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Chapter 1

Comparison of the four most common VaR methods in stock and option portfolios [1]

Saldanha, Augusto

Abstract

This paper presents, compares and evaluates the strengths and weaknesses of four Value at Risk (VaR) approaches for measuring risk, namely the delta normal, delta gamma, Monte Carlo simulation and historical simulation. The analysis was based on an option (non-linear) and on a stock (linear) portfolio, computing the four approaches to one and five days' time horizon with 95% and 99% of confidence level. It was concluded that the Monte Carlo Simulation provides the most accurate risk measure and delivers consistent results for both portfolios. Although delta gamma provided an accurate VaR for the option portfolio, it also showed to be complex, demanding a higher level of calculation which can be costly and also complicated. On the other hand, the conclusions from the historical simulation for the two portfolios were overestimated because this one is based on historical data. Additionally, the delta normal method proved to be a weak model because it doesn't present proper accuracy even for the stock portfolio. This is due to the fact that the delta normal method is based on normal distributions and, in practice, fat tails are more frequent than what the model predicts. Additionally, this paper proved the improvement that portfolio diversification can have in the VaR measures, being the Monte Carlo simulation the one that presents the highest efficiency in the VaR measures. Lastly, this work suggests an approach to improve the VaR measures when dealing with extreme values in the sample, that is Extreme Value Theory (EVT).

Keywords: Value at Risk, delta normal, delta gamma, historical simulation, monte carlo simulation, extreme value theory

[1] This paper is based on Martins Neto, D. (2016). A comparison of Value at Risk methods in portfolios with linear and non-linear financial instruments (Master's Thesis). University of East London.

1. Comparison of the four most common VaR methods in stock and option portfolios

The last economic disasters were caused because of a deficiency of the risk management systems, which, in addition to the interconnection between financial institutions led to bankruptcies. The bigger the interconnections between these financial institutions, the bigger the size of the disaster (Neto, 2016). According to Jorion (2009), the 2007-2008 crisis emphasized the existence of serious deficiencies in the way that risk was managed. The importance of an efficient risk management process led to the necessity of a more rigorous international regulation to monitor and control the financial market, which led to the establishment of the Dodd-Frank Act and the SIFI regulation (Neto, 2016).

With these new conditions, the financial institutions had to develop systems and tools to control and measure their risk exposure. Per example, JP Morgan developed the RiskMetrics that was published in 1994 and available for all market participants as a technical document, which amplified the popularity of the VaR methodology which became a reference in market risk estimation. Also, other financial institutions started to develop variants and improvements of the VaR (Neto, 2016).

According to Neto (2016), VaR reflects the extreme loss expected that an institution can obtain given a confidence level and a time horizon. Therefore, it is commonly used by financial regulators and banks as a standard measure to monitor and compare the risk existent in different sectors (Neto, 2016). As stated by Jorion (2007), its popularity derived from a combination of factors such as, the enhancement of the banking regulation on risk management (p.e., the Basel Accord); the globalization of the financial markets, which increases the volatility and exposure to numerous risks, majorly through interest rates, stock prices, exchange rates and widespread derivatives; and the technology, which improves the risk control. By using the VaR, banks and regulators can assess the likely loss of a given portfolio.

Additionally, the growth of over the counter (OTC) derivatives' market allowed an improvement in funding management, security trades and foreign transaction due to the enhancement of the interconnections between companies in a global level (Neto, 2016). This led to the elevation of the number and complexity of the instruments in the companies' portfolios which are often traded, leading to the change of their risk positions (Neto, 2016). Therefore, a risk model that monitors and provides proper levels of controls appears to be essential. The VaR methodology can in fact provide it, however, it is of difficult application.

Moreover, it is crucial that all financial institutions must decide which model to use for risk measurement. In this context, the Basel Committee on Banking Supervision (BCBS) recommends the VaR application for measuring market and default risks and to compute diverse forms of risk exposure (Neto, 2016). To achieve efficiency in managing risk, all financial institutions invest energy in choosing a VaR methodology best suited to their risk exposures, portfolios and capital requirements, often creating their own model based on the VaR. The biggest reason for this is the fact that banks need to be in obedience with regulations concerning the terms of holding capital according to their measured risk (Neto, 2016).

Thus, VaR is a risk measure recommended by regulation with a widespread reach in the international financial market. Its models are divided into parametric and non-parametric models. The parametric models are the delta normal and the delta gamma. On the other hand, the non-parametric models are historical simulation and Monte Carlo simulation (Neto, 2016). However, it is important to know which VaR method can deliver the most accurate estimation of risk exposure. In this context, the literature's most consensual idea is that the answer depends on the portfolio strategy and composition (Neto, 2016). For instance, Skiadopoulos, Lambadiaris, Papadopoulou and Zoulis (2003) compared the Monte Carlo simulation and historical simulation for linear and non-linear portfolios, concluding that the Monte Carlo simulation was the one that showed the most exact performances in the stock portfolio; however, in the option portfolio, both models performed well.

With the purpose of evaluating and comparing the four most common VaR approaches (delta normal, delta gamma, historical simulation and monte carlo simulation) and of presenting the strengths and weaknesses of each methodology, a master thesis from Daniela Martins Neto from the University of East London will be analyzed. Neto (2016) compared the four most common VaR approaches, computing each for a linear and a non-linear portfolio. The linear portfolio was composed by twenty stocks and, the non-linear portfolio was composed by two stock options and one index option. Each approach was calculated for one and five days of time horizon with 95% and 99% of confidence level. Furthermore, Neto (2016) suggested a model called Extreme Value Theory (EVT) with the objective of improving the VaR methodology when there are extreme values in the observations.

2. Literature Review

In the literature regarding risk measurement, there are several views regarding which measure is the most accurate. For instance, considering the VaR methodology, Duffie and Pan (1997) found that the Monte Carlo Simulation, with a lognormal distribution of the returns and a stochastic process, with 99% confidence level and considering short and long positions, presents a higher VaR compared to the delta gamma model. The difference between both methodologies was 0,1% of the portfolio value for 1-day VaR and 1,8% for 10 days VaR, due to the non-linearity and non-normality (fat tails) of the options.

Additionally, the RiskMetrics (1996) by JP Morgan and Reuters assume that the standardized returns (return divided by the standard deviation) have a conditional normal distribution although fat tails are common, due to the non-normality. These standardized returns mean that, a great return in a low volatile scenario might result in a high standardized return, while a high return due to a great volatility might lead to a low standardized return. Also, RiskMetrics (1996) consider that there are three essential parameters to estimate the VaR: the confidence level, the time horizon and the currency used to measure risk. Moreover, RiskMetrics (1996) highlight the importance of identifying the cash flows, the Marked to Market (MtM) of the portfolio positions, and the importance of applying the mapping process where the portfolio positions are aggregated in risk factors. Therefore, it is important to choose the method of estimating the VaR accordingly. If the portfolio is exposed to non-linearity and normality isn't expected, the choice must be between the delta gamma and Monte Carlo. On the other hand, if the portfolio is expected to have and approximated normal condition, the delta normal should be chosen (Neto, 2016). Another important factor to have in mind is the fact that it is progressively harder to measure losses with fat tailed and asymmetric distributions than with normal distributions (Neto, 2016).

Furthermore, the most traditional models of measuring risk believe in the hypothesis that the volatility of the returns is constant during the given time (homoscedasticity process) (Neto, 2016). Contrarily, Engle (2001) considers that VaR can be more accurately calculated when possible changes in standard deviation over time are considered, arguing for the generalized autoregressive conditional heteroscedasticity (GARCH) and the autoregressive conditional heteroscedasticity (ARCH) to more precisely deal with standard deviation. These techniques to calculate the variance and covariance of the VaR are only used in portfolios with linear exposure to market risk, therefore not including options (Neto, 2016).

