Logit Model Use to Assess Credit Risk Levels on Service Sector Companies in Emerging Markets: Venezuela’ Case

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Abstract

Objectives: This article describes the use and advantages of the Logit Statistical Model to assess the risk levels of default of service sector companies. Methods/Statistical Analysis: With some level of certainty, it was developed a statistical model to measure the probability of default of some Venezuelan companies. This measure was performed between 2004 and 2007 (just before this country got immersed in the serious economic situation that is going through now). The implementation of the Logit Model permitted to put into practice a pattern of predictive modelling to foresee the risks of financial stress of a company hindering the payment of the credit obligations, originating the stimation of default or non-default condition. This stimation was achieved taking into account the financial indicators, either theoretical variables or exogenous assessment variables (considered by the authors of this study)such as the commercial accounts receivable in correspondence with the total assets, the net inventory and the total current liabilities in correspondence with the total assets, of several Venezuelan companies that belong to the financial sector. Findings/Application: Finally, despite the volatility features of the markets of emerging countries, it must be highlighted that it is possible to come up with the design of statistical models that permit to figure out the prediction of capacity of payment through the use of audited accounting financial statements, which provide valuable information for strategically decision – making purposes of the organization.

Keywords: Companies Risk, Credit Risk Levels, Default Prediction, Emerging Markets, Logit Model, Volatility

1. Introduction

Given the current worldwide economic situation, it is crucial to understand the internal and external economic pressures that a company generally goes through. Likewise, it is important to be aware of the institution risk and business uncertainty that corporate leaders ought to face when they perform duties of giving adequate guidance for the best decision – making in favor of the sustainability of the company in the market. These issues, for the development and design of good management practices turn more complex, rigorous and strategically each time.

Companies play a fundamental role in the economy of a country. They are the main engine of development of its population. As a consequence, the company’s failure impacts the society deterioration in general as it affects the Gross Domestic Product (GDP) growth, the labour force, the investment and the income distribution among other areas of the economy field.

The economic uncertainty that it is being experimented these days cause the need of companies to study and control their credit risks and liquidity. As a result, business researchers, financial analysts, among others social and economic agents, have felt interested in identifying the variables that permit to detect the likelihood of failure of a business, making emphasis on detecting and preventing such situation.

Along the last forty years, the business failure issue and its prediction have gained importance within the scope of accounting research and its development has also brought about a wide applied empiric background. However, it has not been possible to gather enough information to draw a theoretical framework.

In every economic system, the credit portfolio level of the company’s default indicates the existence of a
latent problem that can hinder the payment of debts as well as the payment of credits in the terms and deadlines set by both parts. For these reasons, it is considered that the prediction of the probability of companies to pay the creditors their debts, or what is also known as “risk of service” (Service Risk), would be of great help for the financial institutions to detect the companies whose financial stress may be at the brink of a, temporarily or permanent, default.

The meaning of the expressions “risk of bankruptcy” (default) or “financial difficulties” (financial distress) are not easy to define. However, it is generally thought that a firm has bankruptcy risk or goes through financial difficulties when it presents certain characteristics that distinguish the “pay cessation estate” such as, for example, unfulfillment of the obligation services or bond issues, non-payment of the dividends to the preferred shareholders or interruption of payment to providers. Yet, rather than discuss such terminology, this research work intends to estimate the probability of some companies of a particular economic sector to get (close) to a bankruptcy situation taking as reference the information provided by the behavior of some financial indicators (ratios).

Besides that, it is intended to model statistically the default performance of Venezuelan companies in the service sector using indicators that come from the annual financial balance of each company. The indicators assessment is based on the information provided by a well-known financial entity of the country, as well as their portfolio of clients and their credit debt service during 2005 and 2007. The data structure identification is kept under reserve in respond to the bank institution safety demand.

