Proceedings of the World Congress on Engineering 2014 Vol II,
WCE 2014, July 2 - 4, 2014, London, U.K.

Strategic and Financial Risk Model for Small and Medium Enterprises

Efrain Alvarez-Vazquez, J. Raul Castro, Pablo Perez-Akaki, Pilar H. Limonchi, Mario Alberto Lagunes

Abstract— The small and medium enterprises (SMEs) are exposed to different kind of risks, which should be measured, identified, and controlled. Currently, different risk measures are used for finance, operation and management strategies. Therefore, a model able to identify and analyze different kind of risks is required for the enterprise. Then the evaluation and treatment of this risk should be done. One of the most popular and successful model used for studying enterprise risk is logit. In this paper, a model for risk identification in Mexican SMEs is presented. Qualitative and quantitative variables in a logit method are applied by performing a diagnosis using a Likert scale for evaluating enterprise's areas. Besides, financial ratios are also included and relevant variables were obtained using a hypothesis test. This model is designed for different kind of SMEs, and its application depends on the variables that are evaluated. A practical example shows the benefits of significant variables that predict risk.

Index Terms— Business failure, financial ratios, logit method, scoring.

I. INTRODUCTION

The corporations are surrounded by an economic process of high complexity. They are characterized by strong concentration of variables and phenomena that influence financial development of companies. This is why it is recommended to identify and categorize macroeconomic variables, as employment, savings, investment, profitability, competitiveness, growth, among many others. In the long run, all of them are part of the country's economy.

Figure 1 shows the set of variables and indicators that have an impact on corporate processes for decision taking that generate strategies, systems of control for specific desired results.

Manuscript received March 23, 2014; revised April 9, 2014.

The 2014 International Conference of Financial Engineering

Efrain Alvarez-Vazquez is with Universidad Popular Autonoma del Estado de Puebla, 21 sur 1103 Barrio Santiago, 72410, Puebla, Mexico (e-mail: ralvarez@esecorporativo.com.mx).

J. Raúl Castro, is with Benemérita Universidad Autonoma de Puebla, 4 Sur 104, Centro Historico, 72000 Puebla, Mexico (e-mail: j_raul_castro@hotmail.com).

Pablo Perez-Akaki, is with Universidad Nacional Autonoma de Mexico, Yaquis, Santa Cruz Acatlan, 53150 Naucalpan de Juarez, Estado de Mexico, Mexico (e-mail: ppablo@apolo.acatlan.unam.mx).

Pilar H. Limonchi, is with Universidad Politecnica del Estado de Morelos, Boulevard Cuauhnahuac 566, colonia Lomas del Texcal, 62550, Jiutepec, Morelos, Mexico (e-mail: mhernandez@upemor.edu.mx).

Mario Alberto Lagunes, is with Universidad Popular Autonoma del Estado de Puebla, 21 sur 1103 Barrio Santiago, 72410, Puebla, Mexico (e-mail: marioalberto.lagunes@upaep.mx).

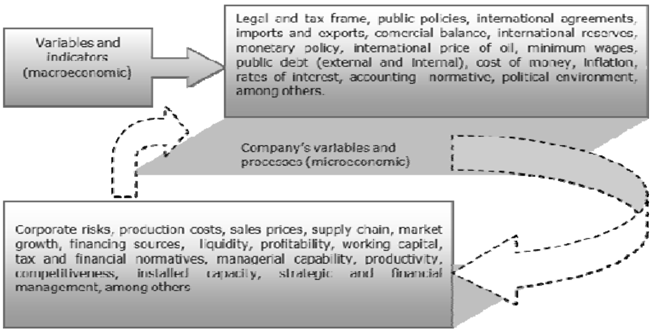

Fig. 1. Variable, indicators and processes that affect SMEs

SMEs in Latin America represent a set of multiple economic agents that contribute significantly to the creation of employment, and even the Gross Domestic Product.

Most of decisions and results are based on the experience of the entrepreneur, especially in the financial area, due the fact that they are not supported by appropriate scientific tools.

