OPERATIONAL RISK ANALYSIS OF INDUSTRIAL SMALL AND MEDIUM ENTERPRISES

Jorge A. Restrepo, Universidad Autónoma Latinoamericana
Jairo Angel Díaz, Universidad Autónoma Latinoamericana
Juan Esteban Ocampo, Universidad Autónoma de las Américas

ABSTRACT

This paper develops a quantitative analysis of operative risk. We model the volatilities of major financial indices Chemicals Industry for the period 2000-2009. The model uses an Analytical Hierarchy Process (AHP), a multicriterio technique, to identifying the weight of major financial indices: profitability, indebtedness, liquidity, efficiency and viability. Next, we set up an operative risk measure capturing the whole Industry indices. It becomes the risk measurement benchmark to settle level business risk by a membership function which qualitatively sorts as severe, moderate or low. The model uses time series analysis to predict industry ratios. We use a linear programming model and choose the method that produces the minimum forecast error. Last, we project ratios and their volatility. We use business information issued by the Annual Manufacturing Survey 2010, and information of the 5000 Money Magazine companies.

JEL: C61, C32, D81

KEYWORDS: Operational Risk, Modeling, AHP, Time Series

INTRODUCTION

According to the Joint Industrial Opinion Survey —JIOS— Antioquia industries represents 20% of the industry totals in Colombia and of 32% of non-traditional exports. Antioquia assembles 141,424 employees out of a total of 641,446. Thus, they represent 22% of people employed in domestic industry, even though Antioquia's population represents 13% of the country's total. On the other hand, Antioquia's imports show great growth: U.S. $ 4,844 million, and a contribution of 11.9%. The most relevant data comes from non-traditional exports, which increased by U.S. $ 4,501 million, up to 31.1%.

The National Association of Financial Institutions showed the results of the "Great SME Survey" for the first half 2010 (ANIF, 2011). The survey was conducted among 1,546 entrepreneurs from different sectors of the Colombian economy: industry, trade and services. The main focus was the current status of the industry and its projections. For 41% of those surveyed, the economic situation improved during the second semester of 2009 compared to the same period in 2008. Chemical companies and printing and publishing companies showed the highest growth according to the views presented. Metal and rubber and plastic companies had the lowest favorable opinions filed.

A study of SME competitiveness in the region recorded the lack of continuous recording of accounting and financial information as a weakness Restrepo M J. (2009). Many studies aimed at analyzing the companies and sectorare based on financial diagnoses. But. there are few studies with the purpose of determining and measuring risk associated with the company's activity. F. Celaya P. & Lopez (2004).

Financial risk modeling for companies and large corporations is widely addressed, particularly LDA methods (Loss Distribution Approach). It shows a high degree of acceptance in modeling loss distributions, which is basic for developing the matrix proposed by Basiles. The following is a chronological list of the authors studied: Restrepo & Medina (2012); Aue & Kalkbrener (2007); Akkizidis & Bouchereau (2006), Dutta & Perry (2006); BÖcker (2006); Medina (2006); NeŠlehová et al. (2006); Chernobai & Rachev (2006); Degen et al (2006); Shevchenko & Donely (2005); Frachot et al (2004); Frachot et al (2003); Frachot et al (2001); Cruz (2002), Lee (2001), but the case of risk quantifying SMEs, as indexed cases are few.

This paper presents a simple scheme for computing business risks in SMEs by calculating the volatility of major financial indices. Next, we develop an AHP analysis, and use time series to predict expected operational and financial risks. The proposed model identifies total risk as a convolution of operational and financial risks. We assess a weighted average of profitability, efficiency, viability, liquidity and debt indices. While "traditional financial indices techniques present major limitations for decision making, they are widely used because they allow for comparisons and analysis of trends in business performance. In addition, they allow for comparison between results and standards measurements which may be the target or averages of the company or industry." Restrepo M J. (2009).

The proposed method allows for determining consistency over time, and the industry's ability to generate high returns and mitigate overall risk. Likewise, the obtained measurement for industrial risk becomes a benchmark for settling the risk that one particular business expects to face. Companies can show high performance in certain periods, and low performance in others. This is called consistency of risk indices. When the company performance has a random behavior of indices that explain their overall risk, greater uncertainty is involved in the estimation of future performance. Bouchaud & Potters (2003, Page 11) argue that "The statistical approach consists in drawing from past observations some information on the frequency of possible price changes. If one then assumes that these frequencies reflect some intimate mechanism of the markets themselves, then one may hope that these frequencies will remain stable in the course of time."

In this paper, we measure the risk for Colombian SMEs in the Chemical industry during the period 2000-2009. In the first part, we discuss literature related to the risk measurement approach for SMEs, and the theoretical framework of the hierarchical analysis technique. In the second part, we mention the data and methodology used to measure the volatility of indices, and carry out the time series analysis to predict indices and evaluate the risk level that these companies take. Finally, we present the main results for the chemical industries, determine the expected risk level, present some limitations of the model, and propose future research.

