Prediction Model for Bankruptcy in Micro and Small Enterprises (MSEs)

Modelo de predicción de quiebra en micro y pequeñas empresas (MiPyMEs)

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Abstract

The main purpose of this research is to validate and improve the Weighted Ratio Valuation Model (RPV) model in micro and small enterprises in Central Mexico, in order to propose an alternative to financial valuation methods to anticipate bankruptcy in this sector of the economy. To achieve this objective, the study proposes the empirical application of Mosqueda 2010. The results shed important information that allowed the identification of variables that lead to bankruptcy, making risk detection more accurate, which, in turn, made it possible to validate and consolidate the model.

Keywords: bankruptcy, risk, ratio, weighting, prediction models.

Resumen

La presente investigación sobre la predicción de fracaso empresarial tiene como objetivo aplicar y validar el modelo ponderado de la valoración de riesgo RPV en las micro y pequeñas empresas (MiPyMEs) de la región sur del estado de Hidalgo (México), a fin de identificar las variables relacionadas con el proceso de quiebra. Para alcanzar este objetivo, el estudio se propone la contrastación empírica del (RPV) de Mosqueda 2010. Los resultados arrojan información importante que permite corroborar las variables que inciden en la quiebra, obteniendo valores más precisos al riesgo, lo que permitió validar y reforzar el modelo.

Palabras clave: quiebra; riesgo; ratio; ponderación; modelos de predicción.

1. Introduction

Business failure has been studied in order to understand the factors that lead an enterprise to bankruptcy. Based on the pioneer work carried out by Fitzpatrick (1932) and Winacor, (1935), the models developed consider the hypothesis of using accounting variables in order to determine the probability of bankruptcy with certain anticipation.

Later on, Beaver (1996) tried to improve the prediction capacity, Altman (1968) being the main reference for financial theory using the multiple discriminate analysis technique. Since then, four techniques have been the most widely used: multiple discriminate analysis and conditional probability models (Ohlson, 1980), artificial intelligence models among which neural networks stand out (Odom y Sharda, 1992) and decision trees systems . Here, it is important to mention that over the past decade artificial intelligence models incorporated more innovative techniques and developments because of their potential of application in expert systems, artificial neural networks and the theory of approximate groups (Rough set).

Despite the conceptual progress observed, studies on financial failure generally exhibit a lack of theoretical approaches proposing a formal model that can be used to describe the process of a company going bankrupt. Some authors argue that a big risk of using models is the possibility of introducing financial information that has been manipulated to increase the level of confidence (Beaver, 1966). There is also evidence that shows how statistical techniques over adjust the forecasting models in order to reach a better success rate, reducing the forecasting validity of the model. There are some theories that consider bankruptcy a result of having liquidity issues; others propose failure is due to either a deficient administration or economic cycles that produce structural changes in the market that only benefit some enterprises while others turn inefficient. This leads us to determine that the processes and factors involved in bankruptcy are complex and specific, turning this subject into a very important contributor to slowing down the world's economy over the last years.

Small businesses are the primary source of new jobs in the México economy. The incidence of important bankruptcy cases has led to a growing interest in corporate bankruptcy prediction models since the 1960s. Several past reviews of this literature are now either out of date or too narrowly focused. They do not provide a complete comparison of the many different approaches towards bankruptcy prediction and have also failed to provide a solution to the problem of model choice in empirical application.

The main purpose of this research is to validate and improve the RPV model in micro and small enterprises in Central Mexico, in order to propose an alternative to financial valuation methods to anticipate bankruptcy in this sector of the economy.

First, we review bankruptcy theory and the forecasting model, in order to understand their evolution and the limitations they entail. Later, we discuss the difficulties that measuring bankruptcy has posed. Next, we introduce and explain the fundamentals of the RPV model. Finally, we discuss the results derived from the practical application of the RPV model and contrast such results with those obtained using other more traditional forecasting models, and we draw practical conclusions for the MSEs.

