or Z value where discriminant coefficients (weights) and independent variables (ratios) were determined. Altman (1968) concluded that all firms having a Z score of greater than 2.99 clearly fall into the "non-bankrupt" sector, while those firms having a Z score below 1.81 are all bankrupt. The area between 1.81 and 2.99 was defined as the "zone of ignorance" or "gray area" because of the susceptibility to error classification. So, the Z-score discriminant function remained as follows:

$$Z= 1.2\ X1 + 1.4\ X2 + 3.3\ X3 + 0.6\ X4 + 1.0\ X5$$

Where:

X1= Working capital/Total assets

X2= Retained Earnings/Total assets

X3= Earnings before interest and taxes/Total assets

X4= Market value equity/Book value of total debt

X5= Sales/Total assets (Altman, 1983).

The discriminant model proved to be exceptionally accurate using financial information of one year prior to bankruptcy but, it was also significantly accurate with results of two years prior to bankruptcy.

In 1977, Altman *et al*. developed a new revised model of the original Z-score and registered it as the ZETA analysis. The new model improved the accuracy of prediction by measuring a new sample of seven financial ratios. Several years later, Altman (1983) again re-estimated the model to adapt it, and to include prediction for private manufacturing firms. As well, he developed the "revised Z'-score model" in which the market value was substituted by the book value and the weights of the five variables formula had to be re-stated. However, in 2017, Altman *et al.* analyzed the accuracy of a new revised four-variable *Z''-Score* model that excluded the Sales/Total assets ratio, X5, from the revised model" (p. 136). The other variables of the formula remained the same as in the revised Z'- score but the weights were re-stated. So, the new *Z''-Score* discriminant function was determined as follows:

$$Z'' = 6.56\ X1 + 3.26\ X2 + 6.72\ X3 + 1.05\ X4$$

Where:

X1 = Working capital/Total assets

X2 = Retained earnings/Total assets

X3 = Earnings before interest and taxes/Total assets

X4 = Book value equity/Book value of total debt

Where $Z'' < 1.10$ indicates bankruptcy prediction

$1.10 \geq Z'' \leq 2.60$ indicates grey area (ignorance)

and $Z'' > 2.60$ indicates non-bankrupt sector (Altman, 1983).

The *Z''-Score* could be applied to all kinds of firms, including small and medium companies. The model was tested under the univariate and multivariate discriminatory tests and Altman (1983) concluded that the results of the analysis "showed impressive evidence that bankruptcy can be predicted as much as two reporting periods prior to the event" (p. 125). This new version of the model showed 90.9 % of successful prediction of firms in a bankruptcy situation and 97.09 % of successful prediction of firms in a non-bankrupt situation. The average efficiency of the model was 93.94 % and this demonstrates only 6.06 % of error.

Application of the *Z''-Score* model in developing countries

Regarding the application of *Z''-Score model in developing countries*, Altman *et al.* (2017) mention that,

> Grice and Ingram (2001) used a novel dataset of US firms and posed three questions about the efficacy of Altman's model, concluding that the prediction accuracy of Altman's model had declined over time and that the coefficients of the model had significantly changed, which means that the relation between the financial ratios and the signs of financial distress had changed over time. (p. 138)

Other researchers used different methodologies of analysis to evaluate bankruptcy based on conditional probability (Balcaen & Ooghe, 2006), artificial intelligence (Kumar & Ravi, 2007), logit, neural and contingent claims (Jackson & Wood, 2013), and accounting based, market based and hazard models (Bauer & Agarval, 2014). Yet, Altman's MDA analysis proved to perform accurately in the updated model. Findings of Altman *et al*. (2017) demonstrated that the model was still accurate including prediction in other countries but, including some country-specific variables the accuracy of the model could grow. This was confirmed by Manaseer and Oshaibat (2018) in their research on Jordanian insurance companies by recommending that the Altman model should use other variables, such as the prevailing economic conditions to predict a true image of the company in the economy. Gao *et al.* (2018) stated that there is high volatility in the results between countries when it comes to methodologies applied to emerging markets. "The economic environment, legislation, culture, financial markets, and accounting practices in a country may affect the financial behavior of firms and the boundary between bankrupt and non-bankrupt firms" (Altman *et al.*, 2017, p. 145). However, Anuj *et al.* (2018) found in their study on Indian steel companies a good level of competitiveness for the *Z''-Score*. Also, Begovic *et al.* (2020) discovered in their research on Serbian firms a high accuracy of the model, and Bermeo and Armijos (2021) demonstrated that the Z2 model (*Z''-Score*) had a better level of efficiency than the original Z-score in construction companies in Ecuador. Nevertheless, despite these findings, there have been more studies that underline the need of adapting the model to specific contexts. This was corroborated by Panigrahi (2019) in his study on Indian pharmaceutical companies where he acknowledged a possible restriction of his study due to geographical limitation. Prasetiyani and Sofyan (2020) concluded that calibration of the model is needed for country specific conditions on Indonesian firms. Fito *et al.* (2018) mentioned that the predictive power of the model increases when its formulation is adapted to the context of the analysis.