The responsibility of the shareholders, GEOs, CFOs, and managers is to decide to contribute with their own money or to apply a leverage strategy; in any case, risk is present and should be estimated and minimized [1]. Therefore, the financial strategies should be constantly improved all the time. As a consequence, the application of best practices of control and financial is highly recommended for different scenarios in order to make the best decisions. The usage of a diagnostic model is essential to identify the weakest areas of a company, to recommend actions and mitigate risks. Moreover, the availability of a method for measuring strategic management decisions would be a plus for evaluation of different areas of the organization.

These facts bring out the necessity of developing and implementing financial models that contribute to the increase of competitiveness of the SMEs in Mexico. In order to identify, study, and control all different types of risks, it is necessary to use quantitative and qualitative techniques for develop appropriate feedbacks.

The purpose of this paper is to use the ZETA Analysis Method proposed by Altman, Haldeman and Narayanan in the Journal of Banking and Finance (1977), as a startup model. We intended to identify bankruptcy risk of corporations in terms of return of assets, stability of earnings, debt service, cumulative profitability, liquidity, capitalization and size of the firm.

ISBN: 978-988-19253-5-0
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

The proposed model will also includes qualitative variables such as strategic planning, market behavior, production and human resources management.

The paper is organized as follows. Section two, presents research works related with this method. In section three, the methodology for achieve the proposed model is developed; section four, shows the obtained results by applying this model in several SMEs. Finally, in section five the conclusions of the paper are presented.

II. RELATED WORKS

Academic researchers have dedicated to search the best corporate failure prediction model. The classical statistical methods (multivariate discriminant analysis and logit models) are popular methods for the development of corporate failure prediction models. Moreover, the researchers also used several alternative methods, as a result of the progress in computational possibilities and in artificial intelligence [2].

The pioneer in bankruptcy prediction is Fitzpatrick, with his studies about the use of ratio analysis to predict the future of the firms [3]. Subsequently, Beaver developed an empirical study to identify 79 firms in Moody`s Industrial Manual that failed during 1954 to 1964. He suggested a methodology for evaluating financial ratios, by a single ratio. However, a multi-ratio analysis can be establish, by using different ratios for different financial tasks and even to improve predictions [4]. Altman selected five variables for prediction of corporate bankruptcy. Using multivariate discriminant analysis, the variables were: working capital, retained earnings, earnings before interest and taxes, market value equity, and sales [5]. Wilcox purposed a simple theoretical model offering an explanation of Beaver's empirical results, and improving predictors of financial failure. Therefore, if the model prediction is devised on base of the variance of the cash flow, incomes and expenses, the total risk can be minimized and the prediction is improved [6].

Deakin proposed an alternative model, applying the discriminant analysis to predict business failure that can avoid substantial losses to creditors and stockholders [7].

Later, Altman proposed the Zeta model which consists of 53 bankrupt firms and 58 non-bankrupt entities. He selected 27 variables that can be classified in five groups as profitability, coverage and other earnings relative to leverage measures, liquidity, capitalization ratios, earnings variability, and a few miscellaneous measures [8].

Zmijewski transformed the Zeta model (based on a logistic regression) into a Probit model by using the Normal distribution instead of the logistic function at the moment of calculating bankruptcy probabilities [9].

The discriminant analysis in failure prediction was the method used until 1980´s. The logistic analysis replaced this method. Afterwards, the neural networks, genetic algorithms and logit analysis leads to different failure prediction models [10].

A multilogit approach was developed and tested by Peel and Peel with the purpose of predicting the probability and timing of corporate failure [11]. Additionally, it was later modified by Richard, Allaway and Womack to examine when if-and-when consumers will choose [12].

Lehto also used a multilogit model to estimate the probabilities that a firm will acquire or become a target for a Merger or Acquisition, by establishing three different categories for the possible results [13].

Anandarajan and Lee rather than use multiple financial ratios, included a single variable of financial distress into a genetic algorithm neural network model [14] and support vector regression [15].

III. METHODOLOGY

A score summarizes the information contained in factors that affect default probability. Standard scoring models take the most straightforward approach by linearly combining those factors. Let x denote the factors (their number is K) and b the weights (or coefficients) attached to them; we can represent the score that we obtain in scoring instance i as:

$$\text{Score}_i = b_1 x_{i1} + b_2 x_{i2} + \ldots + b_K x_{iK}$$

Where i = 1, 2,... n for a total of n observations. Therefore, each observation i considers the indicators associated to a specific company in a given year of study.