2. Literature Review

In the financial world, *bankruptcy* can be interpreted as the "lack or loss of economic solvency to cover a debtor's entire debts". However, the debtor has different alternatives regulated under the law to prevent his goods from being seized (Morales, 2006).

Siu (2008) summarizes bankruptcy as a situation where the assets are not capable to satisfy the debts; for that reason, the expression "being bankrupt" means not being able to pay all those who have the right to being paid; in other words, it means there does not exist a balance between liabilities and liquid assets.

In the light of the previous definition and for the purpose of this research, we consider bankruptcy as a critical in which a business cannot afford the obligations with its creditors. The situation can be seen as the accumulation of losses and a consequence of a deficient financial structure.

Business failures began long ago. Scholars engaged in the study of this phenomenon have been interested in understanding the internal factors that cause bankruptcy, identifying the bankruptcy processes, and failure prediction tools.

Fitzpatrick, (1932) and Beaver (1936) stand as the main pioneers of univariate analysis. Since forecasting models have been based on the assumption that a company's history can be traced in the company's accounting variables. Such models have drawbacks for making accurate diagnoses to classify and predict bankruptcy.

After the work of Fitzpatrick (1932) and Beaver (1936), Altman (1968) developed the multivariate analysis. This type of analysis was focused on decreasing the bankruptcy cutoffs details. This places the companies in a gray zone, which allows to increase the efficiency of analysis. However, the results could not explain why companies fail or how the financial analyst can use the information to make decisions. On the other hand, the design problem persisted because the model could define neither the variables to include nor their weight. Multivariate analysis model (ADM) represented an important contribution, but its major drawback was that the results were not fully reliable since maximum plausibility assumptions were not met; i. e., it was impossible to verify both the probability of the model as a whole and of each sample considered. Trying to avoid the design problems and the weaknesses of previous models, in 1980 Ohlson proposed the logit model. This model considers that independent variables can be categorical, which allows explicative variables to go beyond economic or financial ratios, opening the possibility for using non-financial or qualitative information to be taken into consideration.

Unlike Altman, Ohlson does not specify cutoffs points but assigns a bankruptcy probability depending on the selected confidence level. According to Lo (1986), this model is much more solid than the discriminating analysis, because it is applicable to distributions other than the normal one (Ferrando and Blanco, 1998).

Another model that is similar to the logit analysis is the probit model. This model works very well when applied to the study of individual behaviors for a certain population when the dependent variable is binary or dichotomous (Borooah, 2002).

In practice, the probit model leads to the same conclusions as the logit model, but the coefficients obtained using the probit model are harder to interpret, which has been an obstacle to its use. In addition, the probit analysis is limited to standard normal distribution cases and not recommended in asymmetric ones (cf. Pampel, 2000).

In an attempt to overcome the design errors implicit in advanced statistical techniques, other methods based on artificial intelligence have been developed. Such methods attempt to explain and forecast bankruptcy more effectively. The advantage of these techniques over conventional statistical methods is that they consider data in an exploratory fashion and do not start with preconceived hypotheses. These artificial-intelligence-based methods can be regarded as non parametric and include neural networks and rough set.

Neural networks (NN) are better suited to study business solvency because the economic information, especially the data from financial statements, are usually incomplete or involve correlations; this may alter the results. Since financial information may vary and may imply that in fact a company has more than a single path to a healthy operation or to bankruptcy, NN analysis offers the flexibility needed to integrate such variability. However, several authors consider this technique needs further refinement, both theoretically and technically.