Regarding the assessment of financial risk various⁵⁻⁸, among others, have focused their attention on features that can help to explain the term of bank crisis. Some of the typical economic-financial analysis variables that have been considered by these authors are the economic and financial profitability or the ratios of patrimonial structure which include ratio of autonomy case (own resources against external ones) or inverse of the debt ratio, combined with indicators of the financial business itself such as the level of efficiency or the approximation to the exposure to credit or liquidity risk.

Bearing this mind, it has been intended to predict a likely ‘default’ situation of certain service sector companies of an emerging economy country, taking into consideration particular variables of the financial statement. Hence, the logistic regression, a common statistical procedure that is used when a binary variable is intended to be predicted, has been employed. It is important to mention that, since the sample size was quite small, the analysis has been assessed using the exact logistic regression that, different from the standard version, it is not based on the asymptotic properties of the estimators⁹.

In order to develop this research, the variable default was modeled, being defined as a dichotomy or Dummy (Table 1), using the following parameterization:

| Value | Description | Event | Probability |
|-------|-------------|-------|-------------|
| 0     | No default. Fulfill the terms of credit obligations. | Do not belong to the Group. | 1-Pi |
| 1     | Default. Do not fulfill the terms of credit obligations. | Belongs to the Group. | Pi |

Own elaboration (2017)

The modelling of this dichotomous variable was done using the Models of Regression for dependent dichotomy variables (Y), where the dependence is based on certain independent variables (X).

2. **Methodology**

The logistic regression is useful for cases in which it is necessary to predict the presence or absence of a characteristic or a result in correspondence with the value of a set of predictor variables. It is similar to a linear regression but it is adapted to models whose independent variable is dichotomous. The coefficient of logistic regression can be used to estimate the ratio of the advantages of each independent variable of the model. It can also be applied on a range of research situations wider than the discriminate analysis.

According to this perspective, the dependent variable in a logistic regression has to be dichotomous. The independent variables, on the other hand, can be represented by intervals or categories, if so; such categories must be labeled by dummy variables or be codified as indicators.

It is important to incorporate categorical or qualitative variables in the business prediction modelling⁻. In this case, these variables could be incorporated in the equation if it was possible to generate dichotomy vari-
ables n-1 with zero and one values, being “n” the number of categories of the original variable.

This logistic regression model will let us obtain, in the first place, the estimations of the probability of an event and, in the second, the identification of the risk factors that conditioned such probabilities as well as the influence or relative weight that they exert on them. In other words, the probability or dependent variable is affected by the behavior of the explanatory variables or risk factors. In fact, the logistic regression is not based on assumptions of probability distributions. The solution can turn out to be a more stable result if the predictors have a normal multivariate distribution. Additionally, as every form of regression, it is necessary to be careful with the multicollinearity among the predictor variables as it can lead to biased estimations and typical unstable errors.

Based on this contextualization, the modernized Logit uses logistic function as estimation function rather than lineal one. The result of the model is the probability estimation of an event to happen. It means that a new individual will belong to a group or to another one. On the other hand, this regressive analysis, also, permits to identify the most important variables that explain the differences between groups.

According to, the characteristics of the Logit model are:

1. Even though, the transformed model is linear in terms of variables, the probabilities of it are not.
2. It is assumed that the logarithm of the probabilities ratio is linearly related to the explanatory variables in this model.
3. The coefficients of regression express the change in the logarithm of probabilities in this model. This happens when one of the explanatory variables change in a unit and the rest of the variables remain constantly the same.

Considering the characteristics of the variables presented in this study, some of them categorical, the Logit Probabilistic Model seems an appropriate method to use because of the logistic regression that gives the chance to find the ratios of relative probability, also called, Odds-Ratio (OR). The Logit models are, essentially, compound by an endogenous binary variable and some exogenous variables of qualitative and / or quantitative nature. Consequently, the expected result out of this statistical system is the estimation of the probability of an individual to be part of a group or another (p.e. default or non-default).