LITERATURE REVIEW

Risk Definition

The Basel Committee on Banking Supervision (2003) states that risk analysis can be defined as a systematic use of available information to discover the frequency with which some events may occur, and the scale of its effects. Castillo M. (2008) defines operational risk as the possibility of financial losses in in firms because of events associated with failures or shortages. These financial losses can emerge from decision making or business tactics or strategies, internal employees or people somehow related to the company, the technology used orexternal events, including legal risk. The cited author considers no losses resulting from unexpected changes in the political, economic and social environment.

Restrepo and Medina (2012) define risk as the possibility for an event to occur, and the impact or negative consequence derived from it. They state that a company, in its life cycle, can go through operational failures in the execution of its ordinary course of business. Finally, they conclude that operational risk is latent in every activity of any company or organization.

Jorion (2000) defines risk as "the volatility of expected results, generally expressed in the value of interest assets or liabilities". Large companies usually classify risk in four pillars or categories: credit risk, market risk, strategic or business risk, and operational risk. Many entrepreneurs associate risk with negative events: the case of not covering the fixed costs in a given period. However, by analyzing risk, opportunities for improvement can be found, since risk fosters the exploration of all the possible results deriving from an event considered unfavorable.

Risk Variables

For Basel, risk is generally limited exclusively to a financial company's main activity. This concept is generally considered to be true in the business world. However, real economy companies, particularly SMEs, face several risks associated with their course of business. These companies need to identify and manage risk actively to clear the way towards achieving their goals.

For financial institutions, taking risks is a business opportunity. It means managing risks by understanding and controlling them in order to turn them into other risks that can be taken or transferred. De la Fuente and De la Vega (2003) state that most non-financial companies do not use risk management as an opportunity to generate profits because of the lack of techniques that would allow them to manage risks as financial institutions. These two facts make risk management through banks more convenient and comfortable, at different levels, for said companies.

Medina (2006) insists that all investment, financing and dividend-related decisions affect all business units, such as human talent, quality, technology, market, production, etc. Moreover, pressure increases as a result of the changing complexity of business deriving from laws, the influence of other industries and countries, changes in the international monetary system, economic trends, socio-political conditions, and so on.

We mark out four different types of risk, as described below. The so-called business risk associated with an external incident or event that prevents the company from reaching its goals is not considered. This paper focuses on the quantification of operational risk to greater detail. Several authors, such as M. Castillo (2008), Jorion (2000), JP. Morgan (2011), Medina (2006), and Sturm P. (2013) agree on the following classification:

For the purposes of this paper, financial risk is associated with cash flow and a company's inability to fulfill its obligations. This risk is related to the environment of financial transactions, which includes credit risk related to borrowers, and market risk of the investment portfolio. Other types of risk may be included: market price variations of goods and services provided, exchange rate risks, financing costs, liquidity mismatches of liabilities, and commitments and investments within deadlines of assets. In general, all risks offer the possibility of being modeled and managed with techniques developed in the financial world.

Operational risk includes all risks associated with errors or shortcuts in the production line, commercial area, accounting, and internal processes required to perform the ordinary course of business. These risks arise from possible errors in operations performed by the staff, a flawed definition of programs, and information and communication technologies, energy source crashes, etc. Likewise, other types of risks are included, such as delays in production, marketing, supply and entry of merchandise and raw materials, fraud both internal and external, lack of employees, etc.

High severity risks are circumscribed to those risks associated with possible losses derived from high-impact external events that take place rarely, such as strikes, riots, political events and acts, weather conditions, among others. Modeling and managing this type of risk is essential for business continuance. The low probability, but the high impact of this type of risk may bring terrible consequences to the sustainability of the business.

Reputational Risks include all risks derived from possible violations of the laws, policies and standards of national and international organizations, as well as the lack of good practices related to social responsibility, and alterations or lack of awareness of rules and practices that affect business recognition. In short, in risk management, a company's main concern lies in identifying and classifying a subjective group of risks. For example, for travel agencies, the weather represents a critical factor for success. Therefore, it would be an operational risk, not a high severity risk, as it might be for an industrial company that loses its merchandise because of a tornado.

Operational, Financial and Total Risk

This study follows the approach of Celaya Figueroa (2004), which considers that these risks are derived from a company's business strategies and tactics, and the company's relation to the business environment. Operational risks represent the lack of resources in the company to cover fixed and production costs, as well as general costs. Financial risks point to the possibility of not facing the overload associated to debt, while total risk is considered the convolution of the latter two.

This paper defines operational risk from the financial and accounting viewpoint, where operational expenses are divided into fixed and variable expenses. Fixed expenses do not depend directly on the business operation volume. The key driver depends on the manufacture and sale of merchandise, but causation and payment are events that do not depend on income. Production and accounting income are reduced to a product of expenses. Operational risk is defined as a linear weighted average of the profitability, efficiency and sustainability indices

Financial risk, is defined as the probability of occurrence of an event with negative financial results for the company. The general idea includes the possibility for financial results to be above or below estimates. This risk must include the fact that investors may take positions contrary to market movements, which involves the possibility of profit or loss according to the investment strategy.

Some authors argue that this type of risk is the consequence of uncertainty of financial operations, which in turn, is derived from volatility of financial and credit markets. Meanwhile, Mascareñas (1998) holds that financial exposure refers to uncertainty associated with investment profitability derived from the possibility of the company's not fulfilling its financial obligations: payment of interest and amortization of debt. In other words, financial risk has one single cause: fixed financial obligations assumed by the company.