The rough set method (RS) to forecast insolvency is another technique based on artificial intelligence. Although much less used than others, this method allows for the fast processing of a large volume of both qualitative and quantitative data by means of decision rules. In practice, the rules can be used as an automatic diagnostic system to preselect, for example, companies that require immediate or special attention. The results obtained with this method are standardized and relatively easy to interpret, thus contributing to timely decision-making by a company's financial analysts or supervising authorities. The promising potential of this method as an effective alternative to the most efficient multivariate analysis techniques has been documented by Slowinski and Zopounidis (1995), Zopounidis *et al.*,(1999), Ahn *et al.* (2000) and more recently Mosqueda (2008).

2.1. Difficulties predicting bankruptcy

Models to predict bankruptcies use a set of elements or components whose conceptual and technical application definition needs to be accurate in order to obtain empirical results truly valid. Ibarra (2001) states that if you manage to get these items, then it is possible to integrate all of them in a second phase, in which through the application of a methodology, certain percentages of capacity and predictive accuracy on a possible business failure can be obtained ex-post. At this point, the practical usefulness becomes apparent when the models are able to distinguish between firms that fail and succeed (even if they have symptoms of failure) and companies that do fail (but not show symptoms of failure). Throughout the years and various investigations carried out, it was found that the instability of the models may be due to:

1. Classical Paradigm (Type I and Type II Errors).
2. Reliability and accounting information management.
3. Mathematical models that are difficult to generalize.
4. In the absence of a theory of business failure, statistical methods over adjusted predictive results.
5. The use of financial ratios.
6. Specify cutoffs .

It is difficult to find a single homogeneous theoretical conception of failure. The intention of all scholars has been to understand the complexity of the phenomenon of bankruptcy, thereby accounting information administration and manipulation. In this regard, Argentina (1976) and Rosner (2003), Mosqueda *et al*. (2002) found evidence that companies report high profits to give a positive image about their financial situation, especially when they are on the brink of failure. In this way, the design crisis suggests the methodological invalidity to define stable models in time, which in turn interferes with the accurate representation of the companies economic reality, and thus prevent them from making the right decisions.

The main difficulties in experimental designs is to distinguish between healthy companies and those that are not, based just on the existence of a common process, while the companies seem to experience different processes that involve failure (Laitinen, 1991 and 1993). The attempt to capture different failure processes in a unique model has led to the unreliable selection of variables and to spurious models in dissimilar contexts. Under these circumstances methods were oriented to manage combined indicators and dynamic models so that the financial situation can be measured. In an attempt to overcome the design errors implicit in advanced statistical techniques, other methods based on artificial intelligence have been developed. Such methods attempt to explain and forecast bankruptcy more effectively. The advantage of these techniques over conventional statistical methods is that they consider data in an exploratory fashion and do not start with preconceived hypotheses. These artificial-intelligence-based methods can be regarded as non parametric and include neural networks and rough set. In the light of the previous observations, the RPV model offers the possibility of improvement because it uses a mixed methodology according to a dynamic updating model that allows making substantial progress in the attempt to describe the enterprises' economic reality as well as their bankruptcy risk. We aim to build upon previous models in order to propose a more holistic one.

3. *Theoretical foundations of the RPV model*

The RPV model puts forward the study of strategic and organizational factors as an explanation for the economic status of the business. The model represents and alternative to accurately combine and run simulations of scenarios that consider both the process of failure and the prediction of bankruptcy in micro and small enterprises (MSEs).

Furthermore, the RPV model is a dynamic financial analysis model because it gets feedback not only from the business' economic situation but also from its environment (the market), given a certain level of optimization under equilibrium conditions (Mosqueda, 2008).

