

Scherger, Valeria; Terceño, Antonio; Vigier, Hernán P.

Article

Economic-financial diagnosis and prediction of SMEs: An application to the constructin sector

The International Journal of Management Science and Information Technology (IJMSIT)

Provided in Cooperation with:

North American Institute of Science and Information Technology (NAISIT), Toronto

Suggested Citation: Scherger, Valeria; Terceño, Antonio; Vigier, Hernán P. (2016) : Economic-financial diagnosis and prediction of SMEs: An application to the constructin sector, The International Journal of Management Science and Information Technology (IJMSIT), ISSN 1923-0273, NAISIT Publishers, Toronto, Iss. 21, pp. 46-55

This Version is available at:

<https://hdl.handle.net/10419/178829>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

An official publication of The North American
Institute of Science and Information Technology

ISSN:1923-0265

INTERNATIONAL JOURNAL OF

Management Science and Information Technology



NAISIT
PUBLISHERS **III**

www.naisit.org

The International Journal of Management Science and Information Technology (IJMSIT)

NAISIT Publishers

Editor in Chief

J. J. Ferreira, University of Beira Interior, Portugal, Email: jjmf@ubi.pt

Associate Editors

Editor-in-Chief: João J. M. Ferreira, University of Beira interior, Portugal

Main Editors:

Fernando A. F. Ferreira, University Institute of Lisbon, Portugal and University of Memphis, USA

José M. Merigó Lindahl, University of Barcelona, Spain

Vanessa Ratten, La Trobe University, Melbourne, Australia

Assistant Editors:

Cristina Fernandes, Polytechnic Institute of Castelo Branco, Portugal

Jess Co, University of Southern Queensland, Australia

Marjan S. Jalali, University Institute of Lisbon, Portugal

Editorial Advisory Board:

Adebimpe Lincoln, Cardiff School of Management, UK

Aharon Tziner, Netanya Academic College, Israel

Alan D. Smith, Robert Morris University, Pennsylvania, USA

Ana Maria G. Lafuente, University of Barcelona, Spain

Anastasia Mariussen, Oslo School of Management, Norway

Christian Serarols i Tarrés, Universitat Autònoma de Barcelona, Spain

Cindy Millman, Business School -Birmingham City university, UK

Cristina R. Popescu Gh, University of Bucharest, Romania

Dessy Irawati, Newcastle University Business School, UK

Domingo Ribeiro, University of Valencia, Spain

Elias G. Carayannis, Schools of Business, USA

Emanuel Oliveira, Michigan Technological University, USA

Francisco Liñán, University of Seville, Spain

Harry Matlay, Birmingham City University, UK

Helen Lawton Smith, Birkbeck, University of London, UK

Irina Purcarea, Adjunct Faculty, ESC Rennes School of Business, France

Jason Choi, The Hong Kong Polytechnic University, HK

João Ricardo Faria, University of Texas at El Paso, USA

Jose Vila, University of Valencia, Spain

Kiril Todorov, University of National and World Economy, Bulgaria

Louis Jacques Filion, HEC Montréal, Canada

Luca Landoli, University of Naples Federico II, Italy

Luiz Ojima Sakuda, Researcher at Universidade de São Paulo, Brazil

Mário L. Raposo, University of Beira Interior, Portugal

Marta Peris-Ortiz, Universitat Politècnica de València, Spain

Michele Akoorie, The University of Waikato, New Zealand

Pierre-André Julien, Université du Québec à Trois-Rivières, Canada

Radwan Karabsheh, The Hashemite University, Jordan

Ricardo Chiva, Universitat Jaume I, Spain

Richard Mhlanga, National University of Science and Technology, Zimbabwe

Rodrigo Bandeira-de-Mello, Fundação Getulio Vargas – Brazil
Roel Rutten, Tilberg University - The Netherlands
Rosa Cruz, Instituto Superior de Ciências Económicas e Empresariais, Cabo Verde
Roy Thurik, Erasmus University Rotterdam, The Netherlands
Sudhir K. Jain, Indian Institute of Technology Delhi, India
Susana G. Azevedo, University of Beira Interior, Portugal
Svend Hollensen, Copenhagen Business University, Denmark
Walter Frisch, University of Vienna, Austria
Zinta S. Byrne, Colorado State University, USA

Editorial Review Board

Adem Ögüt, Selçuk University Turkey, Turkey
Alexander B. Sideridis, Agricultural University of Athens, Greece
Alexei Sharpanskykh, VU University Amsterdam, The Netherlands
Ali Kara, Pennsylvania State University -York, York, USA
Angilberto Freitas, University of Grande Rio, Brazil
Arminda do Paço, University of Beira Interior, Portugal
Arto Ojala, University of Jyväskylä, Finland
Carla Marques, University of Trás-os-Montes e Alto Douro, Portugal
Carla Pereira, University of Beira Interior, Portugal
Cem Tanova, Çukurova University, Turkey
Cristiano Tolfo, Universidade Federal de Santa Catarina, Brazil
Cristina S. Estevão, Polytechnic Institute of Castelo Branco, Portugal
Dario Miocevic, University of Split, Croatia
Davood Askarany, The University of Auckland Business School, New Zealand
Debra Revere, University of Washington, USA
Denise Kolesar Gormley, University of Cincinnati, Ohio, USA
Dickson K.W. Chiu, Hong Kong University of Science and Technology, Hong Kong
Domènec Melé, University of Navarra, Spain
Dina Miragaia, University of Beira Interior, Portugal
Emerson Mainardes, FUCEPE Business School, Brazil
Eric E. Otenyo, Northern Arizona University, USA
George W. Watson, Southern Illinois University, USA
Gilnei Luiz de Moura, Universidade Federal de Santa Maria, Brazil
Jian An Zhong, Department of Psychology, Zhejiang University, China
Joana Carneiro Pinto, Faculty of Human Sciences, Portuguese Catholic University, Lisbon, Portugal
Joaquín Alegre, University of Valencia, Spain
Joel Thierry Rakotobe, Anisfield School of Business, New Jersey, USA
Jonathan Matusitz, University of Central Florida, Sanford, FL, USA
Kailash B. L. Srivastava, Indian Institute of Technology Kharagpur, India
Karin Sanders, University of Twente, The Netherlands
Klaus G. Troitzsch, University of Koblenz-Landau, Germany
Kuiran Shi, Nanjing University of Technology, Nanjing, China
Liliana da Costa Faria, ISLA, Portugal
Luiz Fernando Capretz, University of Western Ontario, Canada
Lynn Godkin, College of Business, USA