Similarly, Cazorla (2004) points out that, in the framework of SMEs that do not participate in the stock exchange, entrepreneurs' reluctance to issue shares is justified because of the loss of control over the entry of new shareholders. This is why SMEs operate outside financial markets. Hernández (2004) reaches the same conclusion.

Under the above premise, this paper approaches financial exposure from the viewpoint of five first-level indicators: liquidity, indebtedness, profitability, efficiency and business viability. Likewise, this paper is based on 20 second-level indicators to assess and quantify risks for Small and Medium Enterprises. Assessment of volatility of said financial indicators is used. The techniques of Analytic Hierarchy Process and Time Series Analysis are also used to classify the importance of the indicators, and project them to explain and quantify financial risk later.

Hierarchical Process Analysis

Analytic Hierarchy Process (AHP) is a widely used technique for analyzing multi-criteria decisions. Saaty, T.L. developed AHP in 1970, and since then, this technique has been widely studied, and made more sophisticated.
It is specifically used for team decision-making, and is widely accepted in a large variety of multi-criteria decisions, as well as in business, industry, health, education, the government, and so on.
Vadiya & Kumar (2006) present a paper where they list over 150 instances of AHP application, 27 of which present reviews of this technique. This paper presents a succinct theoretical reference of AHP, thus becoming a guide for researchers and experts of this technique. Likewise, (Zahedi, 1986) reviews AHP and its applications to diverse decision-making problems. He also addresses some of the main reviews and extensions of the technique.

Haas & Meixner (2012) argue that AHP is used to aid many decision-makers, both in the government and corporations, in various problems that involve decisions, such as: choosing a telecommunications system, establishing a drug policy, selecting a product marketing strategy, etc.

Thomas (2000) states that credit and behavioral scoring help organizations decide whether or not to grant credit to consumers who apply for it. Surveys, both statistical and operational, are the means to support these decisions. He also discusses the need to incorporate economic conditions of borrowers into the scoring system. In this way, systems could change from estimating the probability for a consumer to default to estimating the benefits derived from the loan for the organization.

In the case of risk estimation, Saaty (1987) shapes the way that risk and uncertainty can be faced through AHP, a new approach to index measurement. It is important to clarify that, instead of proposing a "correct" decision, AHP helps decision-makers find the one that best adjusts to their goal and understanding of the problem. AHP provides an easy to understand, rational and complete framework to organize a problem with multi-criteria decisions. This enables representation and quantification of variables, and allows for linking such variables to global goals, as well as evaluating different solutions.

AHP experts first break down the decision problem into a hierarchy of secondary, less complicated problems. Each can be analyzed on its own. The basis for the hierarchy makes it possible to share any opinion about the problem characteristics, be it tangible or intangible, correctly or almost assessed, correctly or incorrectly understood. That is, any situation that can be applied to the solution.

Assembly comes after the hierarchy. Decision-makers methodically estimate the various foundations for comparison by pairs, and place the impact of a factor above others in the hierarchy. When comparing, AHP users can use concrete variable data. Judgment on the meaning and relative importance of the variables is generally used. The basis of the AHP technique is that human judgment, not only underlying information, can be used in evaluations.

AHP translates these evaluations into numerical values that can be compared and developed in every problem range. For each hierarchy item, a numerical weight or priority is determined, which often generates different and uncountable factors to be compared among themselves in a rational and coherent way. This feature distinguishes AHP from other decision-making techniques.

In the final stage, each decision alternative will have a calculated numerical priority. These numbers represent the relative ability of these alternatives to achieve the decision's goal. For this reason, they allow for a direct consideration of the innumerable courses of action. In short, AHP is a technique to quantify experts' opinions or judgments on the relative importance of each criterion, generally in conflict with one another, used in the complex decision-making process.

It consists of eight stages:

1. Breaking down the decision problem into a hierarchy of components related to one another by determining: (a) the general goal, (b) criterion (i = 1, 2, ... m), and (c) the possible alternatives (j = 1, 2, ... n).

Steps 2-5 converge into a nested loop for each "m" in the judgment criteria involved.

2. Developing the pair-wise ranking matrix of the alternatives for each criterion. It is necessary to establish the degree of relative importance of the alternatives under study.

The degree is established through the following scale: 1 = indifferent, 3 = moderately preferred, 5 = strongly preferred, 7 = very strongly preferred, 9 = extremely preferred. When intermediate values such as 2, 4, 6, 8 arise, there is no incoherence in the model, even for a reciprocal degree of preference, such as 1/9, 1/7, 1/5, 1/3, among others. These are likely to occur when the second alternative presents a degree of preference above the first one. The main diagonal takes the value of 1 as a result of the comparison of alternatives among themselves.

3. Developing the MCN-normalized matrix by dividing each element of the comparison matrix column cells by pairs by the sum of each column.

4. Developing the priority vector for each criterion by averaging out each MCN row. This vector, whose content is the average per row, represents the priority vector of each alternative with respect to the criteria considered.

