# Measurement of liquidity, insolvency and market risk levels in the textile sector of Ecuador

# Medición de los niveles de riesgos de liquidez, insolvencia y mercado en el sector textil del Ecuador

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## Abstract

A company is exposed to different types of financial risk (systematic and non-systematic risks). This research focuses on analyzing the insolvency, market and liquidity risks of the Textile Sector of Ecuador in the period 2007-2018. Regarding the methodology, a non-experimental study was carried out with a quantitative approach. The Superintendence of Companies, Securities and Insurance was used as a source of information; also scientific information on financial risk and the textile sector in Ecuador was analyzed. In the insolvency risk analysis, through the methodologies of Altman and Ohlson, it was determined that the riskiest years are 2016 and 2018: Altman score of 5,545 and 5,690 respectively, and a percentage of insolvency risk of 6,40% and 7,46% in the same years. In the market risk analysis, the Beta coefficient for the textile sector was 1,2. In addition, microenterprises have a higher level of liquidity risk, with 57,06%. Determining the financial risk of a company is an important tool for making decisions and helps to have a better vision of the fulfillment of the proposed objectives.

**Keywords**: Insolvency risk, market risk, Altman, Ohlson, textile sector of Ecuador.

## Resumen

Una empresa está expuesta a diferentes tipos de riesgo (riesgos sistemáticos y no sistemáticos). La presente investigación se enfoca en analizar los riesgos de insolvencia, mercado y liquidez del Sector Textil del Ecuador en el periodo 2007-2018. En relación a la metodología, se realizó un estudio no experimental con un enfoque cuantitativo; la Superintendencia de Compañías Valores y Seguros es la fuente de información principal del estudio. En el análisis de riesgo de insolvencia, a través de las metodologías de Altman y Ohlson, se determinó que los años más riesgosos son el 2016 y 2018: puntaje de Altman de 5,545 y 5,690 respectivamente, y un porcentaje de riesgo de insolvencia del 6,40% y 7,46 %. El riesgo de mercado a través del coeficiente Beta para el sector textil fue de 1,2. Además, las microempresas presentan un mayor nivel de riesgo de liquidez, con un 57,06 %. Determinar el riesgo financiero de una empresa es una herramienta importante para la toma de decisiones y ayuda a tener una mejor visión del cumplimiento de los objetivos propuestos.

**Palabras clave**: Riesgo de insolvencia, riesgo de mercado, Altman, Ohlson, sector textil del Ecuador.

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## Introduction

The Oxford Dictionary (2020) defines risk as a situation involving exposure to danger or the possibility that something unpleasant or unwelcome will happen. In the business field, Celaya and López (2004) define risk as the probability that the company will not be able to face any situation inherent to its activity. Due to the high degree of uncertainty, it is necessary to use methodologies that allow measuring and predicting the level of risk of an activity. Therefore, it must be borne in mind that, at a higher level of risk, the investor will demand a higher level of profitability. According to Circiumaru, Siminica, & Ganea (2009), there is an indirect relationship between the level of the risk effects and the level of the efficiency and efficacy: the smaller are the risk effects, the bigger are the efficiency and the efficacy and vice-versa.

There are different types of financial risk, according to Lara (2008), these can be classified into market, credit, liquidity, legal, operational and reputational risk. In addition, Ross, Westerfield and Jordan (2010) indicates that risk can be classified as systematic and unsystematic risk. Unsystematic risk is caused by the company's own activity and systematic risk is the one that influences many assets, and since it has effects on the entire market, it is also called market risk. With the aim of measuring the different types of financial risk (systematic and non-systematic risks), this research focuses on analyzing insolvency risk (credit), liquidity risk and market risk.

## Literature review and theoretical background

### *Insolvency Risk*

Insolvency risk refers to the uncertainty due to the possibility that the company cannot meet its financial obligations. This is understood as the state of financial vulnerability, which ranges from the impossibility of compliance in the payment of obligations to the bankruptcy and liquidation of the company (Terreno et al., 2017). The methodologies to measure and predict business failure have had a considerable evolution, and two stages can be highlighted in the development of business failure measurement models: descriptive stage and predictive stage.

FitzPatrick (1932) was one of the first researchers to analyze business failure, who was part of the "descriptive stage of bankruptcy model development". Smith y Winakor (1935) analyzed ratios of 183 failed companies from a variety of industries. Merwin (1942) asserted that bankrupt companies showed signs of weakness even four or five years before failure. Chudson (1945) says that the industry to which a corporation belongs is a significant factor in determining the structure of the corporation's balance sheet. Jackendoff (1962) analyzed critical problems regarding the classification, selection, and use of ratios. Horrigan (1965) analyzes the statistical nature and susceptibility of financial ratios. The following group of financial ratios makes up the basic list of his study:

- Short - term liquidity ratios: current assets to current debt (current ratio), current assets less inventory to current debt (quick ratio), cash plus marketable securities to current debt.
- Long – term solvency ratios: Net operating profit to interest, net worth to total debt, net worth to long – term debt, net worth to fixed assets.
- Capital turnover ratios: sales to accounts receivable, sales to inventory, sales to working capital, sales to fixed assets, sales to net worth, sales to total assets.
- Profit margin ratios: net operating profit to sales, net profit to sales.
- Return on investment ratios: Net operating profits to total assets, net profits to net worth.

Subsequently, the predictive stage begins with Beaver (1966), who proposes the prediction of business failure and suggests a methodology for evaluating accounting data for different purposes and not only to determine solvency. The author analyzes the following group of ratios:

- Group 1: Cash flow ratios.
- Group 2:  Net income ratios.
- Group 3: Debt to total assets ratios.
- Group 4: Liquid – asset to total asset ratios.
- Group 5: Liquid asset to current debt ratios.
- Group 6: Turnover ratios.

At this stage, the studies by Altman (1968) and Ohlson (1980) emerged, who developed business bankruptcy forecast models based on univariate, multivariate analysis techniques and conditional probability econometric models of logistic regression. Altman initially developed bankruptcy prediction models aimed at developed countries, later adaptations have been made to its model, including: Altman, Baidya y Ribeiro (1979) in Brazil in the period 1973 to 1976. Pascale (1988) for the Uruguayan manufacturing industry in the period 1978 -1982. Altman, Hartzell y Peck (1995) developed the EMS model, the adjusted model incorporates the credit characteristics of emerging market companies (model applied in this research).