Maggie Chunhui Liu, University of Winnipeg, Canada
Marcel Ausloos, University of Liège, Belgium
Marge Benham-Hutchins, Texas Woman's University, Denton, Texas, USA
María Nieves Pérez-Aróstegui, University of Granada, Spain
Maria Rosita Cagnina, University of Udine, Italy
Mayumi Tabata, National Dong Hwa University, Taiwan
Micaela Pinho, Portucalense University and Lusíada University, Portugal
Paolo Renna, University of Basilicata, Italy
Paula Odete Fernandes, Polytechnic Institute of Bragança, Portugal
Paulo Rupino Cunha, University of Coimbra, Portugal
Peter Loos, Saarland University, Germany
Pilar Piñero García, F. de Economía e Administración de Empresas de Vigo, Spain
Popescu N. Gheorghe, Bucharest University of Economic Studies, Bucharest, Romania
Popescu Veronica Adriana, The Commercial Academy of Satu-Mare and The Bucharest University of Economic
Studies, Bucharest, Romania
Ramanjeet Singh, Institute of Management and Technology, India
Ricardo Morais, Catholic University of Portugal
Ruben Fernández Ortiz, University of Rioja, Spain
Ruppa K. Thulasiram, University of Manitoba, Canada
Soo Kim, Montclair State University, Montclair, NJ, USA
Wen-Bin Chiou, National Sun Yat-Sem University, Taiwan
Willaim Lawless, Paine College, Augusta, GA, USA
Winston T.H. Koh, Singapore Management University, Singapore

Table of Contents

- 1 **MAIN DETERMINANTS OF NEW SERVICES DEVELOPMENT IN ICT FIRMS:
A THEORETICAL APPROACH**
EMERSON MAINARDES, FUCAPE Business School , Brazil
CARLOS MATTOS, FUCAPE Business School , Brazil
HELENA ALVES , University of Beira Interior, Portugal
- 15 **RECONFIGURATION OF THE CUBAN MUSIC INDUSTRY IN THE DIGITAL
ERA**
LUIS CAMILO ORTIGUEIRA-SÁNCHEZ, University of the Pacific, Peru
IDALIA ROMERO LAMORÚ, University of Havana , Cuba
JOHANNES ABREU ASIN, Record label and Publishing Producciones Colibrí , Cuba
- 29 **BIBLIOMETRIC STUDY OF THE SCIENTIFIC PRODUCTION ON
INFORMATION TECHNOLOGY GOVERNANCE**
GUSTAVO RODRIGUES CUNHA, Faculdade Novos Horizontes, Brazil
RODRIGO FRANKLIN FROGERI, Faculdade Novos Horizontes, Brazil
- 46 **ECONOMIC-FINANCIAL DIAGNOSIS AND PREDICTION OF SMES: AN
APPLICATION TO THE CONSTRUCTION SECTOR**
VALERIA SCHERGER, Universidad Nacional Country del Sur, Argentina
ANTONIO TERCEÑO, Universitat Rovira i Virgili, Spain
HERNÁN P. VIGIE, Universidad Nacional Country del Sur, Argentina

This is one paper of
The International Journal of Management Science and
Information Technology (IJMSIT)
Issue 21 (Jul-Sep 2016)

Economic-financial diagnosis and prediction of SMEs: An application to the construction sector

Valeria Scherger^a

Economic Department, Universidad Nacional del Sur
Bahía Blanca, Argentina

Antonio Terceño^b

Faculty of Business and Economic, Universitat Rovira i Virgili
Reus, Spain

Hernán P. Vigier^c

Economic Department, Universidad Nacional del Sur- CEDETS UPSO
Bahía Blanca, Argentina

Abstract. The aim of this paper is to improve one of the limitations of the fuzzy models of business failure. In this sense an application to a group of small and medium –sized enterprises (SMEs) from the construction sector is introduced in a given time horizon to test the diagnosis model capacity to predict diseases. This simulation involves the adaptation of the methodological hypothesis, and the definition of the main variables that interact in the estimation. This research presents the estimation of the matrix of economic–financial knowledge and verifies its capacity of diagnosis. Also, a goodness measure, through approximate solutions, is introduced to test the model’s functionality with companies outside initial sample to demonstrate its ability to predict. Therefore, through this simulation some of the fuzzy model’s restrictions are overcome, the theoretical postulates are adapted; the difficulties associated with the estimation are solved and new criteria and guidelines that enrich the original theoretical model are defined. This application to SMEs can encourage the development of suitable computer systems for monitoring firms’ problems, alert failures and ease decision-making. An increased of management efficiency is also expected.

Keywords: economic-financial diagnosis, prediction, symptoms and causes, fuzzy relations, goodness measure

1. Introduction

Prediction or forecast business failure is widely studied in the literature since the traditional models based on available data and statistic techniques (Altman, 1968; Beaver, 1966). These models compare and classify firms according to quantitative indicators to predict or distinguish between healthy and unhealthy businesses. Also, a variety of parametric and non-parametric techniques (logit, probit, neural networks, expert systems, rough sets, hybrid systems, genetic algorithms, clusters, survival models, data envelopment analysis, support vector machine, among others) are used (Kumar and Ravi, 2007; Bahrammirzaee, 2010; Sun et al , 2014).