The model implies adopting several approaches and to consider the following different areas and corporate objectives, on which the results depend:

- **a.** Defining the business' goals
- **b.** Verifying the company's economic value
- **c.** Improving the company's financial position
- **d.** Overcoming eventual mergers

Thus, the econometric function of the RPV is determined as follows:

$$RPV = \alpha_i + b_{i1}A + b_{i2}B + b_{i3}C + \ldots + b_{ij}N + \varepsilon_1 \quad (1)$$

Where:

RPV is the weighted validation ratio of the business analyzed

α represents a constant and the opportunity cost and its equivalent as the risk free rate.

b is the answer coefficient (specific weights according to each variable within the function)

A, B, C, etc. are the most representative variables of the business analyzed (financial ratios, internal organizational factors, quality of management, etc.)[1]

The following equation is proposed to calculate the enterprise's performance using the WRV model:

$$RPV = \left\{ \Sigma \left(\frac{R_{si} - R_{ci}}{R_{ci}} \right) r_{ij} \right\} \{\pm 1, 0\} \quad (2)$$

Where:

R_{si} is the standard ratio (indicator, variable)

R_{ci} is the simple ratio (indicator, variable)

r_{ij} is the weighting for each representative ratio calculated in Function (2)

A (RPV)>0 represents el performance level of the business under analysis y must be compared with the cost of money (risk free rate) so that the optimization of resources can be determined.

$$EVA = dif\,(RPV_{it},\, i_{lr}) \quad (3)$$

Where:

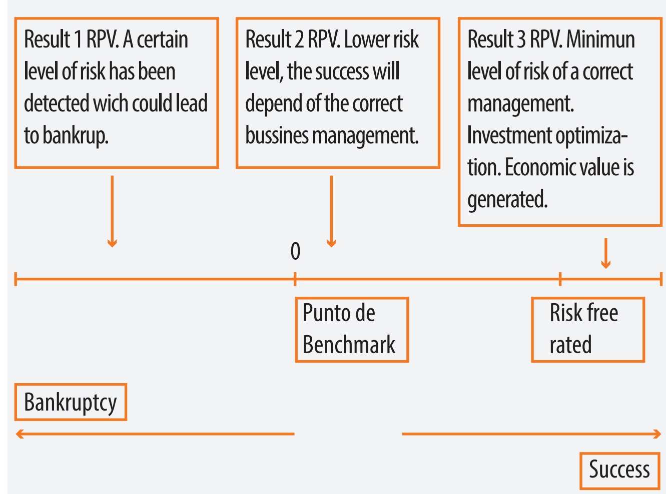
EVA = economic value added

RPV = is the economic performance of the business

i_{jr} = risk free rate, represented by α_i

As can be seen from Figure 1, the result from the RPV model makes the classifications of the financial situation of a business possible.

Figure 1. Financial situations according to the RPV results



Source: Mosqueda (2008).

In an attempt to overcome the design errors implicit in advanced statistical techniques, other methods based on artificial intelligence have been developed. Such methods attempt to explain and forecast bankruptcy more effectively. The advantage of these techniques over conventional statistical methods is that they consider data in an exploratory fashion and do not start with preconceived hypotheses. These artificial-intelligence-based methods can be regarded as non parametric and include neural networks and rough set.

The present study is the result of non-experimental quantitative research with longitudinal dimension criteria (since the data were collected throughout a long period of time)

1. The nature of the qualitative variables was obtained from a diagnostic competitiveness test as specified in the annexes of Mosqueda's work (2008).

and with an exploratory-evolutionary scope. In this study, some aspects of the bankruptcy phenomenon are analyzed: internal and qualitative factors that affect a business and how they can be used to predict bankruptcy early enough in order to improve the financial management of the MSEs.

Our working hypothesis is the following: Experimental design still exhibits problems and the model's structural changes make it necessary to refine or adjust it.

3.1. Variables[2]

a. The quantitative independent variables include the following ratios:
Return on investment (ROI) = Total assets/equity
Financial pressure (FP) = Payment to suppliers/profit before taxes

These indicators were calculated using the financial information contained in the financial statements (balance sheet and income statement) of the business studied.

b. Strategic qualitative independent variables: market knowledge, service quality, management skills, business opportunity, financial management systems, and technology and equipment supply. All these are considered in the Competitiveness Test[3], which covers 17 basic aspects of organizational management and which are grouped in 5 categories: finance, market-customer relationships, productive processes, development of human capital, and prospects.