Commonly, the function of logistic accumulated distribution is defined by the models of logistic regression, which set as main objectives: to classify individuals or cases to each of the categories of the dependent variables, based on the probability of belonging to any of them (predictive) and to quantify the importance of the relation that exists between the dependent variable and the co-variables, and characterize each category (explanatory).

Dichotomous Variable Regression

In the present study, the estimations were obtained using methodologies and applications of regression models of dependent dichotomous variable, taking value 1 (if it belongs to the group) or 0 (if it does not belong to the group). This type of study also requires an affirmative or negative answer. That is why Linear Models of Probability (LMP) have also been employed. Based on Xi, the expected value of the event to happen is interpreted as conditional probability.

In order to deal with models of dichotomous dependent variable, it is necessary to use the following formula:

\( Y = a + \beta X + u \)

These types of models express the dichotomous variable Yi as a lineal function because \( E(Y|X) \) can be interpreted as the conditional probability of an event to happen considering Xi. It means, \( Pr(Yi=1 |X) \).

According to this, if we use the previous formula and add the expected conditional value, we obtain:

\( E(Y|X) = \alpha - \beta X \)

Being \( Pi = probability \ of \ Yi = 1 \) (chances that the default event happen) and \( 1 - Pi = probability \ of \ Yi = 0 \) (chances that the company gets into default).

Then, according to the definition of mathematics expectation we obtain:

\( E(Yi) = 0.(1 - P_i) + 1.(P_i) = P_i \)

Then: \( E(Y|X) = \alpha - \beta X = P_i \)

Hence, as the probability must always oscillate between 0 and 1, it was possible to set the restriction: \( 0 < E(Y|X) < 1 \)
One of the main difficulties with the lineal models of probability, which is characterized by their conditional probabilities, is that the estimated values of \( Y \) might not oscillate between 0 and 1. It is considered that a solution for this difficulty can be provided by the Logit Model\(^1\).

\[
\ln \left( \frac{P_i}{1-P_i} \right) = \alpha - \beta(X_i)
\]

In this model, \( X_i \)'s represent the exogenous variables that are based on the annual financial statements of the analyzed companies.

Likewise, the term that is found on the left hand side represents the logarithm of possibility of a “Company \( i \)” to get in \textit{default}. This equation proposes that the logarithm of this possibility is a linear function of the logarithm of the exogenous variables. The Beta coefficient, then, represents the elasticity of each exogenous variable about the probability of \textit{default}.

Using the Logit estimation, the result of the model is the estimation of the probability of a company to belong to a group of \textit{default} or not (Figure 1). On the other hand, since it also deals with a regression analysis, it permits to identify the more important variables that explain the differences among groups. The most common example is a bank that provides credits to clients that want to know about the possibility of non-payment of a future client.

![Figure 1. Logit model.](image)

Similarly, another way to show the previous formula would be\(^1\):

\[
P_i = \frac{1}{1 + e^{-\alpha - \beta X_i}}
\]

Its graphic representation is share below:

2.2 Logit Model Parameters Estimation

In this study, it was analyzed the types of estimation according to the classification of the No repeated observations. In order to do that, it was used the \textit{method of maximum likelihood} which omits the implementation of the method of Ordinary Squared Minimums (MCO) as it is a non-linear method. The estimation of maximum likelihood intends to calculate the parameters value that will generate with high probability the expected sample. This means that they are those values whose joint density function (or function of likelihood) calculation reaches a maximum.

\[
\max \text{ prob } Y_i = \\
\max \text{ prob } u_i = 0
\]

\[
\max f(u_i) = f(u_0) * f(u_0) * ... * f(u_0) \quad \text{(Remainders)}
\]

\[
\max \log(f(u)) = \log(\text{likelihood function}) = \log(L)
\]

In a univariate case, taking logarithms of the maximum likelihood function the result is:

\[
L = \sum Y_i (\alpha + \beta X_i) - \sum \log \left( 1 + e^{\alpha + \beta X_i} \right)
\]

\[
\log(L) = \sum Y_i \ln \left[ \frac{e^{\alpha + \beta X_i}}{1 + e^{\alpha + \beta X_i}} \right] + \sum (1 - Y_i) \ln \left[ 1 - \frac{e^{\alpha + \beta X_i}}{1 + e^{\alpha + \beta X_i}} \right]
\]