Due to characteristics of the forecast problem, which uses a large number of qualitative variables or expert analysts’ opinions, it is very difficult to find a comprehensive solution using a classical method. These considerations open up the possibility of using fuzzy logic tools and methods, which allow working with qualitative variables, weak information and measuring the expert’s knowledge. Fuzzy prediction models arise as an alternative in this context (Vigier and Terceño, 2008; Scarlat et al, 2010; Maracine and Delcea, 2009; Behbood, 2011, Thapar et al, 2009; etc.) to overcome many of the restrictions of the traditional models (the selection of the dependant variable, the selection of the sample, the choice of the explanatory variables, and the treatment and inclusion of the sorted errors). Vigier and Terceño's model (2008) of diagnosis based on fuzzy binary relations advances over other

prediction models, trying to understand the process of business failure that start from the cause-symptom relations and the financial analyst's or expert's role¹. This model, besides predicting insolvency situations, has the capacity to diagnose problems and forecast the diseases affecting firms. In this work, is proposed the application of the model based on the construction of incidence matrices of symptoms and causes that allow define degrees of incidence of various diseases in enterprises. Thus, after estimation of the financial-economic knowledge matrix, a goodness measure, absent in other fuzzy models is proposed to test its functionality inside and outside the initial sample.

2. The Diagnosis Model

The Vigier and Terceño (2008) model is based on the estimation of a economic-financial knowledge matrix (R), that starts in the estimation of the symptoms-causes matrices originated in endogenous and exogenous causes. The matrix (R) is used for predicting the incidence level of each one of the causes defined in the model. The pioneer models of Gil-Aluja (1990) and Gil Lafuente (1996) partially show this diagnosis methodology.

$$R = Q^t \alpha P \quad (1)$$

being, R the Matrix of economic-financial knowledge; $Q^t = [q_{hi}]^t = [q_{ih}]$ the transposed membership matrix of the firms' symptoms; $P = [p_{hj}]$ the membership matrix of the firms' causes; and α the fuzzy relations operator. That is, $R = Q^t \alpha P = [q_{ih}] \alpha [p_{hj}] = [r_{ij}]$, where, $[r_{ij}] = 1$ if $q_{ih} \leq p_{hj}$ and $[r_{ij}] = p_{hj}$ if $q_{ih} > p_{hj}$. Each r_{ij} shows the level of incidence between the symptom S_i (q_{ih}) and the cause C_j (p_{hj}).

The construction of the matrix of economic-financial knowledge (R) is determined by a group of symptoms $S = \{ S_i \}$, where $i = 1, 2, \dots, n$; of causes $C = \{ C_j \}$, where $j = 1, 2, \dots, p$; of periods $T = \{ T_k \}$, where $k = 1, 2, 3, \dots, t$; and of firms in which it is possible to identify symptoms and causes $E = \{ E_h \}$, where $h = 1, 2, 3, \dots, m$.

The set of symptoms (S) is built from the selection of ratios from previous studies on business solvency prediction (Ratios Theory, models of business failure prediction, etc.) to differentiate between healthy companies and diseased (or broken) ones. Once the cardinal symptoms matrix (S) has been obtained, the membership matrix of each symptom (Q) is determined by the cumulative relative frequency.

With regard to the causes, the model proposes the construction of a set of subjectively measurable causes C_j^s with $j = 1, 2, \dots, s$; and a set of objectively measurable causes C_j^o with $j = s+1, s+2, \dots, p$. The membership matrix of objective causes is obtained by the same mechanism used for building the membership matrix of symptoms by the cumulative relative frequency. Whereas, in the case of the subjective causes, the expert's opinion is quantified by linguistic labels in the interval [0,1] that reflect the incidence of each cause for the firm performance. The model logics indicate that the higher values correspond with causes that have a greater influence (Zimmermann, 1987)². This incidence level of each cause is determined by the cumulative frequency applied to the labels in each scale and it is expressed in the causes' membership matrix (P).

The model recommends that to perform a study as homogeneous as possible, the set of selected companies has to be from a region and a specific productive sector (E) and also be composed of healthy and unhealthy companies to detect differences in indicators of both groups. Finally, the set of the years or periods (T) for which the estimate is made must be defined.

As mentioned above, each matrix element r_{ij} is obtained through the operation between the transposed membership matrix of symptoms and the membership matrix of causes that satisfy the smaller ratio ($R = Q^t \alpha P$). As the model proposes the determination of possible causes (or diseases) that the firm presents

¹ This model is used as a reference because it has a comprehensive analysis of causes and symptoms over the pioneers' models of Gil-Aluja (1990) and Gil Lafuente (1996), and the recent proposals of Scarlat et al (2010) and Delcea y Maracine (2009), among others. These recent approaches taken as reference Vigier and Terceño (2008), derive the matrix of causes and symptoms by difference with the performance matrix, and therefore introduce a greater degree of subjectivity and a turn on in favor of the experts' point of views.

² If 5 intervals from shorter to longer, (always, often, sometimes, rarely and never) the scale will lineally distribute between the five states, corresponding in this case 20% of the scale to each state: 0.2; 0.4; 0.6; 0.8; 1.0 respectively. For 7 intervals the incidence would be 0.14; 0.29; 0.43; 0.57; 0.71; 0.86 and 1.0: that is, varying the incidence according to the number of established intervals for each cause by the investigator.

from the estimate of R , each r_{ij} shows the level of incidence between the symptom S_i (q_{in}) and the cause C_j (p_{nj}).