Additionally, Pritsker (1997) found that when the underlying options of the portfolios are with a short time to expiration or deep out the money, the VaR estimations are weaker. Also, for the call options, the delta normal and delta gamma models presented highly overestimated results. Moreover, for the put options, the VaR models presented underestimated values (Pritsker, 1997). Regarding accuracy and time consumption, Pritsker (1997) found that the delta gamma Monte Carlo presented the best performance. Furthermore, based on GARCH, Krause and Paolella (2014) presented a VaR approach for return distributions that contain asymmetric and conditional heteroscedasticity and leptokurtosis, which delivered higher results than the traditional VaR methods.

In addition, Castellacci and Siclari (2003)'s study used 5 models for non-linear instruments which were: delta gamma Monte Carlo, full Monte Carlo, delta normal, delta gamma normal and Cornish Fisher. Contrarily to what the theory suggests, Castellacci and Siclari (2003) found that the delta normal presented a better performance in the VaR measure in comparison to the delta gamma. Furthermore, their study showed relevant improvements in the delta gamma approach instead of Monte Carlo because it considers the gammas (Castellacci & Siclari, 2003). Moreover, the delta gamma Monte Carlo approach showed a good performance with moderate computational time (Castellacci & Siclari, 2003). In other words, their study demonstrated that the parametric models overestimate the VaR measure while this measure was slightly underestimated when using the delta gamma Monte Carlo.

Therefore, it can be inferred that the literature concerning the VaR methodologies provides different views, weaknesses and strengths of the VaR. In this context, when Hendricks (1996) compared the real loss with its estimates in his study, he discovered that extreme values are more frequent than assumed by a normal distribution and that the volatility isn't constant over time, therefore not recommending any VaR method.

Additionaly, Skiadopoulos et al. (2003), through their study in the Greek bond and stock markets, found that in a linear portfolio, the Monte Carlo approach performed well and that the historical simulation presented an overestimated VaR. In the non-linear portfolio, both methods didn't demonstrate clear results since their numbers differed in the measurement test (Skiadopoulos et al., 2003). Furthermore, Skiadopoulos et al. (2003) concluded that in the linear portfolios, the model's accuracy depends on the confidence level and, a negative point of the VaR is that it doesn't account for tail risks which can be worse when in the presence of risks that have different tails.

Regarding which study shows the most accurate results, Kuester, Mittnik and Paolella (2006) found that the best results came from a GARCH hybrid model with Extreme Value Theory, which represents a variant of a heteroskedastic mixture distribution and of a filtered historical simulation. This study also showed that normality can be reached with innovation distribution that includes fat tails and skewness (Kuester et al., 2006). In addition, Christoffersen, Hanhn and Inoue (2001), suggest that to validate a VaR model, a robust measure must be used by following the next steps: attend the efficient VaR premises and then compare the two less accurate VaR methods.

Furthermore, by studying VaR methods during 10 years of financial crisis, Reuse (2010) concluded that the crisis has no effect in the portfolio optimization and that the VaR methods present considerable different estimates. The reasons behind this are: while risk is captured by the difference among expected loss and historical data in historical simulations, in the delta normal, risk is captured by the expected loss and the current value; and, in the delta normal there is a linear approximation which doesn't necessarily illustrate the real data (Reuse, 2010). Furthermore, when considering the portfolio selection, Reuse (2010) considers that the historical simulation gives the best combination of assets and the delta normal increases the risk exposure, therefore, the diversification factor is more efficient when using the historical simulation. Reuse (2010) also concludes that the weaknesses in both models depends on the historical data, because it is difficult to accurately define the period to have a precise VaR estimation. Lastly, Reuse (2010) arguments that the VaR models should be less complicated to understand and apply by risk managers. In this context, Trenca (2011) arguments that the delta normal is slightly easier to apply but it underestimates the capital allocation and VaR since it doesn't take in account the fat tails.

On the other hand, Bozkaya (2013) included high frequency intraday data in the standard deviation to more precisely calculate the VaR. Bozkaya (2013) computed the VaR with the popular approaches to estimate volatility, namely, the MA (moving average), realized volatility forecasting power of the EWMA (exponential weighted moving average) and GARCH. Since these models consider the possibility of the volatility to change over time, they all gave precise estimations. However, the moving average approach used to calculate volatility revealed to be the most accurate way to calculate the market risk through VaR, when considering high frequency intraday data, because the data is highly volatile with extreme values (Bozkaya, 2013).

Moreover, Cabedo and Moya (2003) developed a VaR method called historical simulation with autoregressive moving average model (ARMA) forecast – HSAF. This model uses the distribution of forecasting errors, captures the autocorrelation of historical prices and estimates the historical returns in absolute values, to precisely forecast future returns. According to Cabedo and Moya (2003), the HSAF method showed better performance than standard historical simulation and delta normal, since it doesn't need statistical assumption in the distribution of the historical prices.

Additionally, Boudoukh, Richardson and Whitelaw (1998) developed a hybrid approach which combines RiskMetrics and historical simulation to improve VaR for fat tailed distributions. Boudoukh et al. (1998)'s approach consists in calculating the percentile of the return distribution by declining weights in the historical data through a decay factor. Furthermore, in this approach, as the data is more recent, it's weight increases. By using this approach, the VaR isn't under/overestimated even on the day after the crash because the recent past has more weight in the data, therefore not causing an outlier in the return distribution (Boudoukh et al., 1998). Pritsker (2006) criticizes this methodology and the standard historical simulation, showing that there is a great improvement in the VaR measure when a high loss in the portfolio return is considered but not when a large profit is considered.

With the same objective of updating historical data method, Hull and White (1998) recommend adjusting the data by including changes in volatility over the time, considering that by doing this the risk measure can be improved.

Regarding the Monte Carlo approach, its greatest weakness is the computational time that the model demands due to the huge number of random scenarios required to compute the VaR. In this context, Jamshidian and Zhu (1997) suggest applying a manageable and limited quantity of scenarios as a substitute to multivariate distribution of returns, which leads to a better computational efficiency to estimate VaR for portfolios highly exposed to risk factors. Additionally, with the same aim of reducing the number of random scenarios, Frye (1997) suggests pre-selecting and calculating shocks in the data analysis. Furthermore, Glasserman, Heilderberger and Shahabuddin (2000) propose using the delta gamma approach in the Monte Carlo simulation because deltas and gammas are often accessible without much effort, which leads to a reduction in the quantity of simulations required to achieve accuracy. Lastly, Botev and Kroese (2012) propose a new Monte Carlo model through generalized splitting algorithm.

Concerning the overall VaR methodology, there are relevant researches that don't recommend the VaR methodology. For instance, Yamai and Yoshiba (2005) consider that a problem of its methodology is that it doesn't deal with the loss size that exceeds the VaR, in other words, the tail risk. By making a comparison between VaR and other risk measure, the Expected Shortfall, Yamai and Yoshiba (2005) concluded that the last can properly replace VaR but it needs more sample size to turn into a precise measure. Barrieu and Scandolo (2015) add that VaR has a higher level of model risk in comparison to expected shortfall.

Furthermore, Alexander and Sarabia (2012) propose a model to deal with the problem of inaccurate VaR due to an inadequate choice of the VaR approach to be used or due to inaccurate VaR parameter calculations. This model is based on a comparison between the benchmark VaR and the daily VaR calculated by the institution, considering that the benchmark VaR should reflect the total information, maximum possible distribution and beliefs and should as well be determined by the local regulator, being then applied for institutions (Alexander & Sarabia, 2012). The difference resulting from the quantile between the VaR and its benchmark would determine the model risk, therefore being adjusted in the capital requirement (Alexander & Sarabia, 2012).