Similarly, ohlson's model has been applied in multiple places. For instance, Lieu, Lin and Yu (2008) analyzes financial distress prediction based on Ohlson's Work; they used logit regression to establish an early-warning model using publicly available financial information and includes emerging stock companies from Taiwan; according to the author the logit regression model has significant predictive power and is thus effective in predicting distress. The study uses financial ratios (financial ratios of five types that are often used in financial statement analysis) and non-financial information to establish a financial distress early-warning model; non-financial variables include ownership structure and corporate governance indicators. Furthermore, Krishnasami (2012) uses three regression models in order to analyse the impact of financial risk on debt – equity mix. Boritz, Kennedy and Sun (2007) compare Canadian bankruptcy prediction models developed by Springate (1978), Altman and Levallee (1980), and Legault and Véronneau (1986) against the Altman and Ohlson models using recent data to determine the robustness of all models over time and the applicability of the Altman and Ohlson models. The results indicate that the models developed by

Springate (1978) and Legault and Véronneau (1986) yield similar results to the Ohlson (1980) model.
In the study "forecasting business failure in the Valencian community: Application of the discriminant and logit models, Ferrando and Blanco (1998) conclude that in general the success level of the logit model is somewhat higher than that of the linear discriminant analysis due to its better predictive capacity . Shehni (2013) says that the Altman model predicts the probability of bankruptcy in Iranian listed companies more accurately than the Ohlson model. Efron (1975) showed that with multivariate normal data, the linear discriminant function is better than the logistic regression. The conclusion reached is that none of the methods consistently outperforms the other, but that the choice of one or the other method depends on the database used.
While the Z-score and O-score methods are based on a linear approach, the Neural Network model was introduced to predict bankruptcy with a non-linear approach. Moreover, the development of techniques machine learning (support vector machines, fuzzy systems, neural networks and evolutionary algorithms), prompted researchers to use these techniques in business. In this area we can mention: Ahn, Cho y Kim (2000) who propose an intelligent hybrid system; Hua, Wang, Xu, Zhang y Liang (2007) who use automatic support vectors (SVM); Berg (2007) applied generalized additive models (GAM); Ghazali, Jaafar Hussain, Mohd Nawi y Mohamad (2009) use higher order neural networks (HONN); Chaudhuri y De (2011) address bankruptcy prediction with the Fuzzy Support Vector Machine (FSVM) artificial neural network model, among others.

*Market Risk.*
According to Ross, Westerfield and Jaffe ( 2010) the systematic risk is analyzed in the models of market risk measurement, which influences many assets and because it has effects on the entire market, it is also called market risk. Unsystematic risk can be eliminated through diversification, but systematic risk cannot be eliminated. Markowitz (1952) developed a portfolio selection model that incorporated the principles of diversification, which identifies a set of efficient portfolios of risky assets, and based on this set of risky portfolios for any level of risk, only the portfolio with the highest expected return is the one of interest. Tobin (1958) analyzes liquidity preference as a behavior towards risk, and distinguishes two possible sources of liquidity preference: the lack of elasticity of expectations about future interest rates and the uncertainty about the future of interest rates.

Capital Asset Pricing Model (CAPM). - The traditional capital asset pricing model proposed by Sharpe (1964), Lintner (1965) and Mossin (1966) asserts that an individual views the outcome of any investment in probabilistic terms and considers that the expected return on an asset depends linearly and positively on its systematic risk, measured by its Beta. The CAPM model formula is:

$$E(R_i) = R_f + \beta_i * (R_M - R_f) \quad \textbf{(1)}$$

Where:

- E (Ri) = Minimum profitability expected by investors.
- Rf = Risk-free rate.
- RM = Average profitability for any period.
- (RM – Rf) = Market risk premium.
- B = A measure of the volatility–or systematic risk.

The Beta coefficient represents the most critical variable in the CAPM model, which measures the sensitivity of a company's performance to changes in market performance. A Beta greater than 1 indicates that the non-diversifiable risk of the investment is higher than the market average. The Beta coefficient can be determined in two ways, according to Vélez (2011):

$$\beta = \frac{\mathrm{cov(Rm,Rs)}}{\sigma_m^2} \textbf{ (2) } ; \beta = \frac{\sigma_s \,\mathrm{cor(Rm,Rs)}}{\sigma_m} \textbf{ (3)}$$

*Liquidity risk*

The importance of liquidity risk management is related to the anticipation that companies may have in the face of possible crises that lead to non-payment of obligations in the short term. The short and medium term indices that most affect a company's long-term performance are liquidity, indebtedness, and portfolio or debtor management (Toro et al., 2015); these indicators are directly related to liquidity risk. In the liquidity risk analysis, a logit analysis was used in order to determine the risk level of the textile companies in relation to the levels presented by the industry.

Cowan and Hansen (2008) mention that liquidity risk is a short-term phenomenon linked to the expected cost of debt refinancing. If interest rates increase, the renewal value of short-term debt increases automatically and if the company does not anticipate this rate increase and does not have enough cash flow to cover this increase, it will begin to sell the most liquid assets. Leiva (2009) says that liquidity risk must be analyzed differently from credit and market risk, since, in this case, a single liquidity event can lead to the bankruptcy of the company. For this reason, liquidity risk management must be carried out from its safe side, that is, its objective is to minimize the probability of its occurrence.
In this context, the aim of this research is to apply the models mentioned to measure the different types of financial risk in companies that are part of the manufacture of textile products in Ecuador, which according to the International Standard Industrial Classification (ISIC) corresponds to C13. The sector sheet can be seen inTable 1:

**Table 1.** *Classification of the textile sector*

| Code | Description | Level |
|---|---|---|
| C | Manufacturing | 1 |
| C13 | Manufacture of textile | 2 |
| C131 | Spinning, weaving and finishing of textile | 3 |
| C1311 | Preparation and spinning of textile fibres | 4 |
| C1312 | Weaving of textiles | 4 |
| C1313 | Finishing of textile | 4 |
| C139 | Manufacture of other textile | 3 |
| C1391 | Manufacture of knitted and crocheted fabric | 4 |
| C1392 | Manufacture of made-up textile articles, except appare | 4 |
| C1393 | Manufacture of carpets and rug | 4 |
| C1394 | Manufacture of cordage, rope, twine and nettin | 4 |
| C1399 | Manufacture of other textiles n.e.c | 4 |

**Source:** *United Nations Statistical Commission (UNSD) (2008)*

With the results obtained through the application of insolvency, market and liquidity risk, the research question arises: What levels of risk of insolvency, market and liquidity has the textile sector of Ecuador had in the period 2007 - 2018?