To overcome potential inconsistency problems, the model provides the use of a filtering method based on the decomposition and operation of each of the r_{ij} , that is, $(q_{i1} \alpha p_{1j})$; $(q_{i2} \alpha p_{2j})$;...; $(q_{ih} \alpha p_{hj})$;...; $(q_{in} \alpha p_{nj})$. The inconsistency occurs when there are high intensity levels for many companies, and low ones for a few, therefore the alpha indicator may incorrectly select the lowest intensity. The methodology consists of the removal of companies that can cause inconsistent levels of incidence³. Furthermore, the model develops the distinctive features in the aggregation of matrices and the verification of trends that may distort the results of the model. These techniques allow obtaining an aggregate matrix R with temporary validity and capacity to predict diseases (\mathfrak{R}).

The matrix \mathfrak{R} is used to make predictions regarding the health of the companies, being necessary the determination of significant levels of incidence between symptoms and causes to assign a degree of occurrence of a specific disease. Thus, the degree of occurrence of different diseases can be determined and measures can be taken considering the firm's diagnosis to correct the situation.

3. Application of the Model

This section shows the application of the model of business diagnosis of Vigier and Terceño (2008) to a sample of small and medium-sized enterprises (SMEs)⁴. This model capacity of prediction and diagnosis till moment has not been tested despite its originality. As discussed in section 2, the simulation of the model involves the analysis of a set of healthy and unhealthy companies in a particular sector or region (E) to detect differences in performance. In this sense, we selected the construction sector, which comprises two subsectors: the construction and sale of building materials. These two highly complementary subsectors have very similar performances and are equally affected by changes in external conditions. On a base of 98 SMEs registered in the municipalities of Bahía Blanca and Punta Alta (Argentina) 15 are selected. These companies represent approximately the 15% of the activity in these two cities. Notably, given the high degree of informality and lack of accounting information, the percentage of representation is even greater if only the companies with constituted societies are considered, as they are the only ones required to submit financial statements⁵. This is a very dynamic activity and has a great variety of (healthy and unhealthy) companies that meet the availability requirements of data necessary to estimate the model.

3.1. Estimation of the matrix R_{ij}

The operations and different tests applied to estimate the economic-financial knowledge matrix (R_{ij}) are summarized.

This matrix is determined from a set of symptoms $S = \{S_i\}$, where $i = 1, 2, \dots, n$; of causes $C = \{C_j\}$, where $j = 1, 2, \dots, p$; of periods $T = \{T_k\}$, where $k = 1, 2, 3, \dots, t$; and of companies in which it is possible to identify symptoms and causes $E = \{E_h\}$, where $h = 1, 2, 3, \dots, m$.

- Selection of the sector and companies to analyze ($E = \{E_h\}$, where $h = 1, 2, \dots, 15$).
- Collection of information for the three periods analyzed ($T = \{T_k\}$, where $k = 1, 2, 3$) by means of the design of a standardized questionnaire to detect possible causes of diseases in enterprises, through linguistic labels (the questionnaire is available at <http://fuzzybusinessdiagnosis.blogspot.com.ar/>). Data collection was done by interviews with 15 experts of the companies who, according to their experience and valuable judgment, evaluate (qualitatively and quantitatively) the performance of the firm following the guidelines proposed for the analysis. In most cases the experts are individuals who have had a longstanding relationship with the evaluated company, demonstrating extensive experience and knowledge of the firm and its environment.

³ This methodology is consistent with Sánchez (1982) contributions regarding the general conditions imposed for the solution of fuzzy binary equations.

⁴ A first partial estimation of R is presented in Terceño et al (2012).

⁵ The accounting information is a prerequisite for the estimation of the degree of incidence between causes and symptoms. If only the societies are considered the percentage of representation is around 30%.

Due to the characteristics of Argentine SMEs, this role is fulfilled by accounting advisors, managers and owners of the company, which often are the same person.

- Systematization and analysis of information from interviews with experts and the financial statements.
- Selection and estimation of the economic- financial ratios ($S = \{S_i\}$, $i = 1, 2, \dots, 41$). The ratios are selected to reflect aspects of profitability, productivity, liquidity, leverage, solvency, financial structure, debt coverage, economic structure, activity, turnover, efficiency and self-financing according to the classification proposed by other authors and the frequency of use in prediction models (see Terceño et al, 2012). The list and classification of the 41 symptoms are available at <http://fuzzybusinessdiagnosis.blogspot.com.ar>.
- Construction of the cardinal matrix of symptoms for the 15 companies and the 41 selected ratios ($S_{ih} = 41 \times 15$)
- Estimation of the membership symptoms matrix ($Q_{ih} = 41 \times 15$). This is done ordering the symptoms according to their degree of incidence to generate diseases. The accumulated quotient ($\mu S_i (se_{hi}) = |se_{hi}| / m$) represents the health of companies (lower is the membership value of the symptom more healthier is the company).
- Selection of the root causes of problems in firms based on the detection methodology proposed in Terceño et al (2009 and 2014) through the four perspectives of Balanced Scorecard (BSC) ($C = \{C_j\}$, where $j = 1, 2, \dots, 72$).
- Construction of the membership matrix causes ($P_{hj} = 15 \times 72$). The objective causes are valued according to the same mechanism as the symptoms by the cumulative ratio ($\mu c_j^o (c_j^o) = |c_j^o| / m$) resulting from the management of causes depending on the degree of impact (positive or negative). Subjective causes changes are assessed by linguistic labels that reflect the degree of incidence of each disease according to the methodology specified in section 2.
- Estimation of the matrix R of economic-financial knowledge for the period T_1 ($R_{ij} = 41 \times 72$). This is done through the operation between the transposed membership matrix of symptoms and the causes membership matrix that meets the lower ratio ($R_{ij} = (Q_{ih}^t \alpha P_{hj})$); If $q_{ih} \leq p_{hj}$, then $[r_{ij}] = [q_{ih}] \alpha [p_{hj}] = 1$ and If $q_{ih} > p_{hj}$, then $[r_{ij}] = [q_{ih}] \alpha [p_{hj}] = p_{hj}$
- According to the recommendations presented by Vigier and Terceño (2012), once the incidence coefficients r_{ij} are obtained, the filtering method for the treatment of inconsistencies is applied. Two levels of filter ($\phi^* = 0.75$ y $\phi^* = 0.50$) are applied to eliminate the inconsistent cases; where $\phi = 1 / (m-1) \sum (r_{ij} - r_{ij}^*)$. In other words, $\phi^* = 0.75$ if $\phi > 0.75$, firms with lower incidence level are eliminated until $\phi < 0.75$. Then, a higher filtering factor ($\phi^* = 0.50$) is applied, which reduces the error and discards a higher percentage of inconsistent responses. Applying filtering method does not show elimination firm patterns according to the activity developed within the sector or the size of the firm but simply removes cases considered as "anomalous" for the model.
- Also to evaluate the responses, the coefficient of variation (Cv) is applied to determine the variability of causes. $Cv = \sqrt{1/N - 1 \sum_{i=1}^n (x_i - \bar{x})^2} / 1/n \sum_{i=1}^n x_i$. In this case, high index values are observed, confirming that a higher value shows a greater heterogeneity of responses.