Moreover, the VaR has been recommended by financial regulators as a measure for risk management and capital requirement (i.e., the amount of capital that financial institutions must hold). It is recommended to risk-weight the instruments with the objective to keep more capital for riskier instruments so, if a financial institution is impacted by an unexpected event, it can cover the effect of the event by the internal capital assessment (Neto, 2016). According to BCBS (2005), it can be done by applying a stress testing scenario. On the other hand, Artzner (1999) does not recommend VaR as a risk measure to capital requirement because when he applied it to insurance companies he concluded that it doesn't react satisfactorily when risks are increased, starting aggregation issues. Moreover, Artzenr (1999) considers that VaR doesn't encourage diversification because it doesn't consider economic consequences of events and how to react to it. Additionally, Artzner (1999) recommends the tail conditional expectation measure which represents the expected size of a loss that exceeds VaR.

Having all this in mind, Neto (2016) draws some conclusions about the four most commonly used methods to estimate VaR (delta normal, delta gamma, Monte Carlo simulation and historical simulation). Firstly, according to Neto (2016), the choice between which method to use depends on aspects like the risk factors, the portfolio composition, the cost of implementation and its flexibility. Among all four, the delta-normal, despite its limitations (p.e., it is only applicable for normal distributions), is the simplest, easier, quicker and cheaper to implement, therefore seeming the most suitable choice for small companies (Neto, 2016). On the other hand, the Monte Carlo simulation is generally applied in large financial institutions because it can be applied to portfolios with different sorts of risk factors and because it is more flexible. Historical simulation alternatively is better suited for portfolios with consistent historical data and where the risk factors aren't highly volatile. Lastly, the delta-gamma method presents a good option for portfolios with non-normal distribution and with non-linear instruments (Neto, 2016) A more detailed comparison of the different VaR methods can be seen in Annex 1, Table 2.

Additionally, the development of the derivatives market brings strategies of speculation and hedging and, subsequently, non-linearity exposure to the portfolios. Regarding this non-linear risk exposure, the more accurate risk exposure is the delta-gamma (Neto, 2016). Moreover, in portfolios with options, the Monte Carlo and historical simulation perform better than the delta-normal method, being this last only better when the time horizon is one day. Also, by considering the value of each risk factor in several scenarios, Monte Carlo and historical simulation capture the non-linearity of options and, therefore, they present the right portfolio value (Neto, 2016).

Furthermore, a positive characteristic of the Monte Carlo simulation is that the mapping process of the positions on the selected risk factors isn't mandatory for the VaR calculation. Conversely, its negative characteristics are the intellectual knowledge required for the selection of the distribution of the random vectors and the amount of time required for its calculation (Neto, 2016). Additionally, historical simulation appears to be simpler to implement if the historical data is accessible, being easy to perform in Excel. Contrarywise, if there isn't historical data available it is not possible to apply the historical simulation (Neto, 2016). Conclusively, the difficulty of implementing the VaR methods depends on the risk exposure and the kind of products that compose the portfolio, being more complicated for portfolios with non-standard products like complex derivatives (Neto, 2016). At last, regarding the flexibility of the VaR methods, the biggest limitation of the historical simulation is that it cannot be applied in historical data with outliers that aren't predicted for the future, while the other three are more flexible in this question (Neto, 2016).

3. Methodology

This chapter will be divided in two parts. The first part will describe some definitions required for the data analysis, how each method for VaR estimation (delta normal, delta gamma, historical simulation and Monte Carlo simulation) is computed, also comparing the methods according to some assumptions and, a model to improve the VaR measures will be suggested, the Extreme Value Theory (EVT). The second part will focus more in the research methodology, describing the research approach used in the thesis in study and the data used by Neto (2016) for the VaR estimation.

The principal variable analyzed in this study is the VaR. VaR represents a market risk measure for portfolios and/or investments by presenting the maximum possible loss an investor can endure due to the asset price movements, considering the time horizon and the confidence level (Neto, 2016). Therefore, losses higher than the VaR have low probability to occur. The VaR considers the correlation between the assets in the portfolio which means that, when the assets have symmetric negative correlation, the portfolio VaR is lower and, when the correlation between the assets in the portfolio is positive and symmetric, the VaR is greater. Additionally, since the function of the VaR is to aggregate at the largest level, it implicates lots of positions to consider. A shortcut to this is called VaR mapping which is the procedure of aggregating the individual positions of the portfolio by market risk exposure instead of the values of the portfolio position (Neto, 2016).

However, VaR has its own limitations and weaknesses. For instance, the VaR methodology uses the backward-looking assumption, which means that it uses the historical data to predict the future, therefore it doesn’t take in account the possibility of an unpredictable event to occur. For this reason, VaR should have hypothetical scenarios analysis. Other limitation is the fact that its outcomes can be impacted since its assumptions may not be applied to any environment and moment. Lastly, another limitation of VaR is its complexness, requiring experience and updated knowledge to apply it (Neto, 2016).

As said above, the four most common methods of applying the VaR are: the delta normal method, historical simulation, the Monte Carlo simulation and the delta gamma method.

3.1 Delta normal method

Regarding the delta normal method, it utilizes linear or delta exposures. Also, it uses a normal probability distribution and requires covariance and variance calculations. It is composed by the following steps: firstly, identify the risk factors adequate to the portfolio evaluation; then, define the sensitivity of the assets in relation to these risk factors; then, historical data of each risk factor must be collected to estimate volatility of the return and the covariances between the portfolio’s assets; afterwards, considering the covariances and the sensitivity, calculate the standard deviation of the portfolio and, if there are plenty assets in the portfolio, use the variance-covariance matrix; at last, due to the normal distribution assumption, calculate the VaR according confidence levels of 95% or 99% (Neto, 2016).

3.2 Historical simulation method

On the other hand, the historical simulation method is composed by the following steps: firstly, one must collect the historical returns over some observation period (normally, 250 to 750 days) by risk factor (stock price, interest rate etc.) and compute the daily percent change; then, based on the past, one must create hypothetical scenarios by multiplying the current weight of the asset with its respective daily percent change; next, one must sum all the asset scenarios which results in the total portfolio position; and, at last, the expected VaR comes from the relevant percentile from the distribution of the hypothetical returns, considering the confidence level (Neto, 2016).

3.3 Monte Carlo simulations method

Alternatively, other method that can be used to compute the VaR is The Monte Carlo approach. This approach uses computer simulations by generating random prices for financial instruments which leads to diverse portfolio values, assuming that there is an identified probability distribution for the risk factors (Neto, 2016). The steps required for the Monte Carlo VaR are the following: firstly, after selecting the pricing model, one must calculate volatility and correlation for each instrument from a given portfolio; then, by using random number generator, one must build several hypothetical scenarios of the market returns and then multiply the current price and its random scenarios; after this, the results acquired must all be summed, which results in diverse portfolio values; subsequently, this simulation must be repeated several times to create a more accurate distribution of the portfolio value; at last, considering the confidence level, one can apply the percentile function to find the VaR (Neto, 2016).

3.4 Delta gamma method

The delta gamma method, in its turn, is used when in the presence of non-linearity and non-normality, being mostly applied to options. According to Neto (2016), when there is a movement in the price of the asset, the gamma measures the level of change. Short positions have negative gammas while long positions have positive gammas. A positive gamma means that the price of the underlying asset changes in the same direction as the delta (delta represents the sensitivity to changes in prices). By using its formulas, the gamma defines the curvature of the relationship between the market price of the underlying risk factor and the portfolio value. Additionally, a positive gamma reduces the VaR while a negative gamma raises the VaR (Neto 2016). "The delta-gamma considers the curvature of non-linear risk exposure according to the second-order of the Taylor series" (Neto, 2016, p.27).

3.5 Extreme Value Theory (EVT)

Additionally, and since there is a possibility of an extreme event to occur, Neto (2016) suggests using a risk model to improve the VaR measure called extreme value theory (EVT). The EVT uses a different approach to calculate VaR because it considers the possibility of an extreme event to occur. EVT allows the estimation of the losses with very low probabilities because it focus on estimating the shape of the tail of the probability distribution. It uses two approaches: the block maxima and the peaks-over-threshold. The block maxima approach deals with the greatest observations in samples of similarly distributed observations. On the other hand, the peaks-over-threshold is applied for all observations that surpass a given high threshold. Additionally, this approach considers two models, the semi-parametric and fully parametric models, being both efficient if well applied (Neto, 2016).