In this respect, Altman *et al.* conducted in 2017 a study to test the *Z''-Score* model in an international environment including some developing countries. Based on the feedback received in prior years to the applicability of the *Z''-Score*, Altman *et al*. tested several hypotheses related to the subjects of validity of coefficients, statistical method of estimation, year of bankruptcy, size of the firm, age of the firm, industry of the firm, and country of origin. Altman *et al.* (2017) also tested other similar techniques to MDA such as the logistic regression analysis (LRA), but performance results were similar. Even additional variables were tested, and the improvement of the model was not strong but variation in the effects were stronger by country. Consequently, Altman *et al.* (2017) found that "it is obvious that while a general international model works reasonably well, for most countries, the classification accuracy may be somewhat improved with country-specific estimation" (p. 167). In this sense Xu and Zhang (2009) made a similar conclusion. Altman *et al.* (2017) concluded that the original *Z''-Score* model performs very satisfactorily in other firms of other countries. The results included evidence to assure that original coefficients using MDA are not obsolete but extremely robust across countries and despite the time variable, even using the LRA method. On the other hand, bankruptcy year and size of the firm showed stronger variations, but such variations are stronger between countries. Nevertheless, the variables of age, industry and country showed marginal variations. According to Altman *et al.* (2017), further research should focus on other modifications and extensions to their study such as testing its usefulness with data from emerging markets. This last statement is the basis of this research which focused on testing data of Mexican firms listed in the Mexican Stock Exchange.

Method

The firms for this research were selected as a population of companies listed in the Mexican Stock Exchange, an emerging market. The specific source for the researched data were the annual reports and other financial statements available in the BMV for the selected companies. This research was conducted under a quantitative approach as a census and its scope was situational with a non-experimental and longitudinal research design. The period covered for this research was 2012-2019 since the data was available for those years under a somewhat stable economic situation without significant economic ups and downs. Since there could be a possible impact of previous economic crisis in the selected companies' financial performance, the 2012 year was selected as the initial year of study to allow at least three years of recovery from the latest known crisis in 2008. In that sense, the selected period provides a more standardized and stable period of financial information. A methodological analysis proposal was elaborated as described in fig. 1. Since Altman *et al.* (2017) proved in their latest research that the variables of age, industry and statistical method were not of significant impact on the *Z''-Score* model prediction, the census of firms listed in the BMV constituted a homogenous data based. Even reputation was a homogenous variable according to Diogenes *et al.* (2020) that found signs that companies with a high reputation have a lower risk of bankruptcy, which was the case of firms in the BMV.

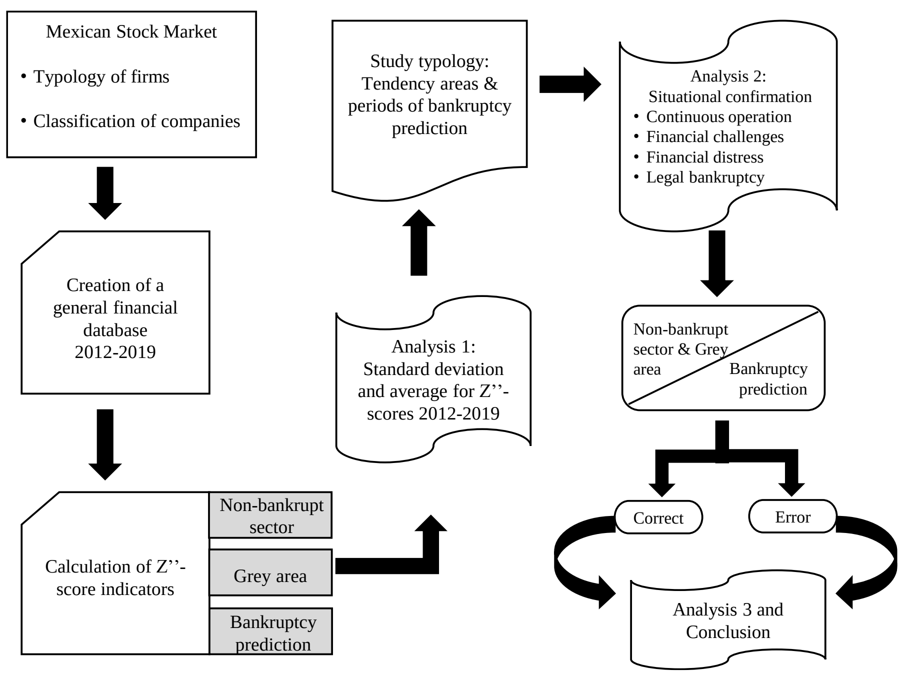

Fig. 1. Methodological analysis proposal for the study.
Fig. 1. Propuesta de análisis metodológico para el estudio.