3.2. Estimation of aggregated matrix \mathfrak{R}

The estimation of aggregated matrix \mathfrak{R} ($\mathfrak{R}_{ij} = 41 \times 72$) valid for predictions involves repeating the estimation steps for the other two periods analyzed (T_2 and T_3). The calculation of \mathfrak{R} involves aggregating the matrices $R_k = [r_{ij}]_k = (R_{ij}^1, R_{ij}^2, R_{ij}^3)$ and the correction for temporal trends that distort the validity of the results. As mentioned in Vigier and Terceño (2008), if an upward trend over time is verified, the use of an "average" aggregation procedure will underestimate the true relationship. However, if the trend is decreasing, the average will overestimate the relationship. For this situation, the behavior of each r_{ij} is evaluated in order to determinate the aggregation process depending on the trend experienced by each component.

- If $\sum [r_{ij}^t - r_{ij}^{t-1}] = 0$; $r_{ij}^t = \text{aggregate } r_{ij}$
- If $\sum [r_{ij}^t - r_{ij}^{t-1}] \neq 0$; r_{ij} is determined by the indicator ξ , which varies between -1 and 1

$$\xi = \frac{\sum_{k=2}^t (r_{ij}^k - r_{ij}^{k-1})}{\sum_{k=2}^t |r_{ij}^k - r_{ij}^{k-1}|} \quad (2)$$

If $\xi = 1$, $r_{ij} = \text{Max} (\text{Min} [r_{ij}^k])$; there is an increasing trend.

If $\xi = -1$, $r_{ij} = \text{Min} (\text{Max} [r_{ij}^k])$; there is a decreasing trend.

If $-1 < \xi < 1$, $r_{ij} = 1/t \sum [r_{ij}^k]$; there is no trend.

For the case analyzed, the aggregation and the correction of temporal trend is carried out for the three matrices ($R_{ij} = 41 \times 72$; R_{ij}^t , R_{ij}^{t+1} , R_{ij}^{t+2}). An increasing trend is observed in 349 r_{ij} , and the aggregation is carried out by means of the $r_{ij} = (r_{ij})_{k-1} \circ (r_{ij})_k = \text{Max} (\text{Min} ((r_{ij})_k, (r_{ij})_{k-1}))$. In 337 r_{ij} a decreasing trend is presented, carrying out the aggregation by $r_{ij} = (r_{ij})_{k-1} \circ (r_{ij})_k = \text{Min} (\text{Max} ((r_{ij})_k, (r_{ij})_{k-1}))$. In the remaining 2,266 r_{ij} no such trend is observed. In the cases in which there is no trend, the aggregation is done through the arithmetic average $r_{ij} = h_\varphi (r_{ij}^1, r_{ij}^2, \dots, r_{ij}^k, \dots, r_{ij}^t) = [1/t \sum (r_{ij}^k)]$. Thus, the estimated r_{ij} coefficients are consistent and significant, and explain the true relationship between causes and symptoms according to the model. Appendix A shows the estimation of the \mathfrak{R} matrix. The disaggregated results of the estimation are available at <http://fuzzybusinessdiagnosis.blogspot.com.ar/>.

4. A measure of diagnosis and forecasting capacity

As Vigier and Terceño (2008) and the other fuzzy models lack a mechanism to verify the model functionality, the inclusion of an index is proposed in this section. This measure, with approximate solutions, is valid to test the degree of fit of the simulation using the answers given by the experts. That means comparison of the two fuzzy subsets. In this case, the construction of an approximation or goodness index between P^* and P' is proposed (Eq. 3)

$$[P^* - P'] = 1 - \frac{1}{n} \sum_{x \in X} |\mu_p(x) - \mu_p(x)| \quad (3)$$

Where,

$P' = Q \alpha \mathfrak{R}$; that is, $P'_{hij} = \max (\min (q_{hi}, r_{ij}))$. This supposes estimated P' by the inverse operation between Q and \mathfrak{R} (r_{ij} valid and temporary consistent). Appendix B shows the estimation of the matrix of diseases (P')

4.1 Diagnosis goodness index

To test the measure of diagnosis, the goodness index of fit is calculated between the causes provided by the experts and the causes simulated through \mathfrak{R} . In terms of this analysis, a degree of fit of 86% for all companies is obtained and the index observed in each of the companies is higher than 80% (see table 1). This improves forecasting by considering more periods, as \mathfrak{R}_{ij} fit is 86% compared with the one calculated for a single period (R_{ij}^T) that accounts for 73%.