Since the EVT deals with the sample extrema, the Generalized Extreme Value distribution is essential since, for a large class of distribution, the normalized sample maxima tends to converge to the GEV distribution with larger sample (Fisher Tipplet Theory) (Neto, 2016). The GEV refers to 3 extreme value distributions according to the ξ parameter, which can be categorized as short tail ($\xi < 0$), thin tail ($\xi = 0$) and fat tail ($\xi > 0$) (Neto, 2016).

The EVT first step consists in observing the portfolio instrument's liquidity in order to determine the frequency of the data return which needs to be large to capture the extreme prices. Then, the data should be divided into sub-periods with identical number of observations. Afterwards, the parameters of the asymptotic distribution of the returns must be selected (Neto, 2016). Then, the shape and scale parameters of the EVT must be estimated with the following formula:

$$G_{\xi,\beta}(x) = 1 - (1 + \frac{\xi x}{\beta})^{-\frac{1}{\xi}}$$

"Where β>0 and $x \geq 0$ when $\xi \geq 0$ and $0 \leq x \leq -\beta/\xi$ when $\xi<0$. $\boldsymbol{\xi}$ represents the shape of the distribution and $\boldsymbol{\beta}$ the scaling parameter" (Neto, 2016, p.40).

Then, the estimation of the tail of the distribution is required, by using the following formula:

"Where **u** is the threshold, n the sample size and $\boldsymbol{N_u}$ the number of exceedances" (Neto, 2016,

$$F(x) = 1 - \frac{N_u}{n}\left(1 + \xi\frac{x-u}{\beta}\right)^{\frac{-1}{\xi}}$$

p. 40).

After this, the EVT can be used to calculate the VaR by using the following formula which represents a quantile (**q**) estimation:

$$VAR_q = u + \frac{\beta}{\xi}\left[\left(\frac{n}{N_u}(1-q)\right)^{-\xi} - 1\right]$$

Additionally, to perform a full valuation to calculate the VaR, it is necessary to obtain the historical return and re-calculate the asymptotic distribution whenever the VaR needs to be estimated which can be time consuming (Neto, 2016). It would be simpler if the positions were decomposed so the VaR could be estimated individually with a risk aggregation formula. Therefore, the EVT weaknesses are the complexness to implement it if more than a single risk factor is included and its complexness to parametrize the assumptions as there isn't much observation of extreme events (Neto, 2016).

3.6 Procedures

Having all this in mind, Neto (2016) made an analysis regarding the four most common VaR approaches. The aim of Neto (2016) was to evaluate the four VaR methods computed for one and five days' time horizon with 95% and 99% of confidence level. For this purpose, a stock and an option portfolio with liquidity (daily traded) were considered. The selected window for the analysis was a sample of 750 days, between 8th August 2013 and 27th July 2016. The risk-free rate was the one from the 10 years UK treasury bond (GILT). The tests were done in Excel. The Monte Carlo simulation used 10.000 random scenarios. The stock portfolio was composed of 20 stocks from FTSE 100 index, with an investment of £5.000 in each company (see Annex 1, Table 3). The option portfolio was composed by 3 options, one put and one call with underlying stocks from the FTSE 100 index and one more call with the FTSE 100 index itself (see Annex 1, Table 4). These 3 options have long positions and the same expiration date, which was 20th January 2017.

Regarding the stock portfolio, the variance, standard deviation and the mean were calculated for each stock. Additionally, for the delta normal VaR, the variance-covariance matrix was calculated based in the following example:

$$\begin{bmatrix} var_1 & cov_{1,2} & cov_{1,3} & \dots & cov_{1,n} \\ cov_{2,1} & var_2 & cov_{2,3} & \dots & cov_{2,n} \\ cov_{3,1} & cov_{3,2} & var_3 & \dots & cov_{3,n} \\ \dots & \dots & \dots & \dots & \dots \\ cov_{n,1} & cov_{n,2} & cov_{n,3} & \dots & var_n \end{bmatrix}$$

With this variance-covariance matrix, the portfolio's standard variance is

$$\sigma_p^2 = w^T C w$$

"where **w** is the column vector of asset weight (amount), **C** is the variance-covariance matrix, and $\boldsymbol{w^T}$ is the transposed asset weight" (Neto, 2016, p.23).

Then, the delta-normal VaR was estimated for 1 day by using the following formula:

$$VaR = \sigma\, N^{-1}(X)$$

"where **X** represents the confidence level, $\boldsymbol{\sigma}$ the portfolio standard deviation and $\boldsymbol{N^{-1}}$ is the inverse cumulative normal distribution" (Neto, 2016, p.23).

Afterwards, the VaR was computed for 5 days by using the following formula:

$$T\ day\ VaR = 1\ day\ VaR\ \cdot \sqrt{T}$$

"where **T** is the time horizon" (Neto, 2016, p.21).

Additionally, the historical and Monte Carlo VaR were estimated. The delta-gamma method was not applied since it is more suitable for non-linear instruments or derivatives. After estimating the 3 VaR, a comparison of the results was made.

Regarding the option portfolio, in order to price the options, the Black-Scholes model was applied by using the following formulas:

$$c = SN(d_1) - Ke^{-rt}N(d_2)$$

$$p = Ke^{-rt}N(-d_2) - SN(-d_1)$$

$$\mathrm{d1} = \frac{\ln\left(\frac{S}{k}\right) + t(r - q + \frac{1}{2}\sigma^2)}{\sigma\sqrt{t}}$$

$$d_2 = d_1 - \sigma\sqrt{t}$$

"where **c** is the call premium, **p** is the put premium" (Neto, 2016, p.31), "**S** the current price of the underlying risk factor, **t** is the yearly time to expiration, **K** is the strike price and **q** the yearly dividends" (Neto, 2016, p.26).

After calculating the put and call prices, the delta normal was calculated by using the formulas described above. Additionally, to compute the delta gamma VaR the following formulas were used:

$$\Gamma = \frac{N'(d1)}{S\sigma\sqrt{t}}$$

$$\mathrm{N}'(\mathrm{d1}) = \frac{1}{\sqrt{2\Pi}} e^{-d1^2/2}$$

$$\mathrm{d1} = \frac{\ln\left(\frac{S}{k}\right) + t(r - q + \frac{1}{2}\sigma^2)}{\sigma\sqrt{t}}$$

$$\mathrm{VaR} = |\Delta|(\alpha\sigma S) - \frac{1}{2}\Gamma(\alpha\sigma S)^2$$

"where **Γ** represents the gamma, **S** the current price of the underlying risk factor, **t** is the yearly time to expiration, **K** is the strike price, **q** is the yearly dividends" (Neto, 2016, p.26), "delta (**Δ**) represents the asset sensitivity to changes in prices and $\boldsymbol{\alpha}$ is the standard normal deviate based on the confidence level" (Neto, 2016, p.26).

After calculating the delta normal, delta gamma, historical and Monte Carlo simulations' VaR for the option portfolio, the results were compared.

4. Application

For the stock portfolio, Figure 1 shows the comparison of the computed VaR for the delta normal method, historical and Monte Carlo simulations.