As a first step, a census of the total listed Mexican companies was conducted, and a typology was identified. According to the BMV typology, a total of 170 companies whose shares are listed in the market were identified. The Mexican stock exchange is small since the companies listed represent less than 0.2 % of the total existing Mexican companies. Nevertheless, this group of companies produce nearly 50 % of the total income of all Mexican firms (INEGI, 2019). In the census, four companies were eliminated from the list at the time this research was conducted, six companies were suspended in the stock market, 15 companies had changed their name or had merged with other companies, and 30 firms were financial companies including the BMV as a corporation. Since the *Z''-Score* was not designed for these kinds of companies, the final census figures were reduced to obtain the annual report and financial statements of 115 firms selected for this research. The study included financial data for 38 % of non-manufacturing companies and 62 % of manufacturing companies.

The following step was to create a general financial database for the years 2012 to 2019 based on the annual reports published by all the companies listed in the BMV. All data from the financial statements for the variables included in the *Z''-Score* model was captured and concentrated in an Excel database to determine the final scores. Next, the results for all Z''-scores were classified into three areas determined by the model: non-bankrupt sector, grey area (or ignorance area) and bankruptcy prediction. The first analysis was conducted calculating the standard deviation, average *Z''-Score* indicator and the upper and lower limit of all Z''-scores per company during the period of study and all companies were classified in each one of the three areas. Results are shown in Appendix A.

A typology for all companies was created to determine the tendency of the *Z''-Score* and to allocate companies into one of the 17 classifications identified based on the propensity to bankruptcy or not in a company. The 17 classifications were place into two groups: 1) non-bankrupt sector and grey area group, and 2) the bankruptcy prediction group, including the number of periods in which the *Z''-Score* appeared to predict a bankruptcy. Later, a second analysis was conducted to determine the operational situation of the companies in the real market to confirm their actual situation regarding four possible options: continuous operation, financial challenges, financial distress, or legal bankruptcy. The first two situations would provide evidence that a company has either none or not significant financial problems that could possibly make them fall into bankruptcy. The last two situations would provide evidence to predict significant financial distress or even existence of a legal bankruptcy process in the companies.

The results obtained were used to conduct the third and final analysis to determine in which cases the *Z''-Score* tendency agreed with the real situation of the company in the marketplace and hence established the percentage of assertiveness or error in the two predicted groups. The *Z''-Score* model was proved in an emerging economy such as Mexico and its level of effectiveness was demonstrated. The results are presented in the next section.

Results

Results for 115 companies for the period 2012-2109 are grouped in table 1 including the total number of indicators and classification under the three categories proposed by the *Z''-Score* model: non-bankrupt, grey area, and bankruptcy prediction. A total of 837 *Z''-Score* indicators were calculated. Regarding the total indicators, 57.23 % were classified into the non-bankrupt sector and 24.85 % were classified as grey area. These two groups represented 82.08 % of the total indicators classified out of the risky area of bankruptcy. Only 17.92 % of the indicators showed risk for companies to perhaps become a bankruptcy prediction. Also, the average indicator for each category was calculated, and the first two categories showed an average result far from the lower limit of each area, but also from the bankruptcy prediction.

Table 1. Number of *Z''-Score* indicators per zone.
Tabla 1. Número de indicadores de *Puntuación Z''* por zona.

Z-Score zone	# of indicators	Percentage	Average indicator
Non-bankrupt sector	479	57.23 %	5.01
Grey area (ignorance)	208	24.85 %	1.92
Bankruptcy prediction	150	17.92 %	-1.81
2012-2019 period	837	100.00 %	2.80

When results were analyzed as a percentage of the total indicators per year as shown in table 2, it was found that the non-bankrupt sector and grey areas had the largest variability measured by the standard deviation of all the years considered in the 2012-2019 period, but still not enough to make companies fall into the bankrupt prediction area. On the other hand, the bankruptcy prediction area was the less variable, only 0.95 %. These first results showed that the 2012-2019 period had somehow economic stability or close to a normal distribution represented by the stability of the financial information of the companies reviewed in the database because of the low variability in the Z''-scores. Table 2 shows the *Z''-Score* indicators result in percentage by zone and per year.