## Methodology

### Insolvency risk

*Altman's Methodology*

In order to measure insolvency risk, Altman's insolvency prediction model developed for emerging markets was first applied, which classifies companies that are at risk of business failure: a higher score means that the company is in the zone safe and not at risk. Altman (1968) chose multiple discriminant analysis (ADM) as the statistical technique for his research. The final function proposed by Altman in his research is:

$$Z = 0{,}012(X1) + 0{,}014(X2) + 0{,}033(X3) + 0{,}006(X4) + 0{,}999(X5) \quad \textbf{\textit{(4)}}$$

Where:

- X1 = Working capital / total assets.
- X2 = Retained earnings / total assets
- X3 = Profits before interest and taxes / total assets
- X4 = Market value of the equity / book value of the total debt
- X5 = Sales / total assets

According to Altman (2000) a more convenient specification of the model is the following:

$$Z = 1{,}2(X1) + 1{,}4(X2) + 3{,}3(X3) + 0{,}6(X4) + 1{,}0(X5) \quad \textbf{\textit{(5)}}$$

Furthermore, Altman (2000) made new estimates of the original model, such is the case of the model for closed capital companies (Z´) and the Altman's model for non-manufacturing companies with closed capital in general (Z´´):

$$Z' = 0{,}717(X1) + 0{,}847(X2) + 3{,}107(X3) + 0{,}420(X4) + 0{,}998(X5) \quad \textbf{\textit{(6)}}$$

$$Z'' = 6{,}56(X1) + 3{,}26(X2) + 6{,}72(X3) + 1{,}05(X4) \quad \textbf{\textit{(7)}}$$

*Adjusted model for emerging markets.-* Altman, Hartzell y Peck (1995) developed the EM Score model, which incorporates the particular credit characteristics of companies in emerging markets. This is the model that is applied in the research work.

$$Z''_{Adjusted} = 6{,}56\ (X1) + 3{,}26\ (X2) + 6{,}72\ (X3) + 1{,}05\ (X4) + 3{,}25 \quad \textbf{\textit{(8)}}$$

According to Altman (2000), the companies 'credit rating is used according to the Z-score, which is equivalent to the creditworthiness rating used by Standars & Poor's. *Table 2* shows the values that the equation takes:

**Table 2.** *U.S. Bond Rating Equivalent Based on EM Score*

| U.S equivalent rating | Average EM Score | U.S equivalent rating | Average EM Score |
|---|---|---|---|
| AAA | 8,15 | BB+ | 5,25 |
| AA+ | 7,6 | BB | 4,95 |
| AA | 7,3 | BB- | 4,75 |
| AA- | 7 | B+ | 4,5 |
| A+ | 6,85 | B | 4,15 |
| A | 6,65 | B- | 3,75 |
| A- | 6,4 | CCC+ | 3,2 |
| BBB+ | 6,25 | CCC+ | 2,5 |
| BBB+ | 5,85 | CCC- | 1,75 |
| BBB- | 5,65 | D | 0 |

**Source:** *Own elaboration based on Altman and Hotchkiss (2006).*

*Ohlson's Methodology*

Ohlson (1980) estimated three models composed of an intersection and nine independent variables. The description of the logistic model variables is as follows:

- X1 = Size (logarithm of total assets divided by the price index).
- X2 = Total Liabilities / Total Assets.
- X3 = Working Capital / Total Assets.
- X4 = Current liabilities / Current assets.
- X5 = Dummy. One if total liabilities exceeds total assets, zero otherwise.
- X6 = Net Income / Total Assets.
- X7 = Funds provided by operations divided by total liabilities
- X8 = Dummy. One if net income was negative for the last two years, zero otherwise.
- X9 = Net income t – Net income t-1/| Net income t|+ | Net income t-1|.

Models 2 and 3 have somewhat weaker goodness-of-fit statistics. Model 1 predicts bankruptcy within a year and presents better results, since it correctly classifies 96,12% of companies. However, in all three models, size appears as an important prediction.

$$Model\ 1 = -1{,}32 - 0{,}407X1 + 6{,}03X2 - 1{,}43X3 + 0{,}0757X4 - 1{,}72X5 - 2{,}37X6 - 1{,}83X7 + 0{,}285X8 - 0{,}521X9 \quad \textbf{\textit{(9)}}$$

Ohlson's logistic model was applied, through which the probability that companies have of falling into risk of bankruptcy or business failure is obtained. In the regression analysis, for the codification of the dependent variable, the criterion of lack of equity was used: those companies that have the total liabilities greater than the total assets; this is provided by Superintendency of Companies, Securities and Insurance (2016).

### Market risk

In order to calculate the market risk, the Beta (β) coefficient was used and also the expected return of the sector was determined through the CAPM. The ROE (return on equity) was used to measure market risk, which, according to Gitman (2007), is calculated as follows.

$$ROE = \frac{Net\ income}{Shareholder's\ equity} \quad (10)$$

An adjusted return (adjusted ROE) was used, which was calculated by dividing the profit for the year by the initial equity for the period. In order to determine the market risk the Beta coefficient was calculated: the relationship between the adjusted ROE of companies in the manufacturing sector with the adjusted ROE of the textile sector. The risk-free rate was established through the reference passive rate of the Central Bank of Ecuador. The final result of the model is based on the CAPM to obtain the return expected by the investor.

This research does not use information from the Ecuadorian stock market because the country's economy is considered developing; this is why it can be affirmed that its stock market is poorly developed and that it concentrates its negotiations on fixed income documents. The Superintendency of Companies, Securities and Insurance (2016a) states that "the poor development of the country's stock market" (p.31) is due to aspects related to the economic environment, the supply and demand of securities. Salcedo (2018) says that “the Ecuadorian Stock Market is dynamic; however, it is incipient” (p.18). Other authors such as Hablich, Toala and Agila (2018) reinforce this idea by saying that "the Ecuadorian stock market is underdeveloped" (p. 791). For this reason, the Ecuadorian stock market performance measures are not used, and instead, accounting measures are used to calculate the Beta coefficient, specifically the adjusted ROE.

For the application of the risk-free interest rate, different criteria were considered: Campos, Castro, Cuy y Ferrer (2005), in the case of the Brazilian electric company Electrobras, considers the country's credit rating, and also selects a company that is at the same time rating level to know the value of the bonds. Sánchez (2010) conducts a study of the food sector in Colombia and used the geometric average risk-free rate of 4,97% of the United States T-Bonds over the 10-year term to apply the CAPM. For this research, the benchmark passive rate of the Central Bank of Ecuador is considered as a risk-free rate, since in the Ecuadorian environment investors will demand a rate of return higher than the rate they obtain for an investment with low risk exposure.