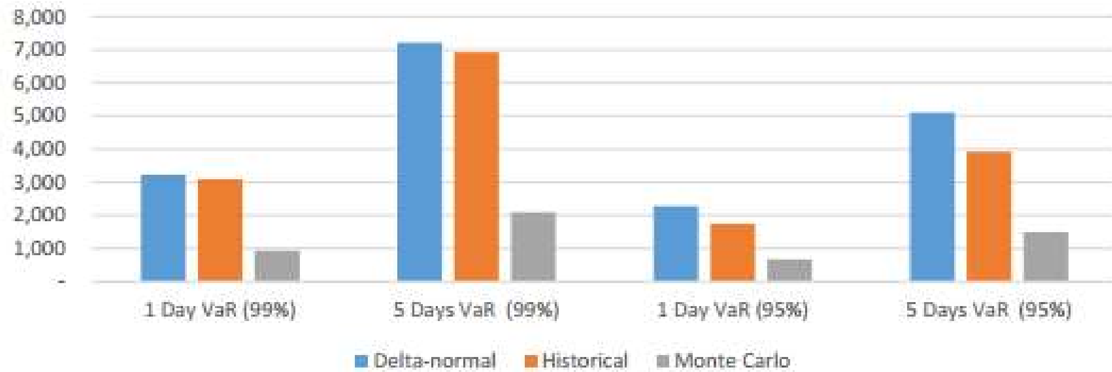

Figure 1 – Stock portfolio's VaR measure computed by delta normal, historical and Monte Carlo simulations considering 1 and 5 days time horizon and 95% and 99% of confidence level (Neto, 2016, p. 32).

As expected, in the three models (delta-normal, historical and Monte Carlo simulation), the VaR amount is increased when the time horizon is also increased, because there is more market risk exposure in five days than in a single day (Neto, 2016). Additionally, when considering a 99% confidence level, the portfolio VaR is higher because, the bigger the confidence level, the more precise the measure is (Neto, 2016). There is less discrepancy among the 3 VaR methods when a 95% confidence level is considered because, according to Hendricks (1996) a fat tail in the distribution can be adjusted by decreasing the confidence level. Moreover, in comparison to the Monte Carlo method, the historical simulation and delta-normal VaR are higher. In the case of the historical simulation this happens because the volatility is totally based on the past performance of the assets which means that, when a high volatility happened in the past, the historical simulation if the standard deviation of the returns since unexpected outliers in the stock returns distribution VaR tends to be high (Neto, 2016). In the case of the delta-normal approach, this happened because (see Figure 2) turn the assumption of normality in this method unreliable.

Therefore, the Monte Carlo approach seems to be the most suitable model for this stock portfolio because it isn't based on historical simulation. Differently to the delta-normal, the Monte Carlo assumes that the returns are lognormally distributed and not normally distributed (Neto, 2016).

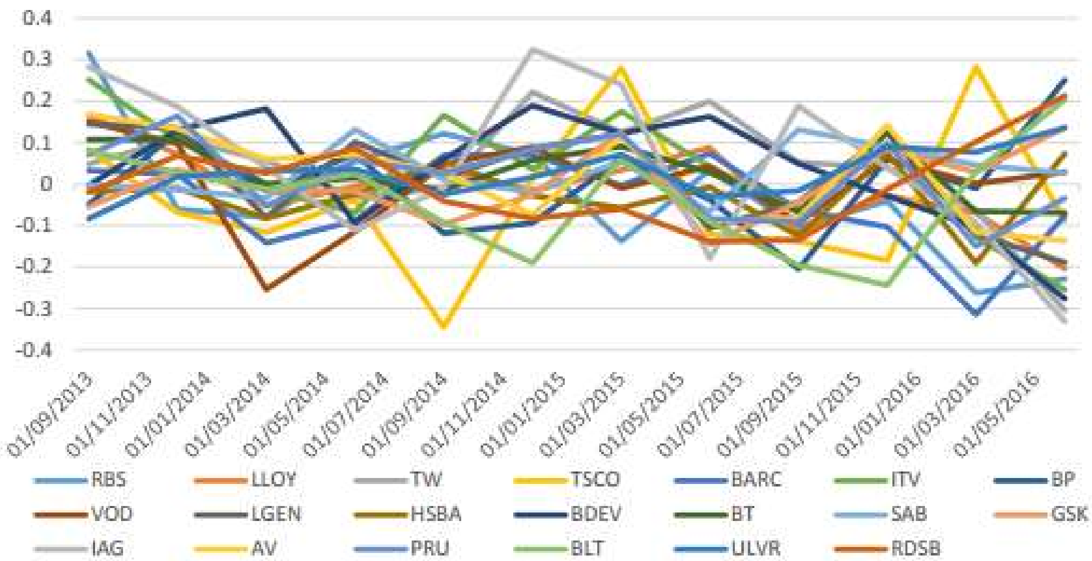

Figure 2 – The share volatilities of the stocks from the stock portfolio over the time (Neto, 2016, p. 33).

For the option portfolio, Figure 3 shows the comparison of the computed VaR for the delta normal method, delta gamma, historical and Monte Carlo simulations.

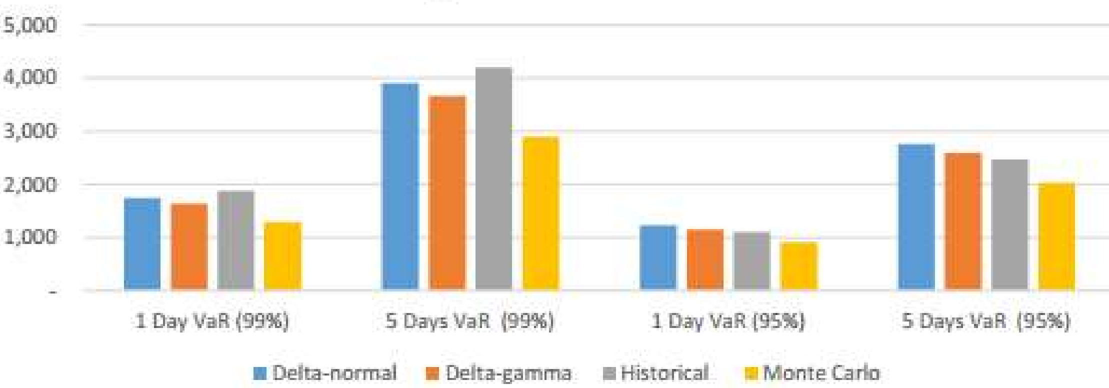

Figure 3 - Option portfolio's VaR measure computed by delta normal, delta gamma, historical and Monte Carlo simulations considering 1 and 5 days time horizon and 95% and 99% of confidence level (Neto, 2016, p. 34).

Regarding the option portfolio, and in congruence with the theory, as the time horizon and the confidence level increase, an increase in the portfolio VaR is expected since these imply a larger possibility of changes in the underlying asset (Neto, 2016). For 99% of the confidence level, the historical simulation and delta normal present the highest VaR numbers between the four methodologies. Since the historical return of the underlying instruments is highly volatile (see Figure 4), it impacts the predicted historical VaR.

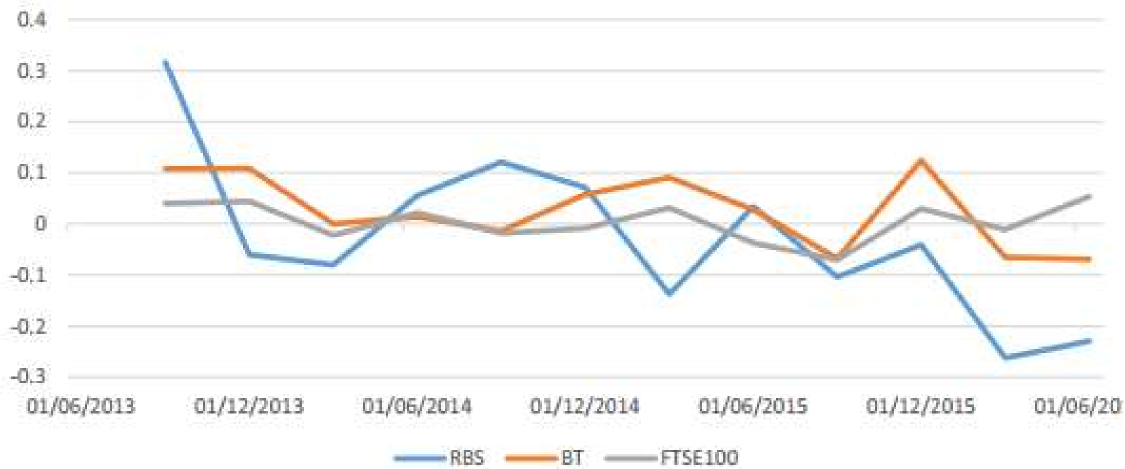

Figure 4 – The volatilities of the option portfolio's underlying (a Put option of BP/ LN Equity, a Call option of RBS LN Equity and a Call option of the FTSE100 index itself) (Neto, 2016, p. 34).