It is convenient to have a shortcut for this expression. Collecting the b's and the x's in column vectors b and x we can rewrite the previous equation to:

$$\text{Score}_i = b_1 x_{i1} + b_2 x_{i2} + \ldots + b_K x_{iK} = \mathbf{b}'\mathbf{x}_i, \quad \mathbf{x}_i = \begin{bmatrix} x_{i1} \\ x_{i2} \\ \vdots \\ x_{iK} \end{bmatrix}, \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_K \end{bmatrix}$$

If the model is to include a constant b_1, we set x_{i1} =1 for each i. Assume, for simplicity, that we have already agreed on the choice of the factors x – what is then left to determine is the weight vector b. Usually, it is estimated on the basis of the observed default behavior.

Upon defaulting, firms often stay in default for several years; in such cases, we would not use the observations following the year in which default occurred. The default information is stored in the variable y_i. It takes the value 1 if the firm defaulted in the year following the one for which we have collected the factor values, and zero otherwise.

The scoring model should predict a high default probability for those observations that defaulted and a low default probability for those that did not. In order to choose the appropriate weights b, we first need to link scores to default probabilities. This can be done by representing default probabilities as a function F of scores:

$$\text{Prob}(\text{Default}_i) = F(\text{Score}_i)$$

Like default probabilities, the function F should be constrained to the interval from 0 to 1; it should also yield a default probability for each possible score. The requirements can be fulfilled by a cumulative probability distribution function. A distribution often considered for this purpose is the logistic distribution. The logistic distribution function $\Lambda(Z)$ is defined as :

$$\Lambda(Z) = \frac{e^Z}{1+e^Z}$$

Therefore:

$$\text{Prob}(\text{Default}_i) = \Lambda(\text{Score}_i) = \frac{\exp(\mathbf{b}'\mathbf{x}_i)}{1+\exp(\mathbf{b}'\mathbf{x}_i)} = \frac{1}{1+\exp(-\mathbf{b}'\mathbf{x}_i)}$$

The models that link information to probabilities using the logistic distribution function are called logit models and have a similar graph as the following:

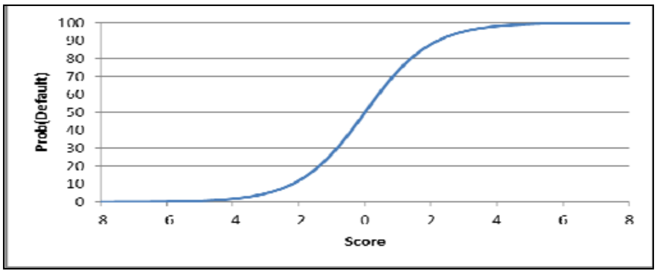

Fig. 2. Logistic Function

Having collected the factors x and chosen the distribution function F, a natural way of estimating the weights b is the maximum likelihood method (ML). According to the ML principle, the weights are chosen such that the probability of observing the given default behavior is maximized.

The first step of the maximum likelihood estimation is to set up the likelihood function [16]. For a borrower that defaulted (Y_i=1), the likelihood of observing this is:

$$\text{Prob}(\text{Default}_i) = \Lambda(\mathbf{b}'\mathbf{x}_i)$$

For a borrower that did not default (Y_i=0), the likelihood function is:

$$\text{Prob}(\text{No default}_i) = 1 - \Lambda(\mathbf{b}'\mathbf{x}_i)$$

The two later formulae can be combined as follows:

$$L_i = (\Lambda(\mathbf{b}'\mathbf{x}_i))^{y_i}(1-\Lambda(\mathbf{b}'\mathbf{x}_i))^{1-y_i}$$

Assuming that defaults are independent, the likelihood of a set of observations is just the product of the individual likelihoods:

$$L = \prod_{i=1}^{N} L_i = \prod_{i=1}^{N} (\Lambda(\mathbf{b}'\mathbf{x}_i))^{y_i}(1-\Lambda(\mathbf{b}'\mathbf{x}_i))^{1-y_i}$$

For maximization purposes the next logarithm likelihood function is more adequate:

$$\ln L = \sum_{i=1}^{N} y_i \ln(\Lambda(\mathbf{b}'\mathbf{x}_i)) + (1-y_i)\ln(1-\Lambda(\mathbf{b}'\mathbf{x}_i))$$