Then, when the logistic function is expressed as linear function, the formula is:

\[
\ln \left( \frac{P_i}{1-P_i} \right) = \ln \left( e^{\alpha + \beta X} \right) = \alpha - \beta X_i
\]

And the interpretations will be structure in the following way:

1. Sign of coefficient: shows the direction in which the probability moves when the explanatory variable, which is obtained from the indicators out of the financial accounting balance of the companies, increases.

2. The parameter value: indicates the increase in \( \ln \left( \frac{P_i}{1-P_i} \right) \) when the explanatory variable increases in a unit while the rest of exogenous variables keep constant.

3. Results and Discussion

The results presented in this study are based on the structure of the Dichotomy Logit Model which is formed by
multiple exogenous variables established on the following expression:

\[
\text{Prob}(Y_i = 1) = \frac{1}{1 + e^{-(\alpha + \beta_1X_{i1} + \beta_2X_{i2})}} = \frac{e^{\alpha + \beta_1X_{i1} + \beta_2X_{i2}}}{1 + e^{\alpha + \beta_1X_{i1} + \beta_2X_{i2}}}
\]

Exogenous variables used:
In order to model the Probability of default of the companies chosen from the service sector, it was necessary to deal with exogenous variables that were obtained from the financial accounting statement of annual periodicity of those companies. In this way, according to 17, it was established the group of theoretical variables:

- S/TA. Sales / Assets total
- EBIT/TA. Gains before interests and taxes / total Assets
- RE/TA. Retained earnings / total assets
- ME/TL. Market value of patrimony / total assets (Liabilities)
- WC/TA. Working Capital / total assets

The additional exogenous variables that have been valued in this study are:

- AR/TA. Ratio of Commercial Accounts receivable / total assets
- I/TA. Ratio of Net Inventory / total assets
- CL/TA. Ratio of Total Current liabilities / total assets
- Accounts payable to providers / total assets
- Current Assets / total assets
- Company size

### 3.1 Analysis and Interpretation of Results

The following description presents an analysis from different angles:

#### 3.1.1 Statistical Analysis of the Information

This statistical analysis was done during 2002 and 2007 when it was observed a significant difference in the macroeconomic performance of GDP in Venezuela during 2002, 2003 and 2004.

According to 18, the GDP went through a consecutive economic contraction between 2001 and 2002, trimester after trimester (Figure 2). Then, as a consequence of the oil strike in the first trimester of 2003, the country dropped to the lowest point of development. However, it experienced a gradual recovery which was accompanied by the increase of the public spending of the Government and the fast growth of the oil prices the following trimesters of the year.

![PIB](image)

(Own elaboration with information obtained from BCV, 2017)

**Figure 2.** GDP Trimestral evolution in Venezuela, from 2001 until 2008.

This fluctuation originated a change of perspective in the management of various Venezuelan companies as there was neither confidence nor growth in the country’s economy (management performance) at the end of 2003 and beginning of 2004.

The present analysis estimated a significant variation in the general vision of Venezuelan businesses and companies. They modified their actions and decisions in responds to the short term country’s evolution which affected the composition of the companies in different scenarios. This situation put at risk their liquidity in certain occasions causing a likely crisis of solvency.

#### 3.1.2 Analysis of Explanatory Variables

It was analyzed a set of explanatory variables obtained from Two Hundred and Sixty Three (263) registers out of the bank credit portfolio of a national bank institution linked to different companies of the service sector. Each of them was studied separately, taking into account their annual evolution and their development in correspondence with the companies that got in default that year. As it was said before, this variable analysis was segmented according to a group of theoretical variables and a set of variables proposed in this study.
3.1.3 Group of Theoretical Variables

- A. S/TA: Sales / Total Assets (Ratio of total sales between total assets)

This indicator sets the relation for each company, representing the proportion of total sales in correspondence with the total assets (Figure 3).