Additionally, the delta normal VaR was one of the highest because options have non-linear payoffs. This turns the delta normal a non-accurate measure because a great discrepancy can be expected (Neto, 2016). This reflects the delta normal weakness of being only designed for instruments with linear relationship between the instrument prices and risk factors (Neto, 2016). Furthermore, the delta gamma and Monte Carlo's VaR are more precise in practice since they don't require only linear approximation, being the option premium behavior a function of the underlying stock price.

Concerning the gamma (i.e., "the rate of change in the delta when the price of the underlying asset changes" (Neto, 2016, p.35)), options that are in the money (the price of the underlying asset of a long call is greater than the strike price) and close to expiration have very high gammas. Conversely, options that are out the money or have a farther expiration date have lower gammas. Therefore, the higher gammas in the portfolio come from the ITM options (underlying RBS and BT stocks). Since the three options have the same weight in the portfolio, the impact of the gamma in the portfolio tends to increase the VaR. Additionally, the higher gammas come from underlying assets with bigger standard deviation (see Figure 5 and Table 1).

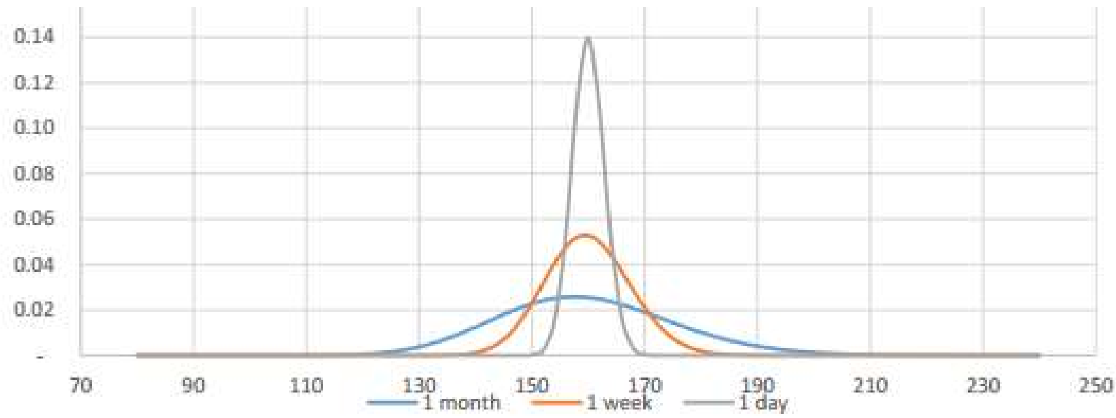

Figure 5 – The gamma behavior of ITM option (underlying RBS) with £160 strike price and hypothetical stock price as time-to-maturity decreases (Neto, 2016, p. 35).

Table 1

Comparison of gammas and standard deviations of the option portfolio's options

Position	Underlying	Gamma	Standard Deviation
ITM Long call	RBS stock	0,86%	33,90%
ITM Long put	BT stock	0,51%	22,62%
OTM Long call	FTSE stock	0,06%	15,30%

Note. Retrieved from Neto (2016, p.35).

Additionally, an important variable to be analyzed is the correlation. According to Neto (2016, p.36) "the correlation between financial instruments represents their reaction between themselves to the market price movements, positive or negative, and the magnitude of this movement". According to the theory, there is a gain in the risk measure when a portfolio composed by correlated instruments is considered. When comparing the non-diversified and diversified option portfolio's VaR, Neto (2016) concluded that the Monte Carlo simulation offers higher efficiency with the diversification. In contrast, the delta gamma is the less efficient of the four VaR methods when correlation in the risk measure is considered (see Figure 6).

Therefore, it can be inferred that the correlations between the options of the portfolio considered are advantageous because they stop or limit the loss of money with unanticipated change in prices, which decreases the VaR in the diversified portfolios in comparison to the undiversified portfolios.

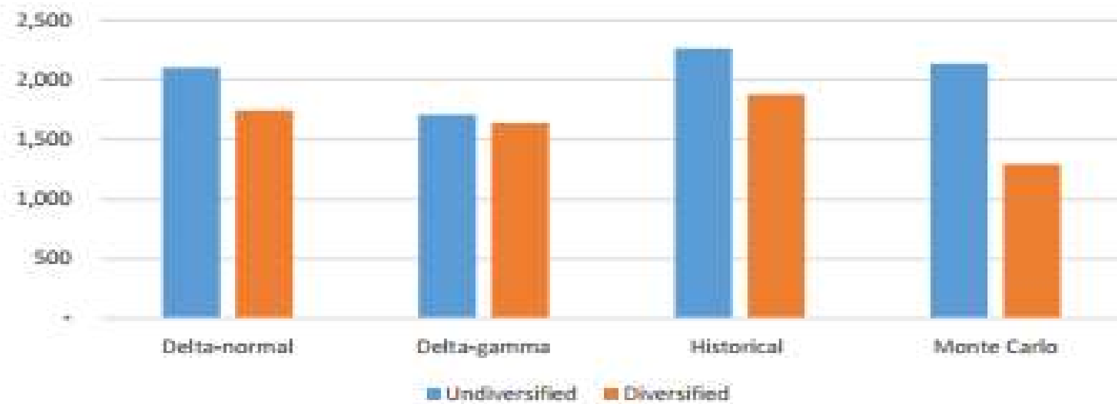

Figure 6 – Option portfolio's VaR measure computed by delta normal, delta gamma, historical and Monte Carlo simulations considering a diversified vs. undiversified portfolio, 1-day time horizon and 99% of confidence level (Neto, 2016, p.36).

5. Conclusions

Currently, VaR is one the most used methods to evaluate market risk, being recommended by the central bank regulations. However, VaR has several approaches. Therefore, there is a question in the market regarding which VaR approach is the most precise. By applying the four approaches (delta-normal, delta gamma, historical simulation and Monte Carlo simulation) in two portfolios, a stock and an option portfolio and, by computing the methods for one and five days' time horizon with 95% and 99% of confidence level, Neto (2016) found that most results were consistent in both portfolios. When the time horizon was increased, the VaR amount increased for all cases since, by increasing the time horizon, the market risk exposure also increases. Additionally, when the confidence level increased from 95% to 99%, the VaR also increased because a higher confidence level represents more precise measures. Furthermore, the discrepancies between the four VaR approaches were bigger when a 95% confidence level was considered since, according to Hendricks (1996), Skiadopoulos et al. (2003) and Jorion (2007), a higher confidence level increases the VaR misestimating and, a lower confidence level can calibrate the VaR measure.

Regarding the delta normal VaR, Neto (2016) found that it is easy and fast to apply because it just requires a simple variance-covariance matrix. However, some of its weaknesses can make it unreliable, namely: since most financial instruments have outliers in their historical data that can cause fat tails in the return distribution, the delta normal VaR estimation can be inaccurate, which worsens with greater confidence levels; and, by not considering the non-linearity of options, it cannot be applied to non-linear instruments. Having this in mind, Hendricks (1996) and Engle (2001) suggest including changes in the volatility (conditional volatility) over time. Regarding the two portfolios considered in this study, the delta normal VaR was overestimated because the model is totally based in high standard deviations of the returns (Neto, 2016).