Table 1. Degree of fit [$(P^*) = (P')$]

Firm	Degree of fit [$(P^*) = (P')$]
1	0.85
2	0.85
3	0.86
4	0.91
5	0.84
6	0.85
7	0.85
8	0.85
9	0.82
10	0.83

11	0.86
12	0.84
13	0.86
14	0.88
15	0.91
Mean	0.86

These results show that the estimated relationships between causes and effects are significant, with a high degree of accuracy (86%). Therefore, a set of consistent and significant incidence levels (r_{ij}) has been obtained. This r_{ij} explains the true relationship between symptoms and diseases (effect and causes). That is, the estimation of the \mathfrak{R} matrix allows the simulation or modeling of the expert knowledge when making diagnostics or its use as a complementary tool that can assist and guide the difficult task of the analyst.

4.1 Forecasting goodness index

Also, the reference model, Terceño and Vigier (2011) is valid for prediction. That is, having obtained the \mathfrak{R} matrix, it is possible to make the prediction of economic and financial situation of a company that has similar characteristics regarding sector and size to those used to determine \mathfrak{R} .

To simulate the prediction of a company with \mathfrak{R} , the relative state of symptoms is required. That is, $B' = A \alpha \mathfrak{R} = [b'_{hj}]$; being $b_{hj} = \max(\min(a_{hi}, r_{ij}))$, where B_h is the incidence level of each cause C_j in the company E_h and A_h is the incidence level of each symptom S_i in the company E_h . Therefore, to make the forecast with \mathfrak{R} , it is necessary to calculate the vector of symptoms A_h ($A_h = 1 \times 41$). Thus, the cardinal vectors of symptoms (S_{ih}) and the membership vectors of symptoms ($A_{h'}$) for the two companies, which were not included in the initial sample (E_1 y E_2), are estimated. The degree of membership of each symptom is determined by the membership value that minimizes the distance between the values of the s_{ih} and $s_{ih'}$ ratios. Then, the vectors of diseases of the firms used in the prediction ($B'_h = 1 \times 72$) are estimated.

Finally, the model's ability to predict diseases is tested by the proposed methodology. In this case, it is tested the degree of fit of the projected diseases (for the companies not included in the sample) to the answers given by the experts, that is $[(P^*) = (B')$. In this simulation, a rate of 85% for firm 1 and 86% for firm 2 is obtained in both cases using the financial economic knowledge matrix \mathfrak{R} estimated from the initial sample of firms calculated in 3.2. This high degree of approximation to the answers provided by the companies confirms the validity of the model to forecast the diseases affecting firms.

5. Diseases evaluation

One of the model applications is the possibility of viewing which the main problems or diseases affecting the firms are. As the firm sample is representative of the sector (30% of societies), a sectoral analysis can be done with the data from \mathfrak{R} matrix by evaluating the impact of each of the BSC perspectives. Diseases or more frequent problems are detected through column analysis of P' matrix,

Another possibility of analysis is evaluating the existence of the different diseases in each company or at least by an auto diagnostic to detect those major problems that could generate some diseases. In this case, the analysis of (P') is performed horizontally for each of the companies and the degree of incidence of different causes for each company ($p_{hj} < 0.50$; $0.50 \leq p_{hj} < 0.75$; $p_{hj} \geq 0.75$) is evaluated. This also allows sorting or grouping companies into three categories: healthier firms or those with less intensity diseases ($p'_h < 0.50$); moderately sick companies ($0.50 \leq p_{hj} < 0.75$) and sicker companies or those with problems of greater intensity ($p'_h \geq 0.75$). This grouping is presented in Table 2. An extended analysis of the firms' diseases is presented in Scherger et al (2014).

Table 2. Sorting of firms

	Firms
Healthier firms	2, 4, 10, 15
Moderate sick companies	3, 6, 7, 8, 14, 13

Also, this application allows a priori evaluation of the predicting diseases in the firms outside the sample ($B'_{hj} = 1 \times 72$) with a certain temporal validity (for periods not exceeding three years). Therefore, this model is able to identify problems and implement measures to correct the warning indicators (high incidence levels of b'_{hj}). It is observed that both firms used in forecasting have problems in the four perspectives of BSC, although the company 2 has more diseases and higher incidence rates than firm 1. That means that firm 1 is less unhealthy (or more healthy) than firm 2. The estimated matrices of diseases of both firms are presented in Appendix C.

In this sense, studies are intended to continue on the difficult task of proposing a handbook of alternative or corrective measures for identifying diseases according to their degree of incidence. This selection of appropriate policies to solve each relative situation involves not only experts, but also the evaluation of results.

6. Conclusions

The most relevant aspect of this proposal is the enrichments of the Vigier and Terceño's (2008) model by introducing an index measure of its functionality and disease forecasting capacity. Also, these proposals are tested through its application to a specific SMEs sector. This analysis allows overcoming some of the limitations of other models by the incorporation of qualitative aspects, the formalization of experts' opinion and the validity of the estimates over time. This application to SMEs can encourage the development of suitable computer systems for monitoring the problems affecting firms, alert failures and ease decision-making. Also the continuous use of firms' information systems can increase the management performance.