**Liquidity risk**

Finally, the liquidity risk was measured through a logistical analysis. The dependent variable of the logistics model was established based on companies with lower or higher levels of relevant financial indicators of the total number of manufacturing companies analyzed: liquidity index, indebtedness index and average collection period. Dichotomous or dummy variables are used in relation to the manufacturing industry average: Companies without liquidity risk = 0, and companies with liquidity risk = 1. The result of the logistic equation indicates the probability of liquidity risk of the companies in the sector, this, in relation to the financial indicators of the manufacturing industry. Indicators from Table 3 were used in order to determine the dependent variable of the model. Dichotomous variables were used in relation to the average of the manufacturing industry:

**Table 3.** *Manufacturing sector financial indicators*

| Year | Average collection period | Liquidity index | Indebtedness index |
|---|---|---|---|
| 2007 | 75,016 | 2,756 | 0,684 |
| 2008 | 71,691 | 2,716 | 0,700 |
| 2009 | 73,800 | 2,522 | 0,685 |
| 2010 | 74,668 | 2,685 | 0,689 |
| 2011 | 71,567 | 2,678 | 0,686 |
| 2012 | 62,326 | 2,868 | 0,669 |
| 2013 | 76,183 | 2,917 | 0,655 |
| 2014 | 77,905 | 2,982 | 0,643 |
| 2015 | 84,044 | 3,177 | 0,628 |
| 2016 | 87,497 | 3,244 | 0,638 |
| 2017 | 88,986 | 3,464 | 0,638 |
| 2018 | 72,664 | 3,357 | 0,637 |

**Source:** Own elaboration based on Superintendency of Companies, Securities and Insurance (2019)

Table 4 shows the explanatory variables used for the logistic model:

**Table 4.** *Explanatory variables of the model*

| Independent variable | Description |
|---|---|
| X1 | Average collection period |
| X2 | Average payment period |
| X3 | Average age of inventories |
| X4 | Cash conversion cycle |
| X5 | Annual cash turnover |
| X6 | Liquidity index |
| X7 | Indebtedness index |
| X8 | Working capital |
| X9 | Need of funds |
| X10 | Need of funds / Sales |

**Source:** Own elaboration based on Superintendency of Companies, Securities and Insurance (2019)

**Data**

The quantitative analysis was performed based on information from the Superintendency of Companies, Securities and Insurance in the 2007-2018 period. This information was refined due to inconsistent information. The database was refined using the following analysis criteria: companies that present information on assets and companies that present ordinary income, that is, that have activity.

Once the database was refined, 2,082 companies were included in the analysis, which are classified as: large = 176, medium = 539, small = 835 and micro = 532. Moreover, it was determined that an average of 173 companies have submitted financial information in the 12 years of analysis. In addition, in the data analysis the Chauvenet criterion was used to eliminate outliers.

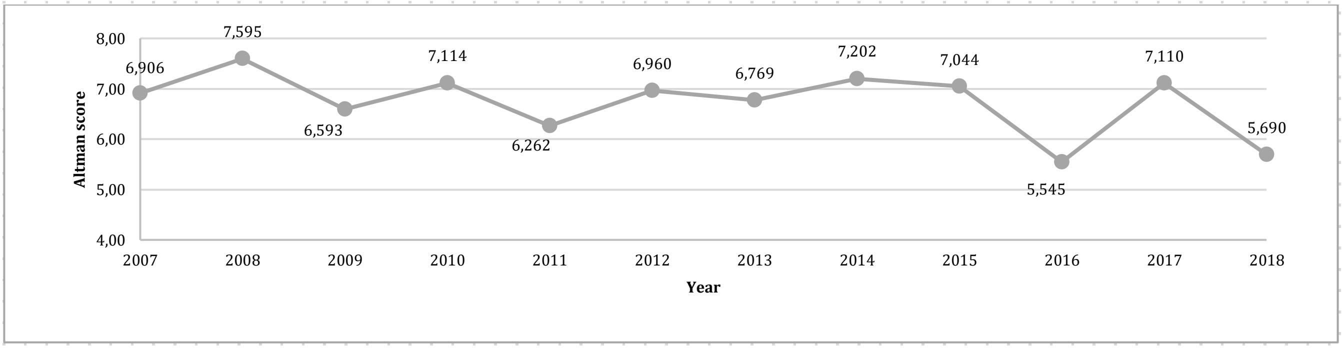
It is worth mentioning that the data analysis was carried out through Microsoft Excel. In addition, the SPSS software was used for the regression analysis in the analysis of insolvency and liquidity risk.

## Results

### Insolvency risk

#### *Altman's methodology*

*Annual insolvency analysis.* - Figure 1 shows that, on average, companies are in a safe zone, except for the years 2016 and 2018 where they are in the gray zone.




**Source:** Own elaboration based on Superintendency of Companies, Securities and Insurance (2019)

**Figure 1**. Altman's annual analysis.

*Insolvency analysis by business size.* - Altman's analysis indicates that microenterprises have the lowest score, that is, they have a greater tendency to fall into an insolvency risk zone. However, the data indicates that companies classified by size are in a safe area. (see Table 5).

**Table 5.** *Altman analysis by business size*

| Size | Year | | | | | | | | | | | | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | |
| Micro | 6,57 | 7,64 | 5,43 | 6,59 | 4,19 | 7,16 | 6,62 | 7,38 | 6,53 | 5,50 | 5,46 | 3,28 | 6,03 |
| Small | 7,21 | 6,73 | 7,25 | 7,31 | 7,49 | 7,35 | 6,65 | 7,16 | 6,87 | 5,05 | 7,10 | 5,21 | 6,78 |
| Medium | 7,51 | 9,78 | 7,42 | 7,61 | 7,02 | 6,08 | 6,49 | 6,58 | 8,26 | 6,13 | 9,12 | 9,10 | 7,59 |
| Large | 5,09 | 6,40 | 5,83 | 6,83 | 6,95 | 6,47 | 8,58 | 8,17 | 6,87 | 6,44 | 6,54 | 8,87 | 6,92 |

**Source**: *Own elaboration based on Superintendency of Companies, Securities and Insurance (2019)*

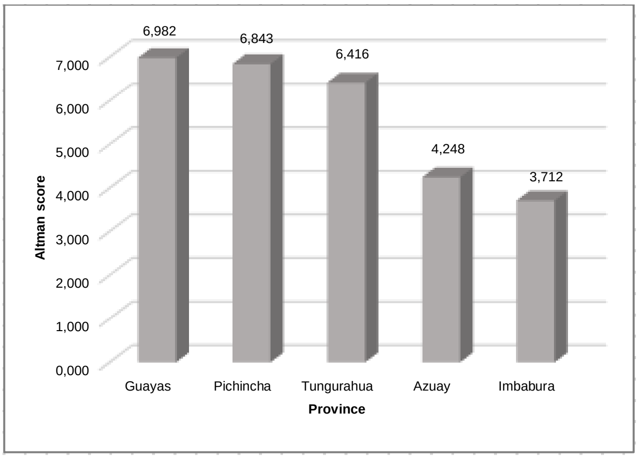
*Provincial insolvency analysis.- Table 6* shows the provinces with the highest concentration of textile companies, which will be analyzed.