On the other hand, if the historical data for each risk factor is available, the historical simulation can be the simplest method to compute VaR. Some of its strengths are the fact that it considers the fat tails of the past data and the fact that it can deal with the gamma and vega risks (the delta and volatility effects on option prices). However, by being strongly dependent on the past, it can consider or omit events that could or not happen soon. Also, it is difficult to define the data sample to apply the historical simulation. Furthermore, by being based upon a series of past returns, if the data is stable, the historical simulation can underestimate the VaR and, if the data is unstable, the historical simulation can overestimate the VaR (Neto, 2016). Therefore, if the portfolios are highly liquid and volatile, the historical simulation isn't a good VaR method. To deal with the problem of outliers in the return distribution, Boudoukh et al. (1998) and Hull and White (1998), which are presented in the literature review, propose alternative models based on historical simulation by weighting the data. Regarding the two portfolios considered in this study, the historical simulation VaR was overestimated because, as said above, this method is strongly based on historical data and the portfolios are highly volatile and liquid.

Alternatively, the Monte Carlo simulation seems to be the most flexible and fairest method of VaR estimation. It can lead with assumptions such as non-normality, non-linearity, time variation in expected return or in volatility, fat tails and extreme values (Neto, 2016). However, the Monte Carlo simulation has its own limitations. By considering randomly determined procedures, some of them can be unreliable. Additionally, it requires a lot of computational time to create the several random scenarios, therefore being the most expensive model to apply (Neto, 2016). To deal with the amount of computational time required, Jamshidian and Zhu (1997), Frye (1997), Glasserman et al. (2000) and Botev et al. (2012) propose improvements to the Monte Carlo implementation, which were described in the literature review. Regarding the portfolios considered in this study, the Monte Carlo simulation proved to be the most accurate method due to its flexibility.

Lastly, the delta-gamma's biggest advantage is that it can be applied to non-normal and non-linear portfolios. However, it is a complex model that demands high levels of calculation which can become costly and complicated to implement. Additionally, the delta gamma method normally rejects the normality even if the portfolio return distribution is normal which, due to the fact that the model uses a second order approximation, can result in a chi-squared distribution rather than a normal distribution (Neto, 2016). Furthermore, although the literature recommends the delta-gamma when dealing with non-linearity, Castellacci and Siclari (2003) found a more accurate measure in the delta normal than in the delta gamma method for non-linear option portfolios.

Neto (2016) also analyzed the impact of portfolio diversification in the VaR measure confirming that, when the correlation between instruments is considered in the calculations, the

VaR measure improves. In this context, the Monte Carlo simulation presented the highest efficiency in the risk measure when the diversification factor was considered.

Moreover, Neto (2016) suggests the Extreme Value Theory (EVT) to improve the VaR measures by including the possibility of an extreme event to occur. The EVT's focus is to estimate the shape of the tail in the probability distribution and, therefore, it can estimate the losses with very low probabilities (Neto, 2016).

By comparing the four most common VaR methods, Neto (2016) contributed to science by presenting in an easy to understand master's thesis, the weaknesses and limitations of each method having in consideration stocks and options portfolios and the diversification. Therefore, Neto's objectives of research were fulfilled.

However, since the VaR measure is used and recommended for financial institutions, the data used should have been more realistic. For instance, rather than two simple portfolios constituted by 20 stocks and 3 options respectively, the portfolios studied could have been current portfolios from a group of banks and/or companies from different sectors. By doing this, the inclusion of different strategies and risk factors in practical situations would be allowed, therefore improving the accuracy of the numbers and better capturing the real challenges that risk managers face when computing the VaR.

Additionally, since Neto suggested the EVT method to improve the VaR measures, the method should have been applicated in the VaR measure to confirm if the VaR estimations do, in fact, become more precise. Additionally, since Neto suggested authors that consider that changes in volatility should appear in the VaR measure, Neto should have also applied models such as the ARCH and GARCH in the VaR measure. A comparison of the VaR measures by considering this methods and models would be richer and with a greater contribution to the literature. Therefore, future researchers should try to compare the VaR methods having in consideration the EVT method and the ARCH and GARCH models.

Furthermore, since the Expected Shortfall model to measure market risk was also stated in this work, it could have been contrasted with the VaR methodology, seeing which one presents the best results. Therefore, future researchers should try to contrast the VaR methodology with other models to measure market risk.

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Annex 1

Table 2

Comparison of different VaR methods

Assumptions	Delta Normal	Historical Simulation	Monte Carlo	Delta Gamma
Can it capture non-normality?	No	Yes	Yes	Yes
Can it capture non-linearity?	No	Yes	Yes	Yes
Can it be applied to options?	No	Yes	Yes	Yes
Is it easy to compute and implement?	Yes	Yes	No	No
Can it be implemented without historical data?	Yes	No	Yes	Yes
Is it generally a flexible method?	Yes	No	Yes	Yes

Note. Retrieved from Neto (2016, p.27).

Table 3

Composition of the stock portfolio

Code	Company	Amount
AV/LN Equity	Aviva PLC	5,000.00
BARC LN Equity	Barclays PLC	5,000.00
BDEV LN Equity	Barratt Developments PLC	5,000.00
BLT LN Equity	BHP Billiton PLC	5,000.00
BP/ LN Equity	BP PLC	5,000.00
BT/A LN Equity	BT Group PLC	5,000.00
GSK LN Equity	GlaxoSmithKline PLC	5,000.00
HSBA LN Equity	HSBC Holdings PLC	5,000.00
IAG LN Equity	International Consolidated Airlines Group SA	5,000.00
ITV LN Equity	ITV PLC	5,000.00
LGEN LN Equity	Legal & General Group PLC	5,000.00
LLOY LN Equity	Lloyds Banking Group PLC	5,000.00
PRU LN Equity	Prudential PLC	5,000.00
RBS LN Equity	Royal Bank of Scotland Group PLC	5,000.00
RDSB LN Equity	Royal Dutch Shell PLC	5,000.00
SAB LN Equity	SABMiller PLC	5,000.00
TSCO LN Equity	Tesco PLC	5,000.00
TW/ LN Equity	Taylor Wimpey PLC	5,000.00
ULVR LN Equity	Unilever PLC	5,000.00
VOD LN Equity	Vodafone Group PLC	5,000.00
	Total	100,000.00

Note. Retrieved from Neto (2016, p.30).

Table 4

Composition of the option portfolio

Option	Underlying	Company	Amount
Put	BP/LN Equity	BP PLC	20,000.00
Call	RBS LN Equity	Royal Bank of Scotland Group PLC	20,000.00
Call	FTSE100	UK Index	20,000.00
		Total	60,000.00

Note. Retrieved from Neto (2016, p. 31).

Chapter 2

MultiCorePricer: A Monte-Carlo Pricing Engine for Financial Derivatives[2]

Rodrigues, André and Moreira, Vitor

Abstract

Given the poor performance of a high-level program of work in relation to the Monte Carlo program, in what concerns the pricing of structured products, we should target more sophisticated solutions obtained through a computational workload distribution for more processing units or faster. However, this project focuses more on hardware acceleration, where computational tasks are performed with dedicated hardware techniques, not simply as a set of software instruments in a processing core. (Guerrero, 2015). The primary goal of this project was to implement a product price structured in a commercially available FPGA and provide a solution analysis in terms of computational acceleration versus software solution. The focus was to implement a thin and efficient architecture, allowing high parallelization and throughput, propelling a price error and an acceptable level for practical applications. (Guerrero, 2015). The Black-Scholes model, which consists in calculating the theoretical price of the European options for buying and selling, is an option "a contract for the right to buy and sell shares later or later. a particular period at a particular price" (Cambridge Online Dictionary 2017a), this uses the volatility of a stock as constant, assuming an estimated rate, giving an approximation of the real behavior of the market. (Bossu and Henrotte, 2012). Given that this model uses random numbers normally distributed, the approach of this project focuses on the central boundary theorem to reduce the area used and achieve a higher speed. (Guerrero, 2015). At the level of results, we find that the chosen components are more than adequate for a Monte Carlo pricing mechanism, a high speed between 550 and 1450 has been achieved compared to a single core software solution. A batch pricing program was also instituted in the processing system to demonstrate a possible way to use it in a real-world application. (Guerrero, 2015).