(Own elaboration, 2017)

Figure 3. Performance of ratio of total sales between total assets according to default.

After analyzing the data, it showed that the relation between the sales evolution and the total assets kept stability, no matter if the company had been affected by some sort of default or not.

During periods of expansion, the growth of the company sales can increase in proportion with the increase of assets. However, in Venezuela, which a country characterized by an uncertain situation of country at risk and other macro-economic and political factors, has the likelihood that these variables (Sales and Assets) do not grow proportionally precisely because of the justification of the position of “company in progress” with minimum of risk (causing the increase of the inventories to levels higher than the growth in sales), obtaining an indicator that lacks consistency and has low level of predictability along the time.

- EBIT/TA. Gains before interests and taxes / Total assets (Profit ratio no distributed between total assets)

This indicator sets the relation for each company for the proportion of the profits no distributed in correspondence with the total assets (Figure 4).

(Own elaboration, 2017)

Figure 4. Performance of No. distributed Profits Ratio between total assets according to default.

As far as this variable concerns, the companies, either the Default or Non-Default ones, express an annual balance. Though, during the years of accelerated recovery of GDP (once the oil strike ended), the companies that got in default showed instability, a reduction during 2003 (probably due to their disbelief in the economic recovery of the country and so the distribution of all profits) and increase in 2004 (possibly due to the re-investment and trust in the economy).

- RE/TA. Retained earnings / Total assets (Earnings before interest and taxes, EBIT, between total assets).

This indicator sets the relation for each company for their proportion of EBIT in correspondence with the total assets (Figure 5).
There is no evidence of a meaningful difference between the Earnings before interests and taxes for the companies that got in default and those that did not. The proportion is even and the level of growth (mild tendency growth) showed the increase of the levels of gain margins.

- **ME/TL.** Market value of patrimony / total assets (Liabilities) (Ratio of total patrimony between total debt.)

This indicator sets the relation for each company for their proportion of the total patrimony between the entire debt (Figure 6).

This graphic confirms what has already been foreseen, there is stability between the relation of liabilities and the patrimony of the companies in default as well as those that were not. Though, it is seen that in 2004, when there was evidence of a steady growth of the economy of the companies, some of them got in financial tension because they financed the growth of assets with their patrimony. This scenario was also observed in 2006.

- **WC/TA.** Working Capital / total assets (Cash ratio and working capital between total assets)

This indicator sets the relation between each company for their proportion of Cash and the working capital between all the company’s assets (Figure 7).

3.1.4 Exogenous Variables

Apart from the traditional explanatory variable, it was established to value and assess the inclusion of other variables which would help to describe the feasibility to predict default of companies.

- **AR/TA.** Ratio of Commercial Accounts receivable / total assets (Accounts receivable ratio between total assets)
This indicator sets the relation for each company for the proportion of the net commercial receivable accounts in correspondence with the total assets (Figure 8). It shows that before 2003, period of time in which the GDP suffered contraction, this indicator did not have any effect on of the feasibility of default of a company. However, from 2004 onwards, period of time in which it was observed a steady growth in the economy, the Accounts receivable relation turns significantly relevant to measure the probability of default.

(Own elaboration, 2017)

**Figure 8.** Performance of accounts receivable ratio between total assets in correspondence with default.

It was seen that when there was lower proportion of Accounts receivable, there was a higher probability of default. This happened, even though the companies that got in default in 2004 had high accounts receivable (this situation probably happened because of the excessive growth of the economy that took place in a short term so the recovery in 2003 allowed them to obtain a high level of accounts receivable but a low level of collection to meet their obligations).

- **I/TA.** Ratio of Net Inventory / Assets total (Net inventory ratio between assets total)

This indicator sets the relation between each company for their proportion of the inventories in correspondence with the total assets (Figure 9).