Table 2. *Z''-Score* indicators result in percentage by zone and per year.
Tabla 2. Resultados de la *Puntuación Z''* en porcentaje por zona y por año.

Period	Non-bankrupt sector	Grey area (ignorance)	Bankruptcy prediction	Total
2012	64.00 %	19.00 %	17.00 %	100.00 %
2013	65.00 %	18.00 %	17.00 %	100.00 %
2014	58.65 %	22.12 %	19.23 %	100.00 %
2015	52.83 %	29.25 %	17.92 %	100.00 %
2016	53.70 %	28.70 %	17.59 %	100.00 %
2017	54.13 %	26.61 %	19.27 %	100.00 %
2018	56.60 %	26.42 %	16.98 %	100.00 %
2019	71.15 %	10.58 %	18.27 %	100.00 %
2012-2019 period	57.23 %	24.85 %	17.92 %	100.00 %
Standard deviation	6.57 %	6.45 %	0.95 %	

Moreover, in table 3, the results of the *Z''-Score* were measured per year in units and the standard deviation of the results in each area showed a high variability, especially in the bankruptcy prediction area. This was the basis to conduct a more detailed analysis of the specific periods in which some companies had lower indicators that could place them into the bankruptcy prediction area for specific years.

Table 3. *Z''-Score* indicators result in units by zone and per year.
Tabla 3. Resultados de la *Puntuación Z''* en unidades por zona y por año.

Period	Non-bankrupt sector	Grey area (ignorance)	Bankruptcy prediction	Total
2012	5.23	1.92	-0.70	3.59
2013	5.05	1.75	-4.38	2.85
2014	5.09	2.00	-4.73	2.52
2015	5.17	1.99	-4.83	2.45
2016	5.14	1.96	-2.29	2.92
2017	4.97	2.04	-2.07	2.83
2018	4.84	1.84	-2.07	2.84
2019	3.96	1.41	-3.03	2.41
2012-2019 period	5.01	1.92	-1.81	2.80
Standard deviation	41.28 %	20.67 %	150.10 %	37.87 %

Based on the above results, it was decided to conduct a more detailed analysis first by calculating the standard deviation, the average result of indicators, and the upper and lower limit of each one of the 115 companies. The results were beneficial to build a typology of 17 categories in which companies were allocated based on the *Z''-Score* performance and tendency in the period of study. The calculations are presented in table 4 including the number and percentage of companies falling into each one of the categories.

Table 4. Typology of companies in the census by tendency of the results of the *Z''-Score*.
Tabla 4. Tipología de compañías en el censo por tendencia en los resultados de la *Puntuación Z''*.

	Category	Number of companies	Percentage
1	Non-bankrupt sector	54	46.96 %
2	Grey area	10	8.70 %
3	Bankruptcy prediction but operating in business	10	8.70 %
4	Previous years in grey area but moved to non-bankrupt sector	4	3.48 %
5	Previous years in bankruptcy prediction but moved to grey area	4	3.48 %
6	First in grey area, later in bankruptcy prediction but moved to non-bankrupt sector	1	0.87 %
7	Non-bankrupt sector and grey area invariably	6	5.22 %
8	Previous years in non-bankrupt sector but moved to grey area	9	7.83 %
9	Previous years in grey area but moved to bankruptcy prediction in the last two years	4	3.48 %
10	Previous years in bankruptcy prediction but left the BMV in last year and started the legal process of bankruptcy	5	4.35 %
11	Previous years in non-bankrupt sector but moved to grey area and last years to bankruptcy prediction, and started the legal process of bankruptcy	1	0.87 %
12	Four years in bankruptcy prediction, leaves BMV but it did not start the legal process of bankruptcy	1	0.87 %
13	Several years in bankruptcy prediction, never suspended in BMV and started the legal process of bankruptcy	2	1.74 %
14	Several years in bankruptcy prediction, suspended in BMV for a while, re-activated and started the legal process of bankruptcy	1	0.87 %
15	Non-bankrupt sector and grey area invariably, but at the end it was suspended in BMV and started the legal process of bankruptcy	1	0.87 %
16	Several years in bankruptcy prediction, last year moves to non-bankrupt sector, suspended in BMV and started the legal process of bankruptcy	1	0.87 %
17	Three years in bankruptcy prediction, moved to non-bankrupt sector, then to grey area and finally to bankruptcy prediction, never suspended in BMV and did not started the legal process	1	0.87 %
	Total	115	100.00 %
	Companies in non-bankrupt sector and grey area tendency	87	75.65 %
	Companies in bankruptcy prediction tendency	28	24.35 %

The categories were also grouped into two sub-groups. Sub-group 1 includes those companies which showed a level of *Z''-Score* indicators with a tendency to fall into the non-bankrupt sector and the grey area, and sub-group 2 includes those companies with a tendency to fall into the bankruptcy prediction. A total of 87 companies were identified to belong to the sub-group 1, and 28 companies belong to sub-group 2.