**Table 6**. *Provinces with the highest concentration of textile companies*

| Province | Year | | | | | | | | | | | | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | |
| Pichincha | 96 | 99 | 101 | 108 | 109 | 103 | 105 | 99 | 104 | 97 | 96 | 90 | 101 |
| Guayas | 31 | 29 | 32 | 36 | 37 | 44 | 51 | 50 | 56 | 55 | 49 | 41 | 43 |
| Tungurahua | 10 | 8 | 12 | 10 | 12 | 10 | 10 | 10 | 10 | 10 | 10 | 8 | 10 |
| Azuay | 3 | 5 | 6 | 5 | 5 | 6 | 5 | 6 | 7 | 6 | 5 | 5 | 5 |
| Imbabura | 3 | 3 | 3 | 3 | 3 | 4 | 4 | 3 | 2 | 5 | 5 | 4 | 4 |
| Others | 7 | 8 | 8 | 12 | 12 | 12 | 12 | 10 | 11 | 10 | 10 | 10 | 10 |
| Total | 150 | 152 | 162 | 174 | 178 | 179 | 187 | 178 | 190 | 183 | 175 | 158 | 173 |

**Source:** *Own elaboration based on Superintendency of Companies, Securities and Insurance (2019)*

Figure 2 shows that Guayas, Pichincha and Tungurahua have higher scores, so they are in a safe area.




**Source:** *Own elaboration based on Superintendency of Companies, Securities and Insurance (2019)*
**Figure 2.** *Altman analysis by province in Ecuador.*

### *Ohlson's methodology*

The significant variables in the regression analysis are found in Table 7:

**Table 7.** *Variables that are part of the logistics model*

| | B | Standard error | Wald | Gl | Sig. | Exp(B) |
|---|---|---|---|---|---|---|
| Size | -0,538 | 0,206 | 6,803 | 1 | 0,009 | 0,584 |
| Working capital / Total assets | -3,245 | 0,421 | 59,494 | 1 | 0,000 | 0,039 |
| Net Income / Total Assets | -3,442 | 0,756 | 20,754 | 1 | 0,000 | 0,032 |
| Constant variable | -1,058 | 0,703 | 2,262 | 1 | 0,133 | 0,347 |

**Source:** *Own elaboration based on Superintendency of Companies, Securities and Insurance (2019)*

Equation 11 shows the beta coefficients of the logistic model:

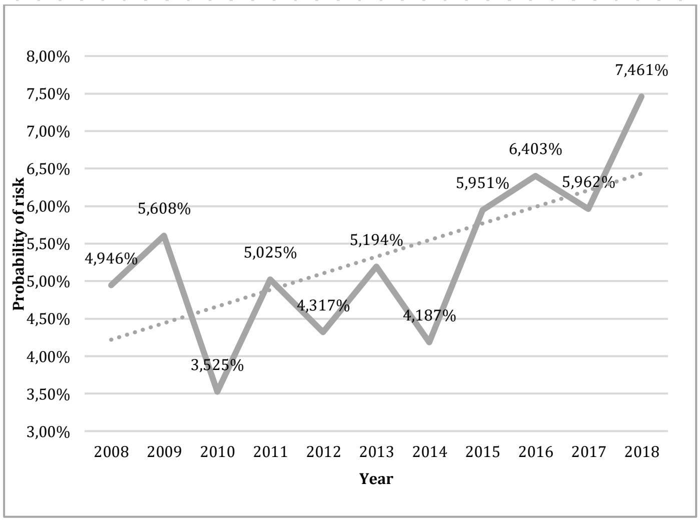
$$P_{(i)} = \frac{1}{1+e^{-(\beta_0+\beta_1 x1+\beta_2 x2+\beta_n xn)}} \quad \textbf{(11)}$$

$$P(i) = \frac{1}{1+e^{-\left(-1{,}058-0{,}538\,Sise-3{,}245\left(\frac{Working\ capital}{Total\ assets}\right)-3{,}442\left(\frac{Net\ income}{Total\ assets}\right)\right)}}$$

Pi = Probability of insolvency

The variables that were statistically significant with a significance level of5% are: working capital / total assets, size, and net income / total assets; they all have an inverse relationship with the probability of business bankruptcy. The variable that has the most weight when explaining the probability of bankruptcy is net income / total assets. Moreover, the Wald test confirms the results mentioned in the previous paragraph, so it is concluded that the variables are important to explain the probability of business bankruptcy.

*Annual insolvency analysis.* - Shows that there is an increasing trend in the percentage of insolvency risk. The year that the highest probability of bankruptcy occurred was 2018.




**Source:** *Own elaboration based on Superintendency of Companies, Securities and Insurance (2019)*
**Figure 3.** *Annual insolvency risk probability - Ohlson's methodology.*

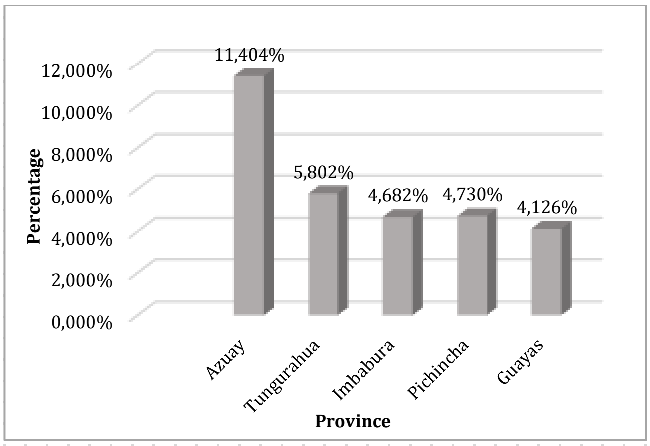
*Insolvency analysis by business size.*- Table 8 shows the probability of insolvency risk by business size, where microenterprises have a higher risk of insolvency. In contrast, large companies have lower levels of risk, even in 2018 this indicator is reduced by approximately 4 percentage points.