3.2. Sample

After setting and applying certain selection criteria, we picked 30 enterprises, out of which 15 had gone bankrupt and 15 with a solid financial situation, representing three economic sectors. They are distributed as follows: 18 from the transformation sector, 9 from the service sector, and 3 from the trade sector. Twenty-four are small enterprises, while the other 6 are micro enterprises. The enterprises under study are located in the cities of Tepeji, Atotonilco, Tula de Allende and Atitalaquia, situated in the southern region of Hidalgo State in Central Mexico.

3.3. Data sources

The data were directly obtained from the businesses in the region considered for the study, using accounting documents (balance sheet and income statement) which allowed getting systematic and objective information concerning the economic and financial reality of the businesses. The data considered correspond to the five-year period prior to the bankruptcy, having set as the base year the year preceding failure. The time series includes data from 2006 to 2010.

3.4. Inclusion criteria

In order to ensure the validity of the comparisons we attempted using the RPV model, we set the following criteria to determine if an enterprise should be included or not in our study:

* Only micro and small enterprises (defined by their number of workers) were eligible.

Matching healthy and failed enterprises was possible, which demanded identifying the bankruptcy year for enterprises with an RVP>0.

* The bankruptcy year was 2010, since the research period would cover from 2006 to 2010.
* The Competitiveness Test had been successfully administered to the business; i.e., the acceptability degree for the information was above the benchmark set in the survey.
* The enterprises have enough qualitative and financial information for at least 3 years prior to bankruptcy.
* The accounting information (i.e. deflated data from balance sheets and financial statements) had exceeded the acceptability degree defined.

3.5. Procedure

We calculated the business performance using the weighting of the RPV[4] was calculated. Then we a matrix was elaborated with the results obtained, in order to determine the RPV.

In order to properly interpret the index obtained with the RPV model, it must be noted that the result is determined not only by the entries (i.e. the values of each variable) but also by the answer coefficients (weight) attributed to each variable, according to Mosqueda (2008). This means that the changes in the variables weighting will have some effects on the economic value of the business.

With this information, the changes in the answer coefficients (ACC) were calculated, using a regression analysis, in order to infer if the variables in each enterprise in the control group were correctly specified by the model.

4. Results

The most important variables that occur in this specific were identified and related to the bankruptcy process by means of the verification of response coefficients (ERC). However, the RVP model's robustness seems to suffer when applied in different contexts and to enterprises with different characteristics: the percentage of predictive accuracy for the bankrupt companies is lower to that obtained with the control group (84.6% and 90%, respectively).

The percentage of global accuracy showed Type I errors represent 0% and Type II errors the 20%. Then for the fifth year prior to bankruptcy, a predictive accuracy of 64% was obtained with 56% of the enterprises having been classified as healthy and 4% as failed, and with Type I and Type II errors of 36% and 4%,

2. See Mosqueda´s work (2008).
3. The test was established in the original research, validated by a group of experts. See Mosqueda´s work (2008).
4. The reason to utilize the weighting from the 2010 study instead of the original 2008 model was because we pretend to corroborate the specifics of the variables from the improved model.

respectively. It should be noted that when the time horizon of the model is broadened, healthy enterprises receive higher classification scores than bankrupt ones, as reported in previous studies. This can be due to the imprecise application of accountancy principles when recording the business' data, which makes it difficult to determine accurately the real performance of the business and which might also lead to conclude that some of the enterprises that were originally included in the study as "healthy" (i.e. in the control group), could in fact be bankrupt (although this could not be demonstrated beyond all doubt).

As for the increase in the errors when classifying failed enterprises in the fifth year of the period considered, we think that the further the failure moment, the more the similarities between healthy and failed enterprises, and the greater the difficulties to tell apart healthy from bankrupt companies.