A second analysis was conducted in the 115 companies selected reviewing each one of the companies' information in the BMV, institutional webpage, financial information reports, stock market brokers reports, and financial newspapers of prestige. Information was gathered to prove if the predicted situation (area) by the *Z''-Score* corresponded to the real situation in the marketplace. In sub-group 1, a total of 87 companies were reviewed and support evidence was collected. In all the cases, evidence showed that the companies classified with a tendency of falling in the non-bankrupt sector and grey area, in fact, did not have significant financial distress that could possibly make them fall into bankruptcy. They could not have entered a bankruptcy process, operationally or legally. In sub-group 2, a total of 28 companies were reviewed to collect enough evidence to confirm, or not, if the companies were falling into the bankruptcy process, operationally, or legally. This review was conducted within the two following years when the *Z''-Score* resulted under the 1.10 level established by the model. A greater detail on each one of the years in which the *Z''-Score* failed under the 1.10 level was needed since the prediction is established to happen within the next two years of operation of the company. Some companies had one or two years of a *Z''-Score* falling under the 1.10 level, but some others had even eight years. Based on the evidenced gathered, the results of the sub-group 2 showed that only seven companies classified as bankruptcy prediction by the *Z''-Score* were effectively in significant financial distress or started a legal process for bankruptcy under the Mexican legislation, or even under the USA legislation (those also listed in the New York Stock Exchange, NYSE). On the other hand, 21 companies showed enough evidence to assume that their financial situation was not distressful enough to go into bankruptcy or to start a legal process. This situation was contrary to the prediction of the model. The model failed to predict the real situation of these companies within the two years following the *Z''-Score* indicator under the 1.10 level. The analysis conducted in sub-group 1 and sub-group 2 is summarized in table 5. As we can see, according to the original *Z''-Score* prediction model 82 % of the total predictions were verified as correct, but 18 % of the total predictions were incorrect.

Table 5. Z"-score model classification effectiveness - Based on original model and time constraint.
Tabla 5. Efectividad en la clasificación del Modelo de *Puntuación Z’’* – Basado en el modelo original y la constante del tiempo.

		Marketplace situation		Percentage	
Z"-Score prediction model	N	Correct	Incorrect	Correct	Error
Non-bankrupt sector and grey area	87	87	0	100 %	0 %
Bankruptcy prediction	28	7	21	25 %	75 %
Total	115	94	21	82 %	18 %

There is a high level of error since Altman (1983) proved his complete *Z’’-Score* model with 93.94 % of effectiveness and only 6.06 % of error. The census of Mexican companies researched had a much greater error, three times larger than the *Z’’-Score* model original error. Nevertheless, it is important to mention that all the companies located by the *Z’’-Score* model as non-bankrupt sector and grey area were classified correctly, which represents a zero error. On the other hand, the companies located in the bankruptcy prediction had all the misclassification cases, that is 75 % of error.

The model is certainly effective while predicting companies in the areas of non-bankrupt sector and grey, yet the aim of the model is to help administrators prevent the possibility of bankruptcy with time to avoid such a painful process. Initially, this model should be effective while warning administrators within a time frame of two years of a possible bankruptcy, so they can conduct re-structuring measures and strategical decisions, internal and external, and assure the company’s survival and further development.