**Table 8.** *Ohlson's analysis by business size*

| | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Micro | 1,5% | 7,7% | 9,4% | 5,1% | 9,0% | 3,7% | 6,3% | 3,2% | 8,7% | 9,4% | 4,9% | 14,6% | **6,9%** |
| Small | 0,5% | 3,9% | 4,1% | 3,2% | 3,2% | 4,6% | 4,8% | 5,1% | 5,0% | 4,2% | 6,1% | 5,6% | **4,2%** |
| Medium | 0,7% | 3,5% | 3,9% | 2,4% | 2,6% | 5,6% | 5,5% | 5,2% | 5,5% | 6,4% | 7,4% | 1,3% | **4,2%** |
| Large | 0,6% | 2,2% | 2,3% | 1,9% | 3,4% | 2,6% | 1,8% | 1,6% | 1,8% | 5,4% | 4,8% | 0,9% | **2,4%** |

**Source:** *Own elaboration based on Superintendency of Companies, Securities and Insurance (2019)*

*Insolvency analysis by province.*- Figure 4 analyzes the risk by province. As in Altman's analysis, companies in the provinces of Guayas, Pichincha and Tungurahua have a low level of insolvency risk. On the contrary, those of Azuay have a high probability of risk. Companies in the province of Imbabura disagree with Altman's analysis, since it has a low level of risk.




**Source:** *Own elaboration based on Superintendency of Companies, Securities and Insurance (2019)*
**Figure 4.** *Ohlson's analysis by province in Ecuador.*

## Market risk

The profitability of the market and the textile sector were obtained through the adjusted ROE. The weighted percentage was calculated based on the percentage participation of the manufacturing industry sectors, this, in relation to the total equity. (See Table 9)

**Table 9.** *Market profitability of the manufacturing and textile sector of Ecuador*

| Year | Profitability | |
|---|---|---|
| | Manufacture (C ) | Textile sector (C13) |
| 2011 | 22,37% | 18,42% |
| 2012 | 17,83% | 11,79% |
| 2013 | 16,70% | 11,51% |
| 2014 | 15,55% | 9,09% |
| 2015 | 13,08% | 4,38% |
| 2016 | 9,56% | 3,15% |
| 2017 | 11,32% | 6,55% |
| 2018 | 10,33% | 2,60% |
| Weighted average | 14,60% | 7,59% |
| Standard deviation | 4,36% | 5,38% |
| Sample variance | 0,00189 | 0,00289 |
| Exchange rate | -0,0167 | -0,0198 |

**Source:** *Own elaboration based on Superintendency of Companies, Securities and Insurance (2019)*

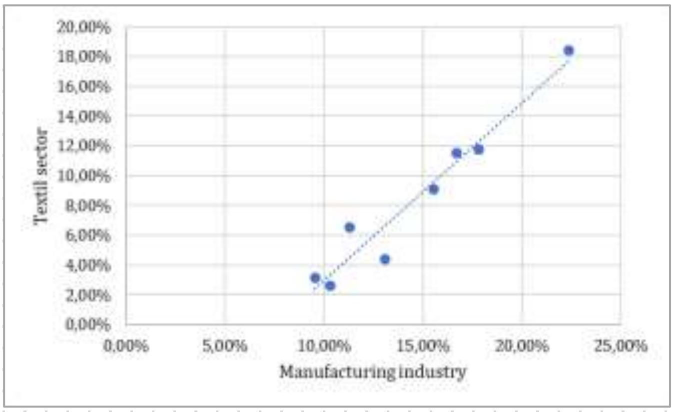
*Calculation of the accounting beta*

When using equations 2 and 3, with the values corresponding to the profitability of the manufacturing market (Rm) and the textile sector (Rs), the Beta coefficient is obtained, which indicates that due to the 1% variation in market profitability manufacturing, the profitability of the textile sector varies by 1,2004%:

$$\beta = \frac{\mathrm{cov(Rm,Rs)}}{\sigma_m^2} = 1{,}2004 \quad \beta = \frac{\sigma_s \,\mathrm{cor(Rm,Rs)}}{\sigma_m} = 1{,}2004$$

When performing the regression between the average yield of the textile sector and the average yield of the manufacturing industry, the following results are obtained (see Figure 5):

$$\begin{array}{lll} \mathrm{Rs} = -0{,}0907 & + & 1{,}2004\mathrm{Rm} + \mathrm{ui} \\ \mathrm{ee:} \quad (0{,}0182) & & (0{,}1202) \\ \mathrm{t:} \quad (-4{,}9820) & & (9{,}9805) \\ \mathrm{p:} \quad (0{,}0024) & & (0{,}0000) \\ \mathrm{F:}\ 99{,}61 & & \\ \mathrm{R}^2\mathrm{:}\ 0{,}9431 & & \end{array}$$




**Source:** *Own elaboration based on Superintendency of Companies, Securities and Insurance (2019)*
**Figure 5.** Average yield of the textile sector and the average yield of the manufacturing industry

As can be seen, the variable Rm is statistically significant at a significance level of 5%, since it has a p value of 0,0000. Additionally, the independent variable Rm explains 94,31% of the dependent variable (Rs).

*Structuring of the CAPM model.* - In the CAPM, the average of the benchmark passive rate of the Central Bank of Ecuador for the last 8 years is used as the risk-free rate. (see Table 10):

**Table 10**. *Ecuadorian benchmark passive rate 2011 - 2018*

| Year | Passive rate |
|---|---|
| 2011 | 4,56% |
| 2012 | 4,53% |
| 2013 | 4,53% |
| 2014 | 4,90% |
| 2015 | 5,34% |
| 2016 | 5,73% |
| 2017 | 4,91% |
| 2018 | 5,13% |
| Average | 4,96% |

**Source:** Central Bank of Ecuador (2018)

The expected minimum return, after occupying equation 1, is as follows:

$$E(R_i) = 4{,}96\% + 1{,}2004 * (14{,}60\% - 4{,}96\%)$$
$$E(R_i) = 16{,}53\%$$

The CAPM indicates that the expected return of the Textile sector is 16,53%.