Therefore, the theoretical model guidelines are followed, the difficulties associated with the estimation are solved and new criteria to enrich the original theoretical model are defined. In this work, the financial economic knowledge matrix \mathfrak{R} is simulated, through the operation of the membership matrix of causes ($P_{hj} = 15 \times 72$) and the membership matrix of symptoms ($Q_{ih} = 41 \times 15$). In addition, the filtering method is applied to solve possible inconsistencies and the subjective experts' answers are evaluated. Matrices $R_k = [r_{ij}]_k = (R_{ij}^t, R_{ij}^{t+1}, R_{ij}^{t+2})$ are added and are corrected for temporal trends to estimate \mathfrak{R} . Also, the validity of the aggregate matrix for diagnostic and medium-term predictions is demonstrated. Once \mathfrak{R} is estimated, a verification mechanism (not included in the initial model) is proposed to test the diagnostic capacity of the model. Through this index, $[(P^*) = (P')]$, a goodness rate of 86% on average is obtained for all businesses. Therefore, the coefficients r_{ij} are consistent and significant, and explain the true relationship between diseases and symptoms (causes and effects). This means that the \mathfrak{R} matrix can be used to simulate or model the expert's knowledge and is useful to guide the difficult analyst's task. Also, the prediction of diseases for two companies outside the initial sample is simulated and a goodness measure of forecasting is obtained (85% for E_1 and 86% for E_2). Moreover, a way to evaluate the most common diseases or causes for the sector (column analysis) and for each of the companies (analysis by queue) according to the incidence of the causes ($p_{hj} < 0.50$; $0.50 \leq p_{hj} < 0.75$; $p_{hj} \geq 0.75$) is proposed to classify the firms. Therefore, any company making a prediction based on its situation can identify diseases and implement measures to correct the warning indicators ($b'_{hj} > 0.50$).

In short, this paper tests the advantage of the fuzzy model for predicting diseases and introduces an index to evaluate the results.

References

- Altman, E. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance*, 23(4), 589-609.
- Bahrammirzaee, A. (2010). A comparative survey of artificial intelligence applications in finance: artificial neural networks, expert systems and hybrid intelligent systems, *Neural Computing and Applications*, 19(8), 1165-1195.
- Beaver, W. (1966). Financial ratios as predictors of failure, *Journal of Accounting Research*, 4, 71-111.

- Behbood, V. & Lu, J. (2011). Intelligent financial warning model using fuzzy neural network and case-based reasoning, *Proceedings of IEEE Symposium on Computational Intelligence for Financial Engineering and Economics*, 1-6.
- Gil Aluja, J. (1990). Ensayo sobre un modelo de diagnóstico económico- financiero. *Proceedings of the V Jornadas Hispano-Lusas de Gestión Científica*, Vigo, Spain, 26-29.
- Gil-Lafuente, J. (1996). El control de las actividades de marketing, *Proceedings of III SIGEF Congress*, Buenos Aires, Argentina, 244, 1-21.
- Kumar, P. R. & Ravi, V. (2007). Bankruptcy prediction in banks and firms via statistical and intelligent techniques. A review, *European Journal of Operational Research*, 180(1), 1-28.
- Maracine, V. & Delcea, C. (2009). How we can diagnose the firm's diseases using grey systems theory, *Economic Computation and Economic Cybernetics Studies and Research*, 3, 39-55.
- Quek, C., Zhou, R. W., & Lee, C. H. (2009). A novel fuzzy neural approach to data reconstruction and failure prediction, *Intelligent System in Accounting, Finance and Management*, 16(1/2), 165-187.
- Sánchez, E. (1982). Solution of Fuzzy Equations with Extended Operations, *Electronics Research Laboratory*, University of California, Berkeley, 8-10.
- Scarlat, E., Delcea, C., & Maracine, V. (2010). Genetic-fuzzy-grey algorithms: a hybrid model for establishing companies' failure reasons, *Proceedings of IEEE International Conference (SMC)*, Istanbul, Turkey, 955-962.
- Scherger, V., Vigier, H., & Barberá-Mariné, G. (2014). Finding business failure reasons through a fuzzy model of diagnosis, *Fuzzy Economic Review*, 19(1), 45-62.
- Sun, J., Li, H., Huang, Q.H. & He, H. Y. (2014). Predicting financial distress and corporate failure: A review from the state of the art definitions, modeling, sampling, and featuring approaches, *Knowledge Based Systems*, 57, 41-56.
- Thapar, A., Pandey, D. & Gaur, S. K. (2009). Optimization of linear objective function with max-t fuzzy relation equations, *Applied Soft Computing*, 9(3), 1097-1101.
- Terceño, A. & Vigier, H. (2011). Economic- financial forecasting model of businesses using fuzzy relations, *Economic Computation and Economic Cybernetics Studies and Research*, 45(1), 215-232.
- Terceño, A., Vigier, H. & Scherger, V. (2012). Application of a fuzzy model of economic- financial diagnosis to SMEs, in: Gil Aluja, J.; Terceño, A. (eds.). *Methods for decision making in an uncertain environment*, World Scientific Publishing, 146-162.
- Terceño, A., Vigier, H. & Scherger, V. (2014). Identificación de las causas en el diagnóstico empresarial mediante relaciones Fuzzy y el BSC. *Actualidad Contable Fases*, 17(28), 101-118.
- Terceño, A., Vigier, H., Barberá-Mariné, G. & Scherger, V. (2009). Hacia una integración de la teoría del diagnóstico fuzzy y del Balanced Scorecard. *Proceedings of XV SIGEF Conference*, Lugo, Spain, 364-379.
- Vigier, H. & Terceño, A. (2008). A model for the prediction of "diseases" of firms by means of fuzzy relations, *Fuzzy Sets and System*, 159(17), 2299- 2316.
- Vigier, H. & Terceño, A. (2012). Analysis of the inconsistency problem in the model for predicting diseases of firms. *Fuzzy Economic Review*, 17(1), 73-88.
- Zimmermann, H. J. (1987). *Fuzzy set decision making and expert systems*, Kluwer Academic Publishers, Norwell, Massachusetts, 41-44.