5. Determining consistency of opinions used in the pair-wise comparison matrix through the Coherence Relation, CR. When the CR value is below 0.10, it is considered acceptable. CR values above 0.10 show that the opinions and judgments must be reconsidered. In this paper, the model proposes some fixed tolerance margins, and a traffic light indicates the CR. When it turns red, it means that it is necessary to redefine opinions and judgments. Yellow stands for a warning of proximity to the border. It means a checkup would be advisable, but not necessary. Green shows the consistency of judgments and opinions of the pair-wise comparison matrix.

6. Collecting the results obtained, and summarizing them in the MP-priority matrix, which presents the alternatives in rows, and the criteria in columns, after the nested cycle of steps 2, 3, 4, and 5 has been completed for all criteria.

7. Implementing the pair-wise comparison criteria of the matrix by using the method described in the alternatives of 2, 3, and 4.

8. Lastly, developing a global priority vector by multiplying the criteria priority vector (7) by the priority matrix for each alternative (6).

For each row of the pair-wise comparison matrix, the weighted sum is obtained based on the sum of the value of each alternate priority cell for each line. Then, the weighted sum is divided by the alternate priority, and the average of the result of step (2) — λ— as well as the calculated consistency index for each alternative are fixed. The RI value is found using the random data in Table 1.

To determine the Consistency Index, CI, Equation 1 is used.

$$CR = CI/R \tag{1}$$

Table 1 Random numbers to Find out The RI

Total Alternatives (n)	Random Index
3	0.58
4	0.90
5	1.12
6	1.24
7	1.32
8	1.41

This table represents the random numbers used to find the consistency index for each alternative.

AHP Limitations

Wang et al (2008) found that traditional AHP only allows for comparing a limited number of decision alternatives, usually not above 15. When there are hundreds or thousands of alternatives to compare, the pair-wise comparison model used by the traditional AHP is unfeasible. For these cases, the author proposes an integrated AHP-DEA method, and illustrates it in the risk analysis and evaluation of bridges, where maintenance priorities must be determined for hundreds or thousands of structures.

DATA AND METHODOLOGY

This paper presents a method to quantify business risk in SMEs by calculating volatility of the main financial indices. It is developed based on the AHP technique, and uses time series to predict expected operational and financial risk. The model is applied in the chemical products sector, the fastest-growing sector in Colombian industry, according to a study that measures business perception through surveys carried out by Encuesta Anual Manufacturera 2011 (Annual Manufacturing Survey of 2011).

The risk faced by SMEs depends on the random behavior of their financial indices. The goal of this paper is to measure the industry's volatility indices by using historical data from 2000-2009. The commercial information in Encuesta Anual Manufacturera of 2010 is used. This survey is late by two years. Therefore, information available for 2013 has partial data for 2011, which are not sufficient for modeling. Since the data obtained through the model are sector data, they become the standard measure or reference point to describe and quantify risk in a particular chemical sector company.

The indices that best explain operational risk are summarized in Table 2. For each major index, the level-two indicators that best explain them are defined. Column 2 in this table displays a code of the indicators' names for later use in the results presented in Table 7.

To quantify Operational Risk, *OR*, through the financial indicators presented in Table 2, Equation 2 is used.

$$Ro = \sum_{j=1}^{m} \sum_{i=1}^{n} Wj\, Xi \qquad (2)$$

Where:

J = 1-5 represent the level-one indices
I = 1-20 represent the level-two indices summarized in Table 1

The database takes the financial indicators of the industry within the period 2000-2009. The average and the annual growth rate are estimated. For risk measurement, we use the volatility of each type-I index, where 1 = 1-5 main units, and J = 1-20 secondary units. Then the analysis is developed based on AHP to quantify experts' opinions about the relative importance of each major financial ratio: profitability, indebtedness, liquidity, efficiency and viability. Later, expected operational and financial risks are predicted through a time series analysis.

To project the expected operational risk through the indices that explain it, we carry out a time series analysis for J = 1-20 secondary units, and for I = 1-5 main units. Then, the corresponding consistency proofs are carried out, and with the aid of a linear programming model, the prognosis method is chosen to minimize the prediction error. The method chosen is applied to project the sector indices, and the indices of a particular company. An Excel matrix is used to evaluate operational risk, which is made up of the weighted average of the two groups of financial indices, and the main (5) and secondary (20) units by the corresponding weight found using AHP.

Table 2: Five Major Financial Indices Level 1 and 20 Secondary Indicators to Explain Operational Risk

Indices	Code Name Ratio
PROFITABILITY	1
Gross Margin (%)	1.1
Operating margin (%)	1.2
Net margin (%)	1.3
Return / Equity (ROI) (%)	1.4
Return of Assets	1.5
EFFICIENCY	2
Asset Turnover (times)	2.1
Portfolio turnover (days)	2.2
Rotation suppliers (days)	2.3
Inventory turnover (days)	2.4
Operating cycle (days)	2.5
INDEBTEDNESS	3
Debt to equity ratio (%)	3.1
Financial obligations / liabilities (%)	3.2
Total Liabilities / Sales (%)	3.3
Current Liabilities / Total Liabilities (%)	3.4
VIABILITY	4
Ebitda (MLL)	4.1
EBITDA / Sales (%)	4.2
Sales / Financial duties (sometimes)	4.3
LIQUIDITY	5
Current ratio (times)	5.1
Acid test (times)	5.2
Working capital (MLL)	5.3