## Liquidity risk

The application of the logistic model is indicated in Table 11:

**Table 11.** *Summary of the logistic model*

| Variable | Coefficient | Std. Error | Z-statistic | Prob. |
|---|---|---|---|---|
| Liquidity index | -0,019266 | 0,00366 | -5,263863 | 0,0000 |
| Indebtedness index | 20,09054 | 0,668856 | 30,03717 | 0,0000 |
| Average collection period | 0,026233 | 0,001658 | 15,82622 | 0,0000 |
| C | -15,62779 | 0,520655 | -30,01562 | 0,0000 |
| McFadden R-squared | 0,669551 | Mean dependent var | | 0,422251 |
| S.D dependent var | 0,493972 | S.E of regression | | 0,240815 |
| Akaike info criterion | 0,451812 | Sum squared resid | | 267,1682 |
| Schwarz criterion | 0,457395 | Log likelihood | | -1037,652 |
| Hanna-Quinn criter. | 0,453777 | Deviance | | 2075,305 |
| Restr. deviance | 6280,258 | Restr. log likelihood | | -3140,129 |
| LR statistic | 4204,953 | Avg. Log likelihood | | -0,225038 |
| Prob(LR statistic) | 0,000000 | | | |
| Obs with dep = 0 | 2.664 | Total obs | | 4.611 |
| Obs with dep = 1 | 1.947 | | | |

**Source:** *Own elaboration based on Superintendency of Companies, Securities and Insurance (2019)*

The model specification is as follows

$$P_i = \frac{1}{1 + e^{-(-15{,}628 - 0{,}0193 * Liquidity\ index + 20{,}09 * \ Indebtedness\ index + 0{,}0262 * Average\ collection\ period\ )}}$$

Where:

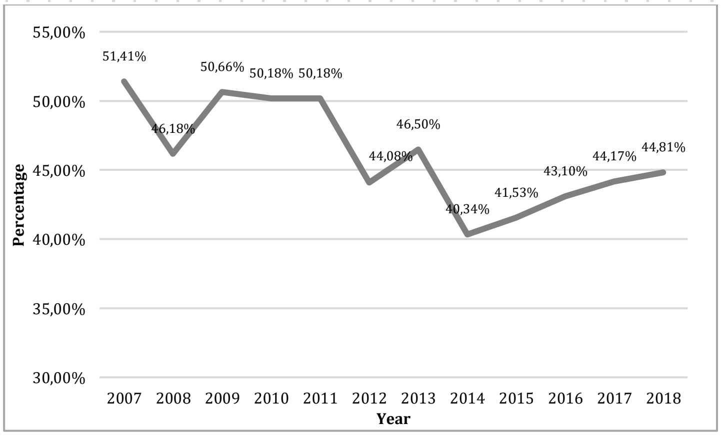
- Pi= Liquidity risk probability.

When using the maximum likelihood method (large samples), the standard errors are asymptotic.

Table 11 shows that the probability of illiquidity of companies is explained by three indicators: liquidity index, debt ratio and average collection period. The first indicator has an inverse relationship and the remaining two have a direct relationship with the probability of business illiquidity. The most important ratio to explain the probability of illiquidity is the debt ratio. All variables are statistically significant with a significance level of 5%.

McFadden's R squared is 0,6695 which, although in this type of model its interpretation and result is secondary, does not give a high value as well as the LR statistic with a value of 4204,953. In general, this indicates that there is a very good global explanation of the analyzed model.

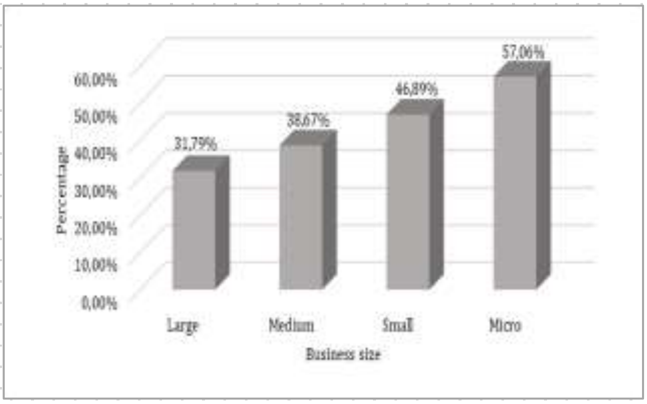
*Annual liquidity analysis.*- In Figure 6 it is observed that there is a decreasing trend in the probability of liquidity risk in the sector until 2014, subsequently the values increase until 2018. It should be considered that the values presented are high, which indicates that on average there is a high risk of liquidity in textile companies.




**Source:** *Own elaboration based on Superintendency of Companies, Securities and Insurance (2019)*

**Figure 6.** *Annual liquidity risk of the textile sector in the period 2007-2018.*

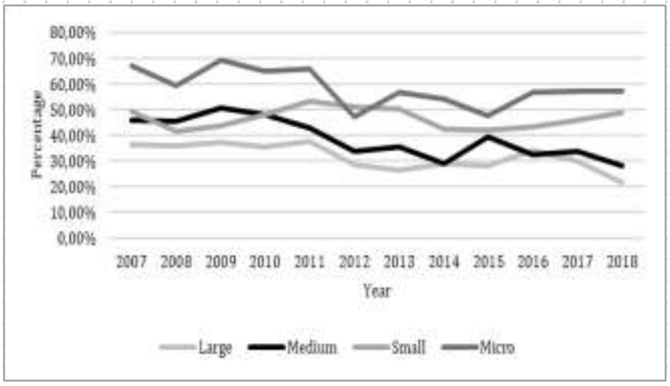
*Liquidity analysis by company size.* - The liquidity risk by business size is higher in microenterprises, with an average value in the 2007-2018 period of 57,06%. On the contrary, large companies have a lower liquidity risk, which is 31,79%. (See Figure 7)




**Source:** *Own elaboration based on Superintendency of Companies, Securities and Insurance (2019)*

**Figure 7.** *Average liquidity risk by business size of the textile sector in the period 2007-2018*

The liquidity risk levels in the period 2007-2018 have a decreasing trend, as can be seen in Figure 8:




**Source:** *Own elaboration based on Superintendency of Companies, Securities and Insurance (2019)*

**Figure 8.** *Liquidity risk by business size of the textile sector in the period 2007-2018.*

*Provincial liquidity analysis.*- Table 12 shows the different levels of liquidity risk by province, where the provinces with the highest concentration of companies are analyzed. Imbabura companies have the highest levels of risk, while those of Tungurahua the lowest. With respect to Azuay, this province has a 53% probability of liquidity risk, a result mainly affected by the risk of 2018 (97%), the year in which the average collection period increased notably.