4.1. Predictive capacity per sector

Table 1. Classification results. Trade Sector

Size	WRV	Interpretation	Status in Dec 2010	EVA
Small	-0.03	Bankrupt	Bankrupt	-4.37
Micro	3.22	Healthy	Healthy	-1.18
Micro	2.3	Healthy	Healthy	-2.07

Source: Taken from processed results of the RPV, calculated on 31st of December, 2010

In an attempt to overcome the design errors implicit in advanced statistical techniques, other methods based on artificial intelligence have been developed. Such methods attempt to explain and forecast bankruptcy more effectively. The advantage of these techniques over conventional statistical methods is that they consider data in an exploratory fashion and do not start with preconceived hypotheses. These artificial-intelligence-based methods can be regarded as non parametric and include neural networks and rough set. In an attempt to overcome the design errors implicit in advanced statistical techniques, other methods based on artificial intelligence have been developed. Such methods attempt to explain and forecast bankruptcy more effectively. The advantage of these techniques over conventional statistical methods is that they consider data in an exploratory fashion and do not start with preconceived hypotheses. These artificial-intelligence-based methods can be regarded as non parametric and include neural networks and rough set As can be seen from the table, when the EVA is considered, the micro enterprises presenting an RPV > 0 but < have a good although not perfect result. It can be inferred that the management and economic results are sufficient to overcome any threat of bankruptcy. However, in terms of economic value of the enterprise, the rate of capital return is neither optimal nor is it higher than what the stockholders could have obtained by investing in CETES (4.4%).

If no action is taken to improve management in order to increase the business profitability, the risk of going bankrupt for this group of enterprises is always present.

Table 2. Classification results. Services Sector

Size	RPV	Interpretation	Status in Dec 2010	EVA
Small	3.71	Healthy	Healthy	-0.69
Small	5.32	Healthy	Healthy	0.92
Small	3.96	Healthy	Healthy	-0.43
Small	-2.79	Bankrupt	Bankrupt	-7.19
Small	2.27	Healthy	Bankrupt	-2.13
77% of cases correctly classified				

Source: Taken from processed results of the RPV, calculated on 31st of December, 2010

The EVA results obtained in this case should be interpreted as the return rate that the enterprises would need to meet their investors' needs. Investors expect a profit at least as high as the free market interest rate (CETES); therefore, financial actions need to be adopted to improve profitability, so that they can compensate for losses derived from no investing in best-performing markets. The value of 0.92 suggests that the enterprise may be at serious risk of going bankrupt if it does not improve its financial efficiency.

Table 3. Classification results. Transformation Sector

Size	RPV	Interpretation	Status in Dec 2010	EVA
Small	3.79	Healthy	Healthy	-1.93
Small	-1.37	Bankrupt	Bankrupt	-0.61
Small	-1.76	Bankrupt	Bankrupt	-6.17
Small	1.68	Healthy	Healthy	-2.72
Small	0.383	Healthy	Bankrupt	-4.02
Small	0.699	Healthy	Healthy	-3.70
Small	1.64	Healthy	Healthy	-2.76
Small	1.75	Healthy	Healthy	2.64
Small	-2.79	Bankrupt	Bankrupt	-7.19
Small	2.58	Healthy	Bankrupt	-1.81
Small	3.82	Healthy	Healthy	-0.58
Small	-3.77	Bankrupt	Bankrupt	-8.18
Small	5.16	Healthy	Healthy	0.76
Small	2.71	Healthy	Bankrupt	-1.69
Micro	-0.54	Bankrupt	Bankrupt	-4.95
Small	-2.67	Bankrupt	Bankrupt	-1.73
Small	6.32	Healthy	Healthy	1.75
Small	0.76	Healthy	Bankrupt	-3.64
78% cases correctly classified.				