This table shows the five major financial indices used to explain Operational Risk: Profitability, Efficiency, Indebtedness, Viability and Liquidity and the nineteen second- level indicators to explain the major indicators. The Code Name Ratio, will be used in table 7 for results

Table 3 shows values of expert opinions assigned in pair-wise comparisons for level-one indices, namely: profitability (Pro), efficiency (Eff), indebtedness, (Deb), viability (Via), and Liquidity (Liq) using AHP. The values in columns 3 and 4 make it possible to infer an index's relative importance with respect to another. For example, if (Pro) and (Deb) in row 2 are compared, the value of (A-4) is highlighted, which means that (Pro) is more important than (Deb) with an intensity of 4, according to experts' opinions.

The method is carried out for all chosen indicators used to quantify operational risk. In Table 4, the pair-wise comparison, and matrix of available alternatives, MCP, are carried out for each main indicator. The degree is established in the following scale: 1 = indifferent, 3 = moderately preferred, 5 = strongly preferred, 7 = very strongly preferred, 9 = extremely preferred. Then, the normalized matrix, MCN, is carried out by dividing each cell in the comparison matrix column by pairs by the sum of the column. The criterion priority vector is generated by finding the average in each MCN column. This vector, which contains the average per row, represents the vector called Priority Alternative regarding the criteria considered. The consistency of opinions used in the pair-wise comparison matrix is determined through the Coherence Relation, CR. The CR value is 0.9, in Table 4, under 0.10, which is considered acceptable.

Table 3: Pair-wise Comparisons

	A	B	More Important	Intensify
1	**Pro**	**Eff**	A	4
2		**Deb**	A	4
3		**Via**	B	2
4		**Liq**	A	4
5				
7				
1	**Eff**	**Deb**	A	5
2		**Via**	B	4
3		**Liq**	A	5
4				
5				
6				
1	**Deb**	**Via**	B	9
2		**Liq**	A	2
3				
4				
5				
1	**Via**	**Liq**	A	7
2				
3				
4				

This table shows the expert judgment values assign by paired comparisons of level 1 indices, namely: Profitability -Pro-, Efficiency-Eff-, Debt -Deb-, Viability-Via- and Liquidity-Liq-, by applying the AHP method, the values in columns 3 and 4 show the importance an indice on another.

After the cycle has been completed for all criteria, the results obtained are collected and summarized in a Priority Matrix, MP. Alternatives are presented in rows, and criteria in columns. For each pair-wise comparison matrix row, the weighted sum is obtained by adding the cells of each alternate priority row. The weighted sum is divided by the alternate priority, and then the mean — λ— is found. The results and calculated consistency index for each alternative are presented in Box 4.

After AHP is executed, the model for each index forecast was developed. A time series analysis was executed for each financial index. In addition, with the aid of a linear programming model on Solver, the value that minimized forecast errors was determined. Once the model that best adjusts to forecasting was identified, the statistical analysis to determine the best adjustment to the time series was begun. Different functions were used for each indicator. Once the best adjustment was identified, we calculated each financial ratio from Table 2.

The analysis time series method applied to the 20 second-level indicators is explained below. The contribution margin is chosen at random to illustrate the process. First, heteroscedasticity is eliminated from the series through an algorithmic transformation, and then the trend graph is analyzed. If the trend in the graph clearly shows a series that does not follow a deterministic trend, it means it is proper to use a linear trend. In this case, a way to estimate the general trend is to suppose that the series evolves slowly over time, and a simple function by intervals could be estimated for a short time.

We have a seasonally adjusted series, and we move on with the selection of the exponential smoothing method. By using Solver, we get the lowest forecast error. Table 5 shows the three methods used to determine the best adjustment to the time series. The single and double exponential smoothing methods were used. The table presents the method's standard error of best adjustment, and the slope obtained with this forecast method. It highlights the mean square error —MSE— with a value of 0.24% for the gross margin forecast (%) by exponential smoothing.

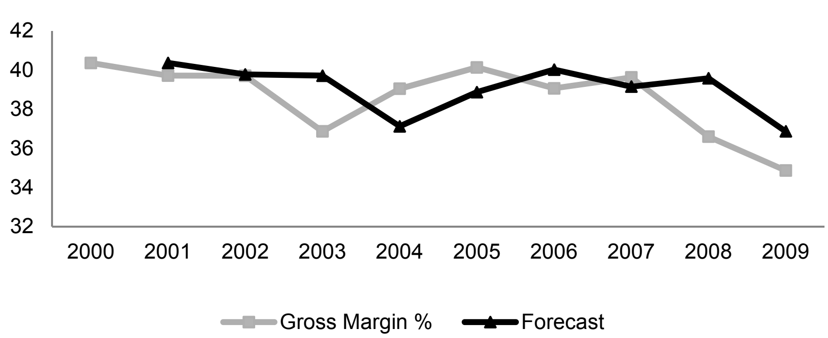
Table 4: Consistency Analysis for Level-One Indicators