(Own elaboration, 2017)

**Figure 9.** Performance of net inventory ratio between total assets in correspondence with default.

In this graph, it can be seen how during the years of contraction of GDP (2002 - 2003), the multiple of the net inventory ratio between the total assets for companies that got in default and those that were financially sound performed in a similar way. However, it was observed that, between 2004 and 2005, a period of time in which the economy growth began, the companies that got in default were mainly those that could not (or did not want to) increase their level of inventory in the short term. Four years later, in 2007, some companies that had grown enormously in terms of level of inventory (bigger proportion of total assets), got in default possibly because they had compromised their free cash flow.

In this sense, it can be said that the companies that did not get in default were those that grew during the corresponding year (end of 2003 and 2004) and kept levels of growth in correspondence with the total assets during the following years.

- **CL/TA.** Ratio of Total Current liabilities / total assets (Total current liabilities ratio between total assets)

This indicator sets the relation between each company for their proportion of the Current liabilities in correspondence with the total assets (Figure 10).
From the economy recovery of the GDP (2003), the companies that got in Default showed high levels of accounts payable to providers, especially in 2007 when the proportion of inventory considerably grew, generating a situation that mainly affected the creditors.

- Current Assets / total assets (Current assets ratio between total assets)

This indicator sets the relation between each company for their proportion of the Current assets ratio between the total assets (Figure 12).

During 2002 and 2003, when there was a contraction of GDP, there was not a clear representativeness of the variable GDP to determine the probability of default. However, as a consequence of the steady growth in 2004, the companies that got in default were mainly those whose proportion of current assets in correspondence with the total assets was lower. This means that those companies, whose level of assets was mainly held on “illiquid” assets, had high levels of difficulty to grow in short term.

- Company size

This indicator sets the relation between the size of the assets of each of the organizations that have been studied in order to detect the average size of the companies that got in default measured in thousands of bolivars Fuertes (Table 2).
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Table 2. Performance of average of assets in correspondence with default.

| Year | Default | Number of companies | Average of assets (Thousands BsF) |
|------|---------|---------------------|----------------------------------|
| 2002 | No      | 19                  | 5347,074                         |
|      | Yes     | 11                  | 2246,928                         |
| Total|         | 30                  | 4210,354                         |
| 2003 | No      | 39                  | 2906,678                         |
|      | Yes     | 4                   | 24,084                           |
| Total|         | 43                  | 2638,530                         |
| 2004 | No      | 50                  | 1984,688                         |
|      | Yes     | 3                   | 6,740                            |
| Total|         | 53                  | 1872,728                         |
| 2005 | No      | 54                  | 147,009                          |
|      | Yes     | 8                   | 31,323                           |
| Total|         | 62                  | 132,082                          |
| 2006 | No      | 49                  | 102,660                          |
|      | Yes     | 4                   | 19,366                           |
| Total|         | 53                  | 96,373                           |
| 2007 | No      | 19                  | 69,794                           |
|      | Yes     | 3                   | 42,591                           |
| Total|         | 11                  | 66,085                           |
| Total general| | 263                 | 1345,143                         |

(Own elaboration, 2017)

It can be observed that the companies that got in default were those that easily got in financial stress as a consequence of their small size and eventual “strength”. This scenario shows that the size of assets and their distribution can be an important factor for the prediction of financial stress of a company in an emerging country like Venezuela which is under constant changeable situations.

3.1.5 Logit Model

The modern statistical Logit Model, on one hand, facilitates the estimation of the probability of a new individual to belong to a group or another (default or no default). On the other, since it is a regressive analysis, it permits to identify the more important variables that explain the differences between groups (based on variable indicators gotten from the general statements and the annual report of gains and lost\textsuperscript{19}.

For the analysis, it was taken into account real accounting results of various Venezuelan companies of the service area (audited financial statements). This information was provided by a national bank entity which was able to show events of default. Such information, obtained from the client’s base, was useful to calculate the countable – financial indicators for each client, making adjustment to the model in correspondence with the historical data.