The later function can be maximized by using the classical optima conditions; than means the first and second derivatives with respect to b. As is well known an equation is established by setting to zero the next first derivative:

$$\frac{\partial \ln L}{\partial \mathbf{b}} = \sum_{i=1}^{N} (y_i - \Lambda(\mathbf{b}'\mathbf{x}_i))\,\mathbf{x}_i$$

Newton's method works very well for solving the later equation; then this solution is used in the second optimal condition which deals with the second derivatives. Thus, we obtain:

$$\frac{\partial^2 \ln L}{\partial \mathbf{b}\,\partial \mathbf{b}'} = -\sum_{i=1}^{N} \Lambda(\mathbf{b}'\mathbf{x}_i)(1-\Lambda(\mathbf{b}'\mathbf{x}_i))\,\mathbf{x}_i\mathbf{x}_i'$$

Next, the variables (xi's) are analyzed in order to estimate the probability as follows:

- Industrial Corporations

A total of 48 variables were considered (31 qualitative and 18 quantitative) as described in the table below. Additionally, we considered for this study the performance of 12 companies through the period 2010 – 2012 (with a total of 36 observations).

Table I. Industrial Variables

Area	Sector	Variable	Description	Type
Management	Strategic Planning	x1	Mission Clearly Defined	Qualitative
Management	Strategic Planning	x2	Well Defined objectives and goals	Qualitative
Management	Decision Taking	x3	Methodical decision taking	Qualitative
Management	Decision Taking	x4	Efficient communication channels	Qualitative
Management	Policies and procedures	x5	Well defined policies and procedures	Qualitative
Management	Policies and procedures	x6	Existence of performance indicators	Qualitative
Market	Sales	x7	Clear sales objectives	Qualitative
Market	Sales	x8	Frequent sales deviation analysis	Qualitative
Market	Customers	x9	There's a clear definition of who the customer is	Qualitative
Market	Customers	x10	There's customer's follow up (CRM)	Qualitative
Market	Competitors & Growth	x11	Knowledge of list of competitors	Qualitative
Market	Competitors & Growth	x12	Area of growth for current product portfolio	Qualitative
Finance	Financial Information	x13	Financial Information well prepared and available	Qualitative
Finance	Financial Information	x14	Frequent use of financial info for decision taking	Qualitative
Finance	Profitability	x15	Constant Cash Flow Generation	Qualitative
Finance	Profitability	x16	Profit generation is positive compared to industry	Qualitative
Finance	Financial Planning	x17	Healthy account of payables with providers	Qualitative
Finance	Financial Planning	x18	Constant follow up of accounts receivable	Qualitative
Production	Costs	x19	Adequate availability of raw materials	Qualitative
Production	Costs	x20	There is a system for cost transactions	Qualitative
Production	Inventory	x21	There is a logical flow of inventory	Qualitative
Production	Inventory	x22	There is an inventory system	Qualitative
Production	Production Systems	x23	There are operation and procedure manuals	Qualitative
Production	Production Systems	x24	Use of statiscal information for production improvement	Qualitative
Human Capital	Selection	x25	There is a policy of selection of human resources	Qualitative
Human Capital	Selection	x26	There is a process of induction for new people	Qualitative
Human Capital	Training	x27	Detailed list of needs for training	Qualitative
Human Capital	Training	x28	Permanent training program in course	Qualitative
Human Capital	Labor environment	x29	Favourable working environment	Qualitative
Human Capital	Labor environment	x30	Turn over of people is within industry's average	Qualitative