AHP	**Pro**	**Eff**	**Ded**	**Via**	**Liq**				
Pro	1	**4**	**4**	**½**	**4**				
Eff	1/4	1	**5**	**¼**	**5**				
Deb	¼	1/5	1	**1/9**	**2**				
Via	2	4	9	1	**7**				
Liq	1/4	1/5	½	1/7	1				
SUM (col)	3.75	9.4	19,5	2.0039	19	1ra	5ª		
Pro	0.26667	0.4255	0.2051	0.2495	0.21053	27%	**27%**		
Eff	0.06667	0.1063	0.2564	0.1247	0.26316	16%	**12%**		
Deb	0.06667	0.0212	0.0512	0.0554	0.10526	6%	**6%**		
Via	0.53333	0.4255	0.4615	0.499	0.36842	46%	**49%**		
Liq	0.06667	0.0212	0.0256	0.0712	0.05263	5%	**6%**		
Lambda	1.0157	1.1525	1.1126	0.9805	1.1434	**5.405**	**Major**		
N	**5**				CI	0.101			
					CR	**9.00%**	**Consistency**		
N	1	2	3	4	5	6	7	8	9
RI	0.	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45
Check	5.405								
l*I		5.405							
			5.405						
				5.405					
					5.405				
A-l*I	-4.4	4	4	0.5	4				
	0.3	-4.4	5	0.3	5				
	0.3	0.2	-4.4	0.1	2				
	2	4	9	-4.4	7				
	0.3	0.2	0.5	0.1	-4.4				
(A-l*I)x	0.01	0.01	0.01	0.01	0.01				
	0.24	0.24	0.24	0.24	0.24				
	0.02	0.02	0.02	0.02	0.02				
	-0.19	-0.19	-0.19	-0.19	-0.19				
	-0.07	-0.07	-0.07	-0.07	-0.07				

This Table presents the consistency analysis results from 5x5 matrixes for level one´s financial ratio: profitability (Pro), Efficiency (Eff) Indebtedness (Deb), Viability (VIA) and Liquidity (Liq). The results shows a CR value of 9%, below 10% which is considered acceptable. The results show the random numbers used to determine the consistency index. Rows 1-5 show the results of paired comparisons using the technique AHP to quantify operational risk. This method is applied consistently to all level 1 financial ratio and their respective explanatory factors for Chemical Industry, Period 2000-2009.

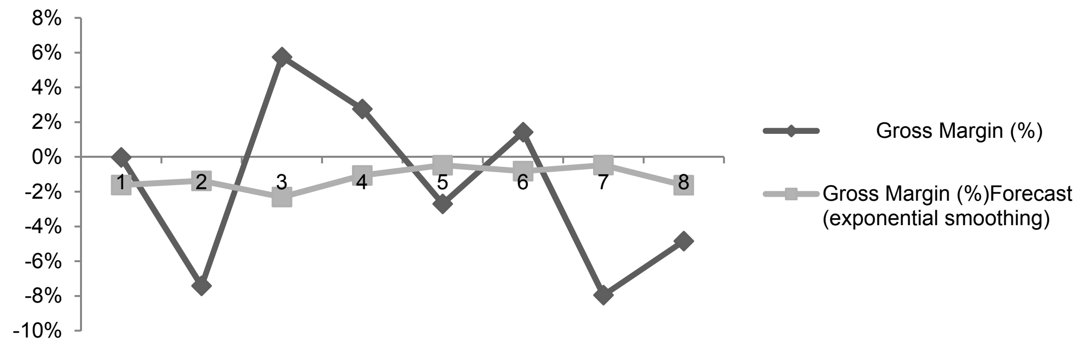
Figure 1 shows the time series trend for real data and gross margin forecasts. Figure 2 shows the time series for the growth percentage of the real data, and the gross margin forecast. The series is seasonally adjusted and the irregular component is removed. Then we complete the data dispersion analysis, and the exponential smoothing method is determined. It presents the lowest forecast error, with MSE = 0.24%.

Figure 1 Real Data vs Forecast for the Time Series of Gross Margin



This figure shows the chart of real data growth vs forecast growth for the time series of gross margin to chemical Industry period 2000-2009.

Figure 2: Real Data Percentage Growth vs Percentage Growth Forecast for Time Series of Gross Margin



This figure shows the chart of percentage growth real data vs the percentage growth forecast for the time series of gross margin to chemical Industry period 2000-2009.

The analysis method illustrated along with the gross margin was applied to each of the five major units: profitability, efficiency, viability, indebtedness and liquidity. It was also applied to the 20 indices of secondary units, which are then summarized in an Excel matrix where the OR is calculated both for the sector and for a particular company. The former and the latter are compared in order to establish an operational risk level for the company with respect to the sector. Table 7 shows the results. It is important to point out that the matrix allows for individual comparison of the indices, such as the global value of operational risk in a company as compared to the sector.

RESULTS AND DISCUSSION

Table 6 shows the summarized results for major and secondary units, respectively, both for the sector and the company. Column 2 shows the value expressed by the sector's risk, while the company's risk is in column 3. Columns 4 and 5 reflect the contrast between the industry's and the company's risk, as well as the weighted average of the main five indicators. For example, for the efficiency index, the industry's risk reaches 178%, and the company's, 168.2%. Hence, it can be inferred that the company's risk is 9.8 percentage points lower that the industry's risk.