Source: Taken from processed results of the RPV, calculated on 31st of December, 2010

Compared with the trade and services sector, the enterprises in the transformation sector exhibit the lowest rates of economic value. Even though only five of these enterprises had gone bankrupt and two of them had a positive EVA (but lower to investment opportunities on the market), the rest of the companies in this sector showed very volatile competitiveness. This suggests that financial and administration management, as well as product marketing and sales, should be substantially improved.

The results discussed so far support the validity of the working hypothesis, concerning the importance of the response coefficient (ERC), since it is evident that seasonal or structural changes create new conditions. This makes it possible (and necessary) to adjust both the ERC and the model, because the optimization of the model precisely involves obtaining the value that better reflects the explanatory variables.

As for the experimental design, the working hypothesis was not demonstrated, because heterocedasticity was not observed.

In general, the model can be said to be robust whenever it is applied to samples others than the ones it was designed for. The explanatory variables affecting a business get properly grouped, both because the risk of misclassification risks are minimized and because a high forecasting capacity is obtained.

5. Optimized Model

As mentioned in the Methodology section, we carried out a multivariate regression of the econometric function EVA (3) in order to determine the explanatory variables degree of response. The results of this regression are shown in the table below.

Table 4. Results of the regression of the RPV model to determine the degree of response of each sector's explanatory variables in the case of the bankrupt companies studied (N = 15 MSEs)

Sector / *Explanatory* variables	*Services*	*Trade*	*Transformation*
Constant	0.52(0.022)	0.29(0.004)	0.33(0.068)
Financial pressure	-.33 (0.000)	-.27 (0.014)	-2.3 (0.000)
Profitability/investment [Podría ser investment profitability]	0.45 (0.000)	0.72 (0.001)	0.30 (0.002)
Financial management system	0.51 (0.023)	0.32 (0.074)	0.38 (0.016)
Business opportunities	0.53 (0.000)	0.74 (0.000)	0.28 (0.000)
Quality of service	2.18 (0.000)	-----------	----------
Management quality	0.45 (0.000)	0.28 (0.104)	----------
Equipment and technology available	-----------	0.91 (0.100)	0.27 (0.002)
Business growth	-----------	-----------	0.42 (0.000)
R_2	0.82	0.94	0.69
Sme	0.45	0.48	0.50

Source: From the calculation from December 2006 to December 2010. The t-student in parenthesis is based on Shapiro-Wilk test with a 95% level of confidence. Data obtained using STATA 11.0 software.

As can be observed from Table 4, the results obtained for the variable ***financial pressure*** (-0.33, -0.27 and -2.3 for the service, trade and transformation sectors, respectively) make it obvious that the MSEs that later went bankrupt are characterized not only by cash flow difficulties and lack of financial autonomy problems, but also by other factors such as low sales, low productivity and low process technification, which prevent one company's assets from generating enough economic value (the higher the financial pressure, the lower the EVA). A priori, we had hypothesized that, considering the period studied, the economic crisis could have an impact upon liquid assets or push the enterprises to take advantage of the opportunities offered by more dynamic markets.

Thus non-financial information may be appropriate to the characteristics of the MSEs because it influences the efficient management of resources, preventive steps that can be taken, the control of the company, and the decision-making process under adverse circumstances. Furthermore, the present environment represents and opportunity for the MSEs to challenge the traditional view of leadership that regards decision making as something that occurs in isolation from the environment. MSEs can become a living proof that strategic decisions are not contingent to the financial and economic reality, in the light of market dynamism.

As for the analysis per sector, it can be observed that for the enterprises in the service sector, "Quality of Service" is the most important variable, followed by "Business Opportunities "and " Financial Management System." This highlights the importance of the knowledge of the market and of correct resources management for the preservation of companies.

On the other hand, although it might be thought that "Equipment and Technology Available" is not so relevant in the trade sector, it can be seen that it is the most important one, followed by "Business Opportunities". It is obvious that the way a company adapts to and integrates technological change is a good indicator of its inner drive to outstand and to perform better on the market.