Since the dependent variable is formed by two groups (failed companies = 1 and non-failed companies = 0), the positive coefficient will imply that when the value of the predictive or model variable increase, the possibilities of the company to fail increase as well. On the contrary, a negative sign will imply that the possibilities of the company to fail decrease.

After analyzing the variables, it was observed that the best way to design an updated predictive model to estimate if a company gets in financial tension, taking the risk to get in Default, would be modelling a statistic equation with data of the years 2005, 2006 and 2007 as these were the years when it was demonstrated the steady growth of the Venezuelan economy (based on the high prices of the oil and the increase of the public expenditure and the politic of consumption of the national government).

Therefore, the following model shows a modelling of the information previously processed for 2005, 2006 and 2007.

The indicators taken as a structure of evaluation for our model as exogenous variables were:

Group of theoretical variables:

- WC/TA. Working Capital / total assets
- RE/TA. Retained earnings / total assets
- EBIT/TA. Gains before interests and taxes / total assets
- ME/TL. Market value of patrimony / total assets (Liabilities)
- S/TA. Sales / total assets

Exogenous variables proposed by the authors, after the validation previously done about the causative effect on the action of default:

- AR/TA. Ratio of Commercial Accounts receivable / total assets
- I/TA. Ratio of Net Inventory / total assets
- CL/TA. Ratio of Total Current liabilities / total assets

It was done an analysis of probabilities of default (Figure 13), considering the performance of indicators that were taken directly from the General Balance and Report of Gains and Lost, obtaining the following results:
(Own elaboration with SPSS use, 2017)

**Figure 13.** Segmentation of the probability of *default*, according to the indicators taken directly from the general balance and report of gains and lost.
These graphs show the performance of each exogenous variable taken into account the default rate of the companies studied; this evaluation was done according to the evolitional performance of the percentiles of each one of the calculated indicators.

### 3.1.6 Statistical Model

Due to the characteristics of the explanatory variables and the nature of the dependent variable of multiple answers, as it is able to capture the various reasons that lead to look for a job position, it has been estimated an Econometric Multinomial Logit Model\(^2\)•

Even though, there are other methods with further specifications such as the model of ordered or graded answer and the model of conditional or sequential character, the Multinomial Model has been chosen because of its process of election which does not imply any order in the answer\(^2\)\(^2\)\(^-\)\(^2\)\(^4\).

The Multinomial Model belongs to a set of discrete choice models that predict the probability of occurrence of an specific event through the value of the independent variables. The dependent variable, on the other hand, is qualitative and describes attributes that are intrinsically non-numeric or that have been measured in correspondence with standards that do not fit the numeric expression\(^2\)\(^5\). However, without losing any information, it is always possible to represent in a quantitative form a qualitative variable. This process is known as codification\(^2\)\(^6\)\(^,\)\(^2\)\(^7\).

Thus, using the information previously analyzed, it was possible to develop the Logit Predictive Model that will allow estimating the probability of Default considering various exogenous variables. This model was figured out dealing with the data of the years 2005, 2006 and 2007 (Table 3).

This study presented a 90% of statistic confidence level, taking into consideration the consistency and self correlation of the exogenous variables, as well as the empiric compulsory theoretical variables proposed by\(^2\)\(^7\).

It was also evident the difference of the performance of the exogenous variables for the companies in Default during the periods of 2002 to 2004 and 2005 to 2007.

Certainly, there is an important amount of exogenous variables to be analyzed through the statistic models to predict the probability of default in countries like Venezuela, which is an emerging country with an economy and a politic system highly volatile. This can also be considered a model with macroeconomic standards in which the effects of the exogenous variables cause impact on the independent variable (Default), even with high levels of p – value.