The data in Table 7 allow us to infer that the company represents an OR of 140.8% as compared to the sector's 145%. This shows that the risk taken by the industry places the company at a lower risk level. Moreover, it presents the risk levels for the main indices. It must be highlighted that the viability indices have a weight of 52.7% for the sector's operational risk calculation, followed by the profitability ratios, with a weight of 22.3%. In the scale, the efficiency indices have a weight of 12.7%, the liquidity indices, of 6.4%, and the indebtedness indices, whose relative weight is 6%.

Table 6: Major Financial Ratios And Their Weighted Using AHP

Name	Industry Risk	Company Risk	Company vs Industry	Weighted AHP
Profitability	97,4%	95,5%	-1,94%	22,3%
Efficiency	178,0%	168,2%	-5,70%	12,7%
Indebtedness	189,1%	191,1%	1,05%	6,0%
Viability	147,8%	143,5%	-2,99%	52,7%
Liquidity	181,5%	174,5%	-3,93%	6,4%

This table shows the risk levels for main indice and is highlight as viability indices, representing a 52.7% weighting in settling operational risk, followed by profitability ratios with a weight of 22.3%, in scale efficiency indices represent a weight of 12.7%, the liquidity of 6.4% and debt closed at 6%. Also shows a Industry and Company Risk and its comparison.

In addition, Table 7 shows the indicator's code to indentify the name given in Table 2 for the 20 second-level indicators. The average weight found using AHP is shown in Table 7. Historical values without average weights are listed in columns 8 and 9, while weighted historical values are in columns 10 and 11. Column 12 shows the risk taken by the company as compared to the industry to which it belongs. For example, the gross margin presents a weighted risk of 18.7% for the company, while for the sector, the value is 19.3%. Based on column 12, it may be inferred that the company takes a lower risk than the sector does by 3.5%. It must be stressed that it is possible to compare the risk that the company faces in relation to the chemical industry for each second-level indicator. The results are shown in column 12.

Table 7: Indices for Five Major Units: Profitability, Efficiency, Viability, Indebtedness and Liquidity

Major Indices Level 1					Secondary Indices Level 2						
Name	Industry Risk	Company Risk	Company vs Industry	Weight AHP	Code Name Ratio*	Weight AHP	Historic Value Risk without Weighted Industry	Historic Value Risk without Weighted Company	Historic Value Risk Weighted Industry	Historic Value Risk Weighted Company	Value Risk Company vs Industry
Profitability	97,40%	95,50%	-1,97%	22,30%	1.1	8,70%	222,60%	215,00%	19,30%	18,70%	-3,50%
					1.2	9,50%	170,80%	165,00%	16,10%	15,60%	-3,40%
					1.3	9,40%	222,40%	225,00%	21,00%	21,20%	1,20%
					1.4	19,90%	205,60%	201,00%	40,90%	40,00%	-2,30%
					1.5	52,50%	194,10%	190,00%	101,90%	99,80%	-2,10%
Efficiency	178,00%	168,20%	-5,66%	12,70%	2.1	30,70%	0,00%	1,00%	0,00%	0,30%	460,50%
					2.2	13,20%	172,60%	155,00%	22,80%	20,50%	-10,70%
					2.3	15,30%	367,70%	350,00%	56,40%	53,70%	-4,90%
					2.4	9,10%	262,80%	250,00%	24,00%	22,80%	-5,00%
					2.5	31,60%	236,50%	224,00%	74,80%	70,80%	-5,40%
Indebtedness	189,10%	191,10%	1,05%	6,00%	3.1	64,50%	183,90%	186,00%	118,60%	119,90%	1,20%
					3.2	8,20%	253,30%	245,00%	20,90%	20,20%	-3,30%
					3.3	13,20%	177,30%	187,00%	23,30%	24,60%	5,30%
					3.4	14,10%	186,80%	187,00%	26,40%	26,40%	0,10%
Viability	147,80%	143,50%	-2,95%	52,70%	4.1	78,20%	137,40%	145,00%	107,40%	113,40%	5,40%
					4.2	12,60%	140,80%	138,00%	17,80%	17,40%	-2,00%
					4.3	9,20%	246,30%	138,00%	22,70%	12,70%	-57,90%
Liquidity	181,50%	174,50%	-3,93%	6,40%	5.1	12,70%	168,00%	152,00%	21,30%	19,30%	-10,00%
					5.2	70,50%	208,30%	204,00%	146,80%	143,80%	-2,10%
					5.2	16,80%	79,60%	68,00%	13,40%	11,40%	-15,80%
Operative Risk	145,00%	140,80%	-3,00%	100,00%	Kind of Risk= minor Industry						

This table shows the Analysis Risk throught Operative Risk Indice for Chemical Industry and Company. It presents the riskiness of first-level financial ratios, industry and company risk and its contrast. Also, show the second-level financial ratios and classified by the weight thrown AHP Techniques for industry and company. The code name radio was defined in table2. In the last line it exhibit the operational risk for company and industry and contrast each other; we conclude the operative risk for company is 140.8, 3% lowest of industry, it is a minor risk for company.