ISBN: 978-988-19253-5-0
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

Table II. Financial Variables

Area	Sector	Variable	Description	Type
Financial ratios	Liquidity ratios	x31	Working capital ratio	Quantitative
Financial ratios	Liquidity ratios	x32	Acid Test ratio	Quantitative
Financial ratios	Liquidity ratios	x33	Treasury ratio	Quantitative
Financial ratios	Activity ratios	x34	Sales / Assets	Quantitative
Financial ratios	Activity ratios	x35	Accounts receivable turn over ratio	Quantitative
Financial ratios	Activity ratios	x36	Inventory turn over ratio	Quantitative
Financial ratios	Activity ratios	x37	Accounts payable turn over	Quantitative
Financial ratios	Activity ratios	x38	Financial Cycle	Quantitative
Financial ratios	Leverage ratios	x39	Debt ratio	Quantitative
Financial ratios	Leverage ratios	x40	Leverage ratio	Quantitative
Financial ratios	Leverage ratios	x41	Interests coverage	Quantitative
Financial ratios	Leverage ratios	x42	Payment coverage	Quantitative
Financial ratios	Profitability ratios	x43	Sales profitability	Quantitative
Financial ratios	Profitability ratios	x44	Asset profitability	Quantitative
Financial ratios	Profitability ratios	x45	Investment profitability	Quantitative
Financial ratios	Other ratios	x46	Equilibrium point / Working Capital	Quantitative
Financial ratios	Other ratios	x47	% of working capital over income	Quantitative
Financial ratios	Other ratios	x48	% of working capital over total assets	Quantitative

- Retail Corporations

The same variables as those for Industrial Corporations are established with the following changes:

Table III. Retail Variables

Area	Sector	Variable	Description	Type
Commercialization	Comercializing process	x19	Well documented processes	Qualitative
Commercialization	Comercializing process	x20	Strong sales force	Qualitative
Commercialization	Distribution and location	x21	Adequate location of stores	Qualitative
Commercialization	Distribution and location	x22	Correct alignment of products to customers	Qualitative
Commercialization	Quality Service	x23	Reliable services and products	Qualitative
Commercialization	Quality Service	x24	Efficiente complaint management	Qualitative

- Service Corporations

As the ones as those of Industrial Corporations with the following changes:

Table IV. Service Variables

Area	Sector	Variable	Description	Type
Service	Servicing processes	x19	Right documentation of processes	Qualitative
Service	Servicing processes	x20	Strong sales force	Qualitative
Service	Distribution Service	x21	There's a logical flow of service	Qualitative
Service	Distribution Service	x22	Clear identification of services portfolio by customers	Qualitative
Service	Quality of service	x23	Reliable services	Qualitative
Service	Quality of service	x24	Good complaint management	Qualitative

It is important to note that qualitative variables were assigned with a value of “0” in case of negative result and “1” if it was positive.

IV. RESULTS

- Industrial Corporations

A total of 34 variables were eliminated in the first part or the selection process. This was done as some of them were linearly dependent with other variables or because the significance value or their coefficients (p-value) was equal to 1. In the second part of the process a step wise procedure was followed in order to find the most significant variables at a 10% level for Alpha. The results are summarized in the following Table:

Table V. The most significant variables in Industrial Corporations

	CONST	x4	x16	x33
b	2.682508	-1.25286	-2.59858009	-5.29809158
p-value	0.03326993	0.02716851	0.01161317	0.09655153
Pseudo R²	0.44495478			
LR-test / p-value	20.3918417	0.00014078		

Where:

x4 = Efficient communication channels

x16 = Profit generation is positive compared to industry

x33 = Treasury ratio

The LR test implies that the Logistic Regression is highly significant (as the p-value = 0.00014708, less than 1%). The hypothesis that these 3 variables add nothing to the prediction can be rejected with high confidence. Additionally, each variable’s p-value is below 10%.

- Retail Corporations

A total of 31 variables were eliminated in the first part or the selection process. The process for eliminating non-significant variables was the same as for the Industrial Corporations. The results are summarized in the following Table:

Table VI. The most significant variables in Retail Corporations

	CONST	x7	x35
b	1.452261318	-2.26384758	-0.06800013
p-value	0.019350343	0.04215168	0.02286032
Pseudo R²	0.315958648		
LR-test / p-value	11.06745314	0.00395124	

Where:

x7 = Clear sales objectives

x35 = Accounts receivable turnover ratio

The LR test implies that the Logistic Regression is highly significant (as the p-value = 0.00395124, less than 1%). The hypothesis that these 2 variables add nothing to the prediction can be rejected with high confidence. Additionally, each variable’s p-value is below 10%.

- Service Corporations

A total of 30 variables were eliminated in the first part or the selection process.