In the case of the transformation sector, the most important indicator is "Business Growth", followed by "Financial Management System" and "Investment Profitability". It can be inferred that knowledge of the market and of the competitors are decisive factors to use resources effectively and to promote the business goals step by step, building up a stability that guarantees better results in the long term. It is necessary to acknowledge the importance of strategic planning as part of a new direction MSEs should undertake if they want to keep operating on the market.

The variable we called "Constant"[5] represents the cost of credit for each sector. The asymmetry is evident: the service and transformation sectors would be paying the higher interest rates on the market (0.54 and 0.33%, respectively) while the trade sector has a lower index (0.29), which suggests the sector has

5. See Mosqueda, 2008.

been affected by a poor economic activity performance and it might need more to pay more attention to short term business opportunities.

On the other hand, the EVA results obtained show the optimization of resources has not been met (with respect to best-performing markets) and the presence of high volatility. This means the enterprises are not generating economic surplus, which might imply bankruptcy is looming on the horizon. Once again, this highlights how important it is for enterprises to have an efficient strategic and financial planning system that can think of something else beyond simply making money (even though it is vital) so that such enterprises can preserve and enhance their business.

6. Validation of Results

The hypothesis concerning the significance of the model is accepted. The value of R^2, with a 95% confidence level, reaches a maximum value of 0.94 in the commercial sector with a critical significance level of 0.000.

However, both the service and the transformation sectors were found to have a low level of significance, which incites us to be cautious when interpreting the data obtained. Because of this, we decided to also perform the heteroscedasticity test. When applying the ARCH test, the errors were found to remain constant variance over the sample.

Volatility could be integrated into the low values obtained in the three sectors of the equation of economic value added of the business (EVA) because, as mentioned previously, when compared with the highest return markets, none of the companies studied showed the economic performance characteristic of successful businesses.

Regarding multicolinearity test, the model seems to have succeeded, having obtained a value of VIF < 10. Explanatory variables of the sectors considered were not found to show exact linear relationship to one another; they only affect the dependent variable.

Regarding autocorrelation, the model also seemed to behave efficiently, because a probability level above 0.05 was obtained. This can be interpreted as model residuals following a pattern of mutual autocorrelation.

Finally the Ramsey Reset test, which refers to testing the model specifications, allowed verifying that the specification of variables was correct and that the model is linear, since the probability values obtained were above 0.05.

7. Conclusions

Far from being a definitive study, this work is the first step in a field of research with a wide range of theoretical and practical issues that should be addressed. Below are the key findings of this study as well as issues that require further research:

The results discussed allowed verifying the effectiveness of the model when applied in environments different from that in which it was originally tested. It was possible, therefore, to refine the model.

This study confirms that in the case of MSEs, the conjunction of accounting and qualitative variables plays an important role, as they impact on all aspects of the operation of the company.

The Earning Power theory on which rests the WRV model perfected in 2010 and which states that the past is repeated in the future, turned out to be invalid in this sample, since in all cases the ERC values obtained were much tighter. However, the degree of predictive accuracy achieved is more than 70% in all sectors, and even reaching a 84.6 % rate of general accuracy at the moment of bankruptcy.

Research suggests that in the case of Hidalgo's MSEs, *business opportunities, financial pressure, return on investment, equipment and technology availability, financial management,* and *market knowledge* are the variables that play the most significant role when modeling the enterprises' functional strategic situation.

In making this claim, it is necessary to acknowledge a methodological limitation that must be addressed in future work on this matter. The model does not control the impact of the macro economy on the MSEs' performance. It would therefore be appropriate to investigate the scope and scale of macroeconomic factors and to determine to what extent they cancel out (or not) the effect of bankruptcy.

The study is open so that further research on enterprise bankruptcy theory can be carried out. It will be necessary to improve experimental design in order to verify other contexts for which the RPV is valid and where its contributions can be of practical use.

8. References

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