Since several companies showed financial distress after more than two years of obtaining a *Z’’-Score* level under 1.10, a reconsideration of the correctly and incorrectly predicted companies was conducted regardless of the number of years that happened. In this case, the results in table 6 demonstrate the changes for five companies located in the bankruptcy sector; that is, twelve companies were correctly classified in the bankruptcy prediction area. For some companies it took more than two years after the *Z’’-Score* had fallen under the 1.10 level to start a bankruptcy process, or to show strong financial distress. On the other hand, without considering the time variable, 16 companies were still not classified correctly according to the *Z’’-Score* indicators obtained. This consideration changed the results reaching an overall level of effectiveness for the model to an 86 % of the total prediction cases. However, 14 % of the total companies were misclassified since those companies never entered a bankruptcy process or showed significant financial distress. The evidence showed that the *Z’’-Score* model still had a significantly high level of error that was much more superior to the original 6.06 % proved by Altman (1983). Even considering these new calculations, all the companies located by the *Z''-Score* model as non-bankrupt sector and grey area continued to be classified correctly. Nevertheless, the companies located in the bankruptcy prediction remained having all the misclassification cases, although the percentage of error went down to 57 %. Yet it was a too high error for prediction if a company has possibilities to be classified between sub-group 1 or sub-group 2. The model still failed in predicting these companies' real propensity to bankruptcy. It is also important to mention that nine out of 28 analyzed companies started a legal process of bankruptcy under the corresponding legislation. So, from the 12 companies that were correctly predicted in the bankruptcy prediction area, three companies had not started a legal process under the corresponding legislation. Those companies solved their financial situation by either conducting an internal re-structure of negotiating debt, bringing new financing to the company, or improving operational decisions, or doing all of them. It was also found that some companies are of a high public interest, such as the airlines, and they are in constant re-structure and being helped to survive.

Table 6. Z"-score model classification effectiveness - Based on original model without time constraint.
Tabla 6. Efectividad en la clasificación del Modelo de *Puntuación Z''* – Basado en el modelo original y sin la constante del tiempo.

		Marketplace situation		Percentage	
Z"-score classification	N	Correct	Incorrect	Correct	Error
Non-bankrupt sector and grey area	87	87	0	100 %	0 %
Bankruptcy prediction	28	12	16	43 %	57 %
Total	115	99	16	86 %	14 %

As it was proved, the *Z''-Score* model applied to an emerging market, such as the BMV, showed to have a 100 % accuracy to classify the companies into the non-bankrupt sector or in the grey area. But the overall model failed significantly at 14 % in predicting companies to enter the bankruptcy prediction area or other areas. That is seen to be a very high percentage of error. Although the *Z''-Score* model was proved efficient and accurate by Altman in 1983 and reviewed in 2017, both applying the research to emerging markets, the *Z''-Score* model applied to Mexican companies for the period 2012-2019 showed that there is a need of a new calibration of the model to have a better performance and reduce the errors of misclassification. The information analyzed was collected within a time frame that presented a normal distribution performance of the economy since there were not special or unusual events that could deviate the regular activity of the economy in Mexico or in the world. It included avoiding the impact in financial figures for the pandemic experienced in the year 2020 and the high economic impact in all the world economies. The previous information based on the warning confirmed by Moreno and Bravo (2018) in their research of Spanish firms proving that Altman's *Z''-Score* indicator is highly conditioned by market values and does not seem to have sufficient predictive capacity in a time of economic and financial crisis.