The process for eliminating non-significant variables was the same as for the Industrial and Retail Corporations. The results are summarized in the following Table:

Table VII. The most significant variables in Services Corporations

	CONST	x2	x31
b	-0.693147181	-2.302585093	-0.415634336
p-value	0.020568935	0.04750726	0.073456326
Pseudo R²	0.163509987		
LR-test / p-value	5.304330547	0.021272473	

Where:

x2 = Well Defined objectives and goals

x31 = Working capital ratio

The LR test implies that the Logistic Regression is highly significant (as the p-value = 0.021272473, less than 5%). The hypothesis that these 2 variables add nothing to the prediction can be rejected with high confidence. Additionally, each variable’s p-value is below 10%.

V. CONCLUSION

In this paper, the model developed is significantly more accurate predicting the risk in small and medium enterprises in Mexico. The logit techniques with qualitative and quantitative variables organized by several groups are

ISBN: 978-988-19253-5-0
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

applied: Qualitative (Management, Market, Finance, Production, commercialization, service, and Human capital) and Quantitative (including financial ratios of liquidity, activity, leverage, profitability, and others).

Firstly a strategic a diagnosis were performed by applying the Likert scale in order to evaluate the areas of the enterprise; then each attribute was quantified as a boolean variable. Therefore a logit method could be applied. In addition, the financial ratios were obtained from the accounting of evaluated enterprises. The relevant variables were obtained using a hypothesis test. Because in this method the variables are organized by the relevance of each of them, different strategies can be performed. In addition this methodology can consider different kind of organization, the application is completely general. As future works, this methodology can be adapted with new regression methods such as neural networks, and support vector machines.

REFERENCES

[1] J. Giral, A. Eroles, V. Estivil, E. Garcia, L. Larraza and G. Viesca. "Competent Companies." Mexico: Editorial Group Latin America, 2002.

[2] S. Balcaen and H. Ooghe, "Alternative methodologies in studies on business failure: do they produce better results than the classical statistical methods?" Universiteit Gent, Faculteit Economie en Bebrijfskunde, Jun. 2004, pp. 1-5.

[3] P. Fitzpatrick, *A comparison of ratios of successful industrial enterprises with those of failed* firms, The Accountants Publishing Company, 1932.

[4] W. Beaver, *Financial Ratios as Predictors of Failure*, Journal of Accounting Research, 1966, pp. 71-111.

[5] E. Altman, *Financial ratio, discriminant analysis and the prediction of corporate bankruptcy*, Journal of Finance, vol. XXIII, 1968, pp. 589-609.

[6] J. Wilcox, *A simple theory of financial ratios ad predictors of failure*, Journal of Accounting Research, 1971, pp. 389-395.

[7] E. Deakin, *A discriminant analysis of predictors of business failure*, Journal of Accounting Research, 1972, pp. 166-179.

[8] E. Altman, R. Haldeman and P. Narayanan, *Zeta analysis: a new model to identify bankruptcy risk of corporations*, Journal of banking and finance, 1977, p. 29-54.

[9] M. Zmijewski, *Methodological issues related to the estimation of financial distress prediction models*, Journal of Accounting Research, 1984, pp. 59-82.

[10] B. Back, T. Laitinen, K. Sere and M. Van Wezel, *Choosing bankruptcy predictors using discriminant analysis, logit analysis, and genetic algorithms*, Turku Centre for Computer Science, 1996, pp. 1-13.

[11] M. Peel and D. Peel, *A multilogit approach to predicting corporate failure-Some evidence for the UK corporate sector*, Omega International Journal of Management Science, 1989, pp. 309-318.

[12] M. Richard, A. Allaway and J. Womack, *A Multilogit model of consumer choice*, The Journal of Marketing, 1994, pp. 39-53.

[13] E. Lehto, *The motives to restructure the industries – The finished evidence on cross border and domestic mergers and acquisitions*, Labour Institute for Economic Research, 2004, pp. 2-27.

[14] M. Anandarajan, P. Lee and A. Anandarajan, *Bankruptcy prediction of financially stressed firms: an examination of predictive accuracy of artificial neural networks*, Intelligent systems in accounting finance and management, 2011, pp. 69-81.

[15] G. Loffler and P. Posch, *Credit Risk Modeling using Excel and VBA.*John Wiley & Sons. USA, 2007. pp. 1-4.

[16] G. Santamaria-Bonfil, J. Frausto-Solis and I. Vazquez-Rodarte, *Volatility Forecasting Using Support Vector Regression and a Hybrid Genetic Algorithm*. Computational Economics, Springer, 2013 pp. 1-6.