Appendix B. Membership matrix of diseases (P')

		Learning and Growth																									Business process																	
		Business learning					Innov. & tech.					Labor quality					Cost optimization					Technical efficiency				Purchase policies				Emergency changes														
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43
E1	.25	.50	.36	.20	.20	.30	.14	.50	.29	.14	.57	.38	.60	.20	.57	.35	.57	.13	.61	.61	.57	.60	.50	.20	.67	E1	.25	.40	.19	.73	.99	.40	.63	.60	.57	.47	.40	.60	.62	.60	.67	.80	.80	.20
E2	.25	.50	.36	.20	.20	.27	.14	.50	.29	.14	.57	.36	.60	.20	.57	.35	.57	.13	.59	.59	.57	.60	.50	.20	.60	E2	.25	.40	.19	.69	.64	.40	.54	.60	.57	.47	.40	.60	.62	.60	.67	.80	.80	.20
E3	.25	.50	.36	.20	.20	.30	.14	.50	.29	.14	.57	.38	.60	.20	.57	.35	.57	.13	.61	.61	.57	.60	.50	.20	.67	E3	.25	.40	.19	.76	.80	.40	.50	.60	.43	.47	.40	.60	.57	.60	.67	.80	.80	.20
E4	.25	.50	.36	.20	.20	.27	.14	.50	.29	.14	.57	.36	.60	.20	.57	.35	.57	.13	.61	.61	.57	.60	.50	.20	.60	E4	.25	.40	.19	.73	.73	.40	.54	.60	.57	.44	.40	.60	.62	.60	.67	.80	.80	.20
E5	.25	.50	.36	.20	.20	.30	.14	.50	.29	.14	.57	.38	.60	.20	.57	.35	.57	.13	.60	.60	.57	.60	.50	.20	.67	E5	.25	.40	.19	.69	1.00	.40	.63	.60	.57	.47	.40	.60	.57	.60	.67	.80	.80	.20
E6	.25	.50	.36	.20	.20	.30	.14	.50	.29	.14	.57	.36	.60	.20	.57	.35	.57	.13	.59	.59	.57	.60	.50	.20	.60	E6	.25	.40	.19	.53	.73	.40	.63	.67	.57	.47	.40	.60	.60	.67	.80	.80	.20	
E7	.25	.50	.36	.20	.20	.30	.14	.50	.29	.14	.57	.36	.60	.20	.57	.35	.57	.13	.59	.59	.57	.60	.50	.20	.60	E7	.25	.40	.14	.53	1.00	.40	.63	.73	.53	.47	.40	.60	.62	.60	.67	.80	.80	.20
E8	.25	.50	.36	.20	.20	.30	.14	.50	.29	.14	.57	.36	.60	.20	.57	.35	.57	.13	.59	.59	.57	.60	.50	.20	.60	E8	.25	.40	.19	.62	.87	.40	.63	.60	.57	.47	.40	.60	.57	.60	.67	.80	.80	.20
E9	.25	.50	.36	.20	.20	.30	.14	.50	.29	.14	.57	.36	.60	.20	.57	.35	.57	.13	.56	.56	.57	.60	.50	.20	.60	E9	.25	.40	.19	.76	1.00	.40	.50	.80	.47	.47	.40	.60	.62	.60	.67	.80	.80	.20
E10	.25	.50	.36	.20	.20	.30	.14	.50	.29	.14	.57	.36	.60	.20	.57	.35	.57	.13	.58	.58	.57	.60	.50	.20	.60	E10	.25	.40	.19	.53	.53	.40	.63	.47	.57	.47	.40	.60	.57	.60	.67	.80	.80	.20
E11	.25	.50	.36	.20	.20	.30	.14	.50	.29	.14	.57	.38	.60	.20	.57	.35	.57	.13	.61	.61	.57	.60	.50	.20	.67	E11	.25	.40	.19	.69	.67	.40	.53	.60	.43	.47	.40	.60	.62	.60	.67	.80	.80	.20
E12	.25	.50	.36	.20	.20	.30	.14	.50	.29	.14	.57	.38	.60	.20	.57	.35	.57	.13	.61	.61	.57	.60	.50	.20	.67	E12	.25	.40	.19	.73	.80	.40	.63	.80	.43	.47	.40	.60	.57	.60	.67	.80	.80	.20
E13	.25	.50	.36	.20	.20	.30	.14	.50	.29	.14	.57	.38	.60	.20	.57	.35	.57	.13	.61	.61	.57	.60	.50	.20	.67	E13	.25	.40	.19	.76	.99	.40	.54	.80	.48	.47	.40	.60	.62	.60	.67	.80	.80	.20
E14	.25	.50	.36	.20	.20	.30	.14	.50	.29	.14	.57	.38	.60	.20	.57	.35	.57	.13	.61	.61	.57	.60	.50	.20	.67	E14	.25	.40	.19	.76	.99	.40	.50	.60	.43	.47	.40	.60	.60	.60	.67	.80	.80	.20
E15	.25	.50	.36	.20	.20	.30	.14	.50	.29	.14	.57	.38	.60	.20	.57	.35	.57	.13	.58	.58	.57	.60	.50	.20	.67	E15	.25	.40	.14	.73	.99	.40	.63	.80	.47	.47	.40	.60	.57	.60	.67	.80	.80	.20

The membership matrix of diseases is also available at <http://fuzzybusinessdiagnosis.blogspot.com.ar/>

Appendix C. Forecast: Estimated matrix of diseases (B')

		Learning and Growth																									Business process																	
		Business learning					Innov. & tech.					Labor quality					Cost optimization					Technical efficiency				Purchase policies				Emergency changes														
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43
E1	.25	.50	.36	.20	.20	.40	.14	.50	.29	.14	.57	.36	.60	.20	.47	.35	.57	.13	.59	.59	.57	.60	.50	.20	.60	E1	.25	.40	.14	.73	.80	.40	.60	.60	.43	.47	.40	.60	.62	.60	.67	.80	.80	.20
E2	.25	.50	.36	.20	.20	.33	.14	.50	.29	.14	.57	.36	.60	.20	.47	.35	.57	.13	.59	.59	.57	.60	.50	.20	.60	E2	.25	.40	.14	.73	.77	.40	.60	.60	.47	.47	.40	.60	.62	.60	.67	.80	.80	.20

The forecast is also available at <http://fuzzybusinessdiagnosis.blogspot.com.ar/>