Finally, according to the assessment of the model results based on the data information previously provided, the following results were obtained (Figure 14):

![Figure 14. Assessment of the probability of default, in correspondence with the non-payment companies.](Image)

**Table 3.** Quantification of the coefficient for the logit model

| Model | Const. | WC/TA | RE/TA | EBIT/TA | ME/TL | S/TA | Accounts Receivable /TA | Inventory /TA | Current liabilities /TA |
|-------|--------|-------|-------|---------|-------|------|-------------------------|-----------------|------------------------|
| b     | 1,313  | -1,887| -2,929| 7,18    | -1,526| 0,1  | 2,403                   | 2,997           | -5,319                 |
| SE (b)| 1,498  | 2,673 | 2,384 | 3,669   | 0,902 | 0,313| 2,948                   | 2,991           | 2,608                  |
| t     | 0,88   | 0,71  | 1,23  | 1,98    | 1,7   | 0,32 | 0,82                    | 1,01            | 2,06                   |
| p-value| 0,381  | 0,48  | 0,219 | 0,05    | 0,091 | 0,749| 0,415                   | 0,316           | 0,041                  |

(Own elaboration with SPSS use, 2017)
This model can make a great difference, if the explanatory variables described earlier are considered, but there are atypical data that prevent it from being significant and different (probably there may be an additional explanatory variable missing).

Unfortunately, the information that was used could not be categorized in economy activity or company structure. It is thought that this categorization could have added further information to the Predictive Statistical Model.

Some Probability Default tests, in correspondence with the size of the company, were also done. Such tests showed a significant impact on the budgetary adjustment but they affected the covariance and the consistency of the model in correspondence with the exogenous predictive variables as a result. That is why, it was not considered for the final version of the Logit model. However, we bear in mind that this aspect must cause an impact on the performance and evolution of financial distress of Venezuelan companies for sure.

It is important to highlight that in this study, the main methodological weakness was the multiple definitions of the word ‘failure’ that were found. There is more than one definition for this term and the use of this concept is rather arbitrary. In order to solve this problem, it was chosen the most used but also the least arbitrary term which relates the definition of failure in terms of legal issues.

In this sense, it is considered that failure takes place when a company is legally declared in state of insolvency. There is not an acceptable theory that academically supports the definition of business failure.

Therefore, the definition of a company as successful or unsuccessful cause a difference between the way the methodological approach is developed to deal with one case or the other. To some extent, one side of a part is common to both approaches, though the features of the other side will depend on the conditions that characterized the specific group that is being analyzed.

4. Conclusions

In an emerging country like Venezuela, the situation of financial stress of various companies not only depends on aspects such as General Statements or Gains and Lost Reports, also depends on the management policies taken when environmental changes and governmental policies are faced.

Based on this perspective, it was developed a statistical model that permits to predict the possibility of a company to get in default in a specific year. Such company belongs to the credit portfolios of a prestigious bank institution in Venezuela and its unplayable condition would cause a Service Risk of the debt that is being kept with this financial institution.

For the design of this probabilistic model, there were taken in to consideration several variables that derive from the annual financial statements of the companies that are part of these credit portfolios. It was even possible to assess the performance of the credit risk over time.

The data showed a great change between the Venezuela that existed before 2003 and the one that emerged after that year. Such change can be noticed with the adjustments of policies that the companies had to make in order to take advantage and make the most of the economic growth that the country experienced during the years. Those actions, however, led the companies to a situation of financial stress and problems with liquidity.

It was found out that the size of the company the economy sector to which the company belongs to and the macroeconomic fluctuation that affects its context are the key factors that have incidence on the credit rating and the financial stress assessment. These aspects, at the same time, depend on the management decisions of growth and the way the market use is performed in a particular moment.

In an emerging country like Venezuela, the companies and businesses have the chance to change the management policies in a short term in order to optimize and increase their sales in the short or medium term. These practices can generate financial stress and lead to default in a specific time.

In a fluctuating or unstable economy of a country like Venezuela, the predominant variable of Default can change in a technically drastic way in the medium term, generating the need to create and adjust statistical forecasting models which are able to suit a particular situation at a particular moment.

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