Conclusions

Predicting financial distress ahead of time is of great interest for all administrators. It is not an easy task but certain signals in the financial indicators can become a warning light and this predicting feature needs to be organized and turned into a useful tool. The Z-score model developed by Altman (1969) proved to be an efficient tool since its creation. As time and economic and social conditions change, the existing models needed to be reconsidered and re-tested. Findings in the latest research showed that the *Z''-Score* model was still highly accurate, but Altman (2005, 2017, 2018) also found that there was still a possibility for the model to grow in accuracy by considering some other variables that are country-specific, such as economic environment, legislation, culture, financial markets, accounting practices and, in the case of Mexico, government support or intervention. It was also proved by Grice and Ingram (2001) and by the authors of this paper that the *Z''-Score* model, in its actual version, does not perform with enough accuracy in the Mexican companies listed in the BMV. The percentage of error of the model is 18 % based on the original time frame. Moreover, even if we do not consider the two years of time frame established in the *Z''-Score* model for the prediction of bankruptcy, the level of error is 14 %. This error is high enough to confirm the low accuracy of the model. So, it can be said that in general the actual *Z''-Score* model is efficient in detecting propensity to bankruptcy in developed countries. Nevertheless, based on the findings of this paper, it cannot be said that the actual *Z''-Score* model can predict bankruptcy in Mexican companies listed in the BMV with a high accuracy. The model needs to be re-calibrated through a set of country-specific variables in more research. Those characteristics can include specifics to the Mexican companies, such as propensity to re-organizing the internal finance, re-negotiation of debt, and the survival attitude before financial challenges. Xu and Zhang (2009) also support this reasoning based on their research on Japanese listed companies, as well as AlAli (2018) who shows that the specific situations in Kuwait companies affect the result of the *Z''-Score*. Several Mexican companies have tried to re-structure the company for several years even before and after declaring bankruptcy legally. Moreover, in the census of this research, a few foreign country companies were included since they are listed in the BMV. Results showed that not even foreign listed companies had a high accuracy level in the prediction of the model. These findings support the idea that the country-specific conditions have an impact in the prediction model for companies listed in the BMV independently of the country of origin. This research provided sufficient evidence for the need to calibrate the *Z''-Score* model concerning the following variables: the time frame of two years prediction, the weights applied to each one of the financial variables (ratios) of the formula, and the numerical boundaries for the zone classification. These variables should be considered in future research on the calibration of the model. As Lizarzaburu *et al.* (2021) mention in their study on Peruvian firms and Mejía and Flores (2020) in their study on Ecuadorian companies, although the emerging economies have some parallel conditions or situations, it is believed that every single economy and stock market have differential characteristics that need to be taken into consideration when proving a model of prediction, in this case of bankruptcy. Based on the research findings it can be inferred that the *Z''-Score* model needs to be constantly updated and calibrated accordingly to conditions of several variables existing in each market. This paper has pointed out the three main variables that should be adjusted: prediction time, weights of variables, and zone values. The findings of this paper show enough evidence to suggest that the *Z''-Score* model cannot be applied accurately in all emerging markets. There will always be economical, cultural, social, and governmental conditions that will impact the performance of the companies in such a different manner. Regarding this, future research on the *Z''-Score* bankruptcy prediction model must be sequential, periodical, and situational. For future research, there is also an opportunity to test the different variables that bankruptcy prediction that the authors have identified with the different models. Despite the selection they have made of the most convenient variables (ratios) to predict bankruptcy in an accurate way, other ratios could be explored under the conditions of the emerging markets to confirm the previous findings or tom propose new variables. Concerning this study's limitations, further research could also be carried out of other authors' models. It also is crucial to mention that this research was conducted in large public corporations. There is also a considerable niche to conduct more research on the bankruptcy model applied to micro, small, and medium enterprises that are not listed in the stock market. Although their financial statements are not published. That is a major challenge to engage in that kind of research, but there is an important need of new knowledge to help that kind of companies to avoid the risk of bankruptcy. We can conclude that there is a need for more research to be conducted on the *Z''-Score* model applying data from different emerging countries, in different times, and different groups of companies to have a more calibrated and accurate adapted model for each country.

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<u>Appendix A</u>

Standard deviation, average, and lower and upper limits of Z’’-score results for the companies studied.