Another example shows that EBITDA has a weight of 78.2% in the viability indices. The acid test has a weight of 70.5% in the liquidity indices. The debt ratio has a weight of 64.5% in the indebtedness indices. The ROA has a weight of 52.5% in the profitability indices, while the volume of assets has a weight of

31.6% in the efficiency indices. Thus, it is inferred that the company has an OR of 140.8% versus the sector's 145%. This means that the risk taken by the industry places the company at a lower risk level.

CONCLUSIONS

We develop a quantitative analysis of operational risk for SMEs. We modeled volatilities of the chemical industry's major financial indices for the period 2000-2009 by integrating 5 first-level financial indices: profitability, leverage, efficiency, viability and liquidity. We used the AHP analysis technique to quantify experts' opinions about the relative importance of every major financial ratio. Then, using time series, we predicted the expected operational and financial risks. This paper determines the operational risk level for the chemical industry through financial indices. Likewise, we highlight the importance or weight of the index groups in their determination, followed by profitability ratios, with a weight of 22.3%. Efficiency indices represent a weight of 12.7% in the scale, while liquidity has a weight of 6.4%. The indebtedness indices, with a weight of 6%, come last in degree of importance.

This study provides a useful tool for SME entrepreneurs for measuring potential risks associated with their business. The study reflects the volatility presented by the chemical industry, with the structure developed over the last decade, in its financial indicators of profitability, liquidity, efficiency, viability and indebtedness, which produces an average risk index of 145%. Meanwhile, the company under study presents a total risk of 140.8%, which is lower than the industry's risk. Likewise, using the AHP technique, we found the weight of the second-level indices. The EBITDA has a weight of 78.2% in the viability indices, whereas the acid test weighs 70.5% in the liquidity indices. The debt ratio has a weight of 64.5% in the indebtedness indices, while ROA weighs 52.5% in the profitability indices. We finally stress how the volume of assets weighs 31.6% in the efficiency indicators.

In addition, we propose a simple measure to evaluate the consistency risk of profitability, since companies may go through periods of high and low performance. Now, since the risk is associated with the industry's ROA random behavior, it is possible to evaluate it by calculating the standard deviation of returns in the period analyzed, and dividing it by the average performance. For the chemical industry, we obtained an ROI value of 29%, and 30% of ROA. Thus, it may be inferred that the chemical industry has a risk of 30% in the profitability behavior.

In this paper we develop a risk analysis for a company, and establish a point of reference for the chemical industry. By applying diverse tools and strategies, it is possible to mitigate operational and financial risks, as well as ROI. Strategies for cost and expense reduction, as well as for performance stabilization are valid.

Risk is attached to any human activity, and industry is not exempt from this reality. It requires leaders and strategies that play an active role in the sustainability of the business. We present a method that is easy to understand and apply to determine operational risk in SMEs. Such risk is attached to a company's dynamics, and its constant interaction with the environment. In this paper, we quantify operational risk in relation to financial indices, which are red flags that may indicate a company's inability to generate cash flow, and cover fixed costs, as well as operational expenses. Quantification also allows for early warnings related to financial risks associated with the likelihood of not covering fixed costs derived from the indebtedness structure, or the company's lack of efficiency in the use of operational resources when they are lower than the industry's average.

From the viewpoint of modeling, this study has limitations that arise from the little historical information of the industry. The records available are only ten years old. If there were an older data base, we would be able to measure leverage and total financing levels. We could thus determine the volatility of these indices financial risk. However, this approach significantly contributes to developing, understanding and approaching financial and commercial risk quantification of small and medium entrepreneurs.

We propose an analysis of operational risk for SMEs by modeling the impact of economic factors such as the exchange rate, producer price index, and consumer price index in order to determine the exposure deriving from international trade dynamics. This requires indentifying the stochastic processes of the variables, and incorporating such processes into financial forecasts of companies.

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BIOGRAPHY

Jorge Aníbal Restrepo is associate professor in the "Institución Universitaria Tecnológico de Antioquia" and "Universidad Autonóma Latinoamericana" at Medellin. Mr. Restrepo is a Ph.D. student in Management at Universidad San Pablo CEU, Madrid, Spain. He has a B.S. in Management Engineering from ''Universidad Nacional de Colombia'', Medellín, Colombia, and a M.Sc. in Management from Universidad Eafit, Medellín. His research interests are: Decision Analysis, Project Management, Financial Analysis and Competitiveness. Email: jrestrepo@tdea.edu.co

Jairo Angel Diaz is coordinator of Financial Management specialization from "Universidad Autonoma Latinoamericana", Medellin - Colombia. Professor in Financial Management at "Universidad San Martin" Medellín-Colombia, "Universidad Autonoma Latinoamericana" and "Institución universitaria Jaime Isaza Cadavid". He has a B.S. in Industrial Engineer, Specialist in Financial Institutions. Email: jairoangeld@gmail.com

Juan Esteban Ocampo is an auxiliar professor in the Administrative and Economics Sciences Faculty, Universidad Autonóma de las Américas. Mr. Ocampo is a M.Sc. student in Systems at Universidad Nacional de Colombia. He has a B.S. in Management Engineering from ''Universidad Nacional de Colombia'', His research interests are: Financial Analysis and Competitiveness. Email: juaneog@gmail.com