**Table 12.** *Average provincial liquidity risk for the period 2007 – 2018*

| Province | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Avg. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Pichincha | 53% | 47% | 51% | 53% | 55% | 43% | 45% | 39% | 38% | 39% | 44% | 46% | 46% |
| Guayas | 44% | 44% | 45% | 51% | 44% | 41% | 52% | 46% | 48% | 50% | 46% | 46% | 46% |
| Tungurahua | 44% | 28% | 52% | 37% | 34% | 37% | 36% | 41% | 37% | 31% | 31% | 37% | 37% |
| Azuay | 44% | 37% | 38% | 44% | 72% | 36% | 40% | 52% | 52% | 72% | 55% | 97% | 53% |
| Imbabura | 49% | 91% | 84% | 66% | 74% | 68% | 47% | 48% | 76% | 57% | 65% | 66% | 66% |

**Source:** *Own elaboration based on Superintendency of Companies, Securities and Insurance (2019)*

## Discussion

Throughout history there have been different ways to quantify the financial risk of businesses. In this research work, three types of financial risk are analyzed: insolvency, market and liquidity.

In the risk of insolvency, FitzPatrick (1932), Smith y Winakor (1935), Merwin (1942), Jackendoff (1962), Horrigan (1965) and Beaver (1966), performed descriptive analyzes to explain the probability of business bankruptcy. The conclusions they reach are based on analysis of current and pre-bankruptcy financial ratios.

Later Altman (1968) and Ohlson (1980) introduce new methodologies: discriminate and logistic analysis respectively. The methodologies used by the two authors are different but they seek the same objective: to predict business bankruptcy and determine which are the variables that explain this behavior. In our study, we adapted the models of the two authors to the Ecuadorian reality in the textile sector.

In this work, the model proposed by Altman was adapted to emerging markets and the results were consistent with the Ecuadorian reality. From the point of view of business bankruptcy 2016 was the most complex year. A logistic regression model was also applied to determine the probability of business bankruptcy, and there were 3 variables that explain this probability: working capital / total assets, size and net income / total assets. Unlike the original Altman and Ohlson models, where the most significant variable to explain business insolvency is the level of indebtedness, the most significant variable to explain insolvency is net income / total assets.

With regard to market risk, there is no developed capital market and therefore there is not enough information to calculate a beta through market measures. For this reason, market risk was calculated through accounting measures using ROE. The beta was determined by measuring the relationship between roe of the textile sector with the ROE of the entire manufacturing sector, obtaining a Beta of 1,20 and a required rate of return of 16,53%.

Regarding liquidity risk, there is no major literature on models applied to companies in the real sector, but rather it has been done in companies in the financial sector using techniques such as liquidity gaps, structural liquidity, liquidity VAR, among others.
In this work, liquidity risk was quantified using a logistic regression model. Three variables were found to be statistically significant: liquidity index, debt ratio, and average collection period; the debt index is the variable with the greatest weight to explain the probability of illiquidity of manufacturing companies in the textile sector.

**Conclusions**

According to the registered information, 83% of the companies in the textile sector in Ecuador are located in the provinces of Pichincha and Guayas, while only 3% are in Azuay. Furthermore, in this sector there are 35% micro-enterprises, 34% small, 23% medium, and 8% are large. Most of the textile companies are only found in two provinces (Guayas and Pichincha), and a greater number are micro and small companies. t is important to indicate that, in this work, it is determined that the Financial Risk of the Textile Sector is a “moderate risk”, an opinion that is based on the quantification and behavior of the three risks that compose it: bankruptcy, market and liquidity.

In the insolvency risk analysis, it was determined that the highest levels of risk occurred in 2016 and 2018, its trend in the period analyzed shows a slight decrease in risk. The companies located in Guayas and Pichincha (both methodologies) do not present a risk of insolvency; on the contrary, those in Azuay present a high probability of bankruptcy risk. In addition, the methodologies used agree that micro-enterprises are more likely to be at risk of insolvency. Despite the fact that, on average, the sector is not in the insolvency risk zone, 22,5% of companies are in the red zone, indicating that a large number of companies could become insolvent. Regarding the variables compared, in Altman's method the most relevant variables to explain and predict business bankruptcy are: working capital / total assets and operating profit / total assets, while in Ohlson's model the variable most important is total liabilities / total assets. Therefore, in the Altman model corporate bankruptcy for emerging markets depends on liquidity and profitability, while in the Ohlson model it depends on the level of indebtedness.

The models developed to find the probability of bankruptcy of a company mentioned in the literature have initially been developed for developed markets. However, adaptations have been developed for emerging markets, such is the case of the Altman model used in the research. There is no standard model to find the probability of bankruptcy of a company, that is why we found a large number, in fact, there is no clear consensus regarding which is the optimal one. Knowing the risk of bankruptcy allows to create an early warning for risky companies, and based on this make decisions that improve financial health.

In market risk, the Beta coefficient for the textile sector is 1,2004, which indicates that this sector has a higher risk than the entire manufacturing industry. The Beta coefficient also indicates that there is a direct relationship between the profitability behavior of companies in the textile sector and companies in the manufacturing sector. In addition, the CAPM results indicate that the return expected by the investor is 16,53%, higher than the expected return of the market (manufacturing sector) which is 14,60%, which means that the higher the risk, the higher the return. The research does not use information from the Ecuadorian stock market because the country's economy is considered to be developing and. For this reason, it can be said that its stock market is still incipient and it concentrates its negotiations on fixed income documents.

The liquidity risk analysis of the sector indicates that there is a higher level of risk in the years 2007, 2009, 2010 and 2011, but in general in the period analyzed there is a decreasing trend in the level of risk. Micro-enterprises have a higher level of risk, with a 57,06% probability of illiquidity. In the provincial analysis, it was determined that the Imbabura companies have a higher risk, followed by the Azuay, Pichincha, Guayas and Tungurahua companies. In the research, the liquidity risk was determined through a logistic analysis, for which financial indicators of the manufacturing industry were calculated in order to compare them with the textile sector and be able to determine the dependent variable.

The importance of measuring risk in the different economic sectors of the country lies in anticipating financial situations that harm the financial health of companies. Exposure to financial markets affects most organizations. When an organization has financial market exposure, there is a possibility of loss but also an opportunity for gain or profit. In addition, the knowledge of the different levels of risk allows offering greater security to potential investors, supporting business decision-making, and even obtaining government support in situations of imminent risk.

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