Num.	Symbol	Std. Dev.	Average	Lower	Upper
1	AC	0.44	3.24	2.80	3.68
2	ACCELSA	0.84	4.39	3.55	5.23
3	AEROMEX	0.63	-0.14	-0.77	0.49
4	AG	1.22	2.33	1.11	3.55
5	AGUA	1.82	6.22	4.40	8.04
6	ALEATIC	0.63	3.31	2.68	3.94
7	ALFA	0.69	2.35	1.65	3.04
8	ALPEK	0.89	3.29	2.40	4.18
9	ALSEA	0.76	0.60	-0.16	1.37
10	AMX	0.50	1.12	0.63	1.62
11	ANB	0.34	1.30	0.97	1.64
12	ARA	0.42	8.72	8.30	9.13
13	ARISTOS	1.99	5.81	3.81	7.80
14	ASUR	2.07	5.71	3.64	7.78
15	AUTLAN	0.83	2.63	1.80	3.46
16	AXTEL	0.86	0.30	-0.56	1.15
17	AZTECA	1.24	2.15	0.91	3.38
18	BACHOCO	0.53	7.82	7.29	8.34
19	BAFAR	0.96	3.47	2.51	4.43
20	BEVIDES	0.75	0.54	-0.21	1.29
21	BIMBO	0.19	1.60	1.41	1.79
22	CABLE	0.63	3.24	2.61	3.87
23	CADU	1.19	5.81	4.62	7.01
24	CEMEX	0.17	0.84	0.66	1.01
25	CERAMIC	0.49	4.20	3.72	4.69
26	CHDRAUI	0.34	2.02	1.68	2.36
27	CIDMEGA	0.31	3.40	3.09	3.71
28	CIE	0.45	2.41	1.96	2.86
29	CMOCTEZ	0.69	10.05	9.36	10.73
30	CMR	0.86	0.10	-0.76	0.97
31	COLLADO	0.47	2.76	2.30	3.23
32	CONVER	0.37	3.30	2.93	3.67
33	CUERVO	0.80	6.25	5.46	7.05
34	CULTIBA	3.60	3.88	0.28	7.48
35	CYDSASA	1.27	3.50	2.23	4.77
36	DINE	0.58	2.12	1.55	2.70
37	EDOARDO		-5.10	-5.10	-5.10
38	ELEKTRA	0.34	2.21	1.87	2.55
39	ELEMENT	0.53	2.28	1.75	2.82
40	FEMSA	0.61	3.94	3.34	4.55
41	FRAGUA	0.34	3.56	3.22	3.90
42	FRES	1.54	6.15	4.61	7.69
43	GAP	2.65	6.02	3.37	8.67
44	GCARSO	0.78	5.98	5.20	6.76
45	GCC	0.90	3.77	2.86	4.67
46	GEO	9.63	-9.69	-19.33	-0.06
47	GFAMSA	1.74	1.62	-0.12	3.36
48	GICSA	0.44	2.20	1.76	2.64
49	GIGANTE	1.19	3.74	2.55	4.92
50	GISSA	1.82	4.44	2.62	6.26
51	GMD	0.59	0.98	0.39	1.57
52	GMEXICO	0.39	4.87	4.48	5.26
53	GMXT	0.40	3.37	2.97	3.78
54	GPH	0.57	3.62	3.05	4.19
55	GRUMA	0.67	3.53	2.85	4.20
56	GSANBOR	1.17	6.14	4.97	7.31
57	HCITY	1.28	3.96	2.68	5.23
58	HERDEZ	0.84	4.13	3.29	4.98
59	HIMEXSA	2.18	-2.04	-4.22	0.14
60	HOGAR	0.68	-0.35	-1.03	0.33
61	HOMEX	9.53	-13.67	-23.20	-4.14
62	HOTEL	1.14	2.80	1.66	3.93
63	ICA	1.85	-0.48	-2.33	1.37
64	ICH	0.70	8.55	7.85	9.25
65	IDEAL	0.75	1.01	0.26	1.75
66	IENOVA	1.17	2.52	1.35	3.70
67	INCARSO	0.28	4.55	4.26	4.83
68	INGEAL	1.10	-1.19	-2.29	-0.09
69	JAVER	0.34	4.56	4.22	4.91
70	KIMBER	0.44	3.03	2.59	3.48
71	KOF	0.69	3.23	2.54	3.92
72	KUO	0.25	2.02	1.77	2.27
73	LAB	1.34	4.54	3.20	5.88
74	LACOMER	2.21	6.66	4.45	8.87
75	LALA	3.35	4.78	1.43	8.13
76	LAMOSA	0.41	3.64	3.23	4.05
77	LIVEPOL	0.47	4.97	4.50	5.44
78	MASECA	1.43	7.58	6.15	9.02
79	MAXCOM	2.60	-0.92	-3.52	1.68
80	MEDICA	2.43	6.03	3.60	8.46
81	MEGA	0.32	5.59	5.27	5.91
82	MFRISCO	1.34	-0.51	-1.85	0.83
83	MINSA	1.01	6.98	5.97	7.99
84	NEMAK	0.25	1.90	1.66	2.15
85	OMA	0.83	4.79	3.95	5.62
86	ORBIA	0.69	2.21	1.52	2.90
87	PAPPEL	0.60	3.31	2.71	3.91
88	PASA	1.51	3.45	1.94	4.96
89	PE&OLES	1.06	5.47	4.42	6.53
90	PINFRA	2.63	6.56	3.93	9.19
91	PLANI	0.17	1.41	1.24	1.58
92	POCHTEC	0.76	1.74	0.98	2.50
93	POSADAS	0.44	2.07	1.63	2.51
94	QUMMA	0.50	2.11	1.60	2.61
95	RASSINI	1.71	1.42	-0.29	3.12
96	RCENTRO	3.57	3.59	0.03	7.16
97	RLH	1.84	2.92	1.08	4.76
98	SARE	3.09	-2.22	-5.31	0.86
99	SIMEC	0.83	7.80	6.97	8.64
100	SITES	0.27	0.51	0.24	0.78
101	SORIANA	0.64	3.07	2.43	3.71
102	SPORT	0.91	1.48	0.57	2.39
103	TEAK	2.72	3.38	0.67	6.10
104	TLEVISA	0.29	2.68	2.39	2.97
105	TMM	2.56	0.74	-1.82	3.29
106	TRAXION	1.18	2.76	1.58	3.94
107	TS	0.90	7.32	6.42	8.21
108	URBI	25.20	-31.42	-56.62	-6.22
109	VASCONI	1.26	4.86	3.60	6.12
110	VESTA	0.66	3.02	2.36	3.68
111	VINTE	0.83	5.20	4.36	6.03
112	VISTA	0.86	0.98	0.11	1.84
113	VITRO	1.93	3.29	1.35	5.22
114	VOLAR	1.58	1.20	-0.38	2.79
115	WALMEX	0.56	3.80	3.24	4.36