[2]This paper is based on Guerrero, M. A. B. (2015). MultiCorePricer: A Monte-Carlo Pricing Engine for Financial Derivatives (Master's Thesis), Swiss Federal Institute of Technology in Zurich.

1. Introduction

This article addresses the market view of structured products and how these stand out in the Swiss market, considering the updated numbers in size and volume. For this, we used the current configurations used in banks and financial institutions, which propel the evaluation of these products and their recent use of FPGA computing. In this project we use the worst barrier option having its price explained, the description of it and its goals. (Guerrero, 2015).

1.1 Structured Products

A key task of investment banking is the search for possibilities to create new financial instruments. This task is usually fulfilled by combining existing components to create new financial instruments. (Guerrero, 2015).

Structured products are financial instruments that are constructed from a linear and non-linear part. The linear part is a zero-coupon bond and represents a risk-free investment. The non-linear part may be of different types of derivatives depending on what properties it may have. Such derivatives may be one or more options. These are products based on multiple underlying assets and are tailored to meet specific expectations and suit a given risk profile. They are projected from traditional assets, such as securities, stocks and derivatives. Due to the possibility of combining several underlying assets, we obtain several scenarios, which in turn helps small investors to speculate by becoming popular with them. Grossly, these products managed to obtain 202 billion Swiss francs in accounts by Swiss banks, accounting for 3.96% of the total volume of securities. (Guerrero, 2015).

1.2 Efficient Monte Carlo Methods

At the level of the pricing of structured products these depend on the forecast of the price distributions of the underlying assets. Given the complexity of these products, the development of fair value pricing requires a considerable amount of work. Two approaches can be used to overcome pricing challenges. (Guerrero, 2015).

First the use of sophisticated signal processing and the use of high-performance computing. The sophistication benefits from advanced techniques of statistical signal processing, such as importance sampling, enabling a consistent price under low complexity Monte Carlo simulations. To this method called Reduction of Variance, a procedure used to increase the accuracy of the estimates that can be obtained for a given simulation or computational effort. (Botev and Ridder, 2017).

Thus, we can ensure that Monte Carlo simulations generate accurate prices by increasing the number of simulated futures prices and reducing the size of the simulation step. Thus, this approach spreads rapidly across the computational boundaries of conventional CPUs.

Several models have sought to capture the essence of market dynamics, but the simplest is a geometric Brownian motion (GBM) (also known as exponential Brownian motion) is a continuous-time stochastic process in which the logarithm of the randomly varying quantity follows a movement Brownian (also called Wiener process) with deviation. (Ross, 2014). This project focused on this model, although it was not proved to be the most appropriate for pricing, given the non-normality of the observed market dynamics, yet this allowed easy calibration of the analytical prices of European options. (Guerrero, 2015).

1.3 Hardware Acceleration

Nowadays, we find a diversity of computer systems with skills for the validation of assets/ portfolio risk by organizations. Typical applications consist of multi-period portfolio, data mining, low latency trading, and in this project the pricing of options is highlighted. Over time software solutions have emerged, with faster pricing algorithm instructions. So, we move from software to hardware, and through it we get the hardware acceleration by performing the computations in the level of bi t logical silicon. This implementation of the silicon-like algorithm of an application-specific integrated circuit (ASIC) is expensive and only compensates for high-volume applications. On the other hand, the use of a FPGA (field programmable gate array) is an intermediate solution. These are used in various applications of financial settings, low trading, derivatives and credit risk, pricing options, and other Monte Carlo applications. (Guerrero, 2015).

1.4 Financial Instruments

A call option is a financial agreement that gives the buyer the right but not the obligation to buy an agreed amount of an underlying asset at a specified time, called maturity, for a specified price called the strike price. Depending on the style of the option (European, American, Asian) it can be exercised during or at maturity or depends on the development of the underlying. (Guerrero, 2015).

About this project, only the European option was used, which can only be exercised on the due date. To offset the associated risk, the buyer pays the option price. Investors in this stock are waiting for the moment to adjust, when the price exceeds the exercise price of the option, to later exercise the purchase for a significantly lower price than the current one and sells it to obtain a certain profit. The payment of this financial product depends only on the underlying price at maturity, while the profit depends further on the premium that was paid by the option. (Guerrero, 2015).

To determine the expected return is necessary to achieve a significant number of price tests and consider the average of all your payments. Through these returns financial institutions can determine the price of the product. Thus, we announce the first statement:

The payment of a European call option depends only on the underlying simulated price at maturity. From this statement, concluding that there should be some price beyond the expiration for the simulation. Since it is possible to accumulate the weighted payoffs to obtain their mean, it is not necessary to store them during the simulation. (Guerrero, 2015).

Aimed at the option to buy a barrier, we characterized it as a type of derivative where the payment depends on whether the underlying asset has reached or exceeded the predetermined price. A barrier option can be a knock-out, which means that it expires without value if the underlying exceeds a certain price, limiting the profits to the holder and limiting the losses to the writer. It can also be a knock-in, which means it has no value until the underlying reaches a certain price. (Investopedia, 2019).

Due to these conditions, we declare the most accessible barrier option over a similar barrier free, therefore, provides security of an option without significant charge of the premium charged. (Guerrero, 2015).

This project focuses on the down-and-out options, which are extinguished if the price of your underlying asset falls or demonstrates a level below. Distinguishing from the call option, the barrier option is defined as a percentage relative to the initial price of the underlying, which acts as a knock-out, due to this event the payment immediately becomes zero and the initial price is lost, therefore, the option can no longer be exercised at maturity. Hence, we mention statement 2: A payoff of the down-and-out barrier options becomes zero if a barrier event occurs. Therefore, a running price simulation can be aborted if the price falls at any point below or the barrier. (Guerrero, 2015).

We can also refer to the worst barrier call option being this a multi-asset version of the barrier call option and belongs to the category of structured products, to calculate the return we use the same principles in what concerns the barrier option with the addition of payment determined by the underlying with the lowest price at maturity, relative to its initial price. Although there are underlying multiples, the barrier level is the same for all the underlying and is considered in relation to the corresponding initial price. (Guerrero, 2015).

A barrier event occurs if the price of any underlying touches or falls on a barrier and causes the product's optionality to become void. Because barrier options have additional built-in conditions, they tend to have cheaper premiums than comparable options without barriers. So, if a trader believes that the barrier is unlikely to be achieved then they may choose to buy a knock-out option, for example, since it has a lower premium and the barrier condition will probably not affect them. Someone who wants to protect himself from a position, but only if the price of the underlying reaches a specific level, he can choose to use substitute options. The lower premium barrier option can make this more attractive than using unrestricted American or European options. (Investopedia, 2019).

In relation to the worst option to buy a barrier, there is a great variety of products with inverted or altered behavior, taking into account the very different market expectations, such as the use of put options as underlying that present an inverted payment profile of the purchase option , the best of style whose payoff is determined by the underlying best performing, the up style barrier option with the barrier up the initial price, the in style option that instead of extinguishing in a barrier event is inactive until an event and can only be exercised if it occurs. These variants require small price changes and are easily derived from the design presented. (Guerrero, 2015).

This method is related to the fundamental concept of this project that sought to use a specific architecture for a single product type with a specific style to obtain a higher yield. In real world application, it would happen that different FPGAs were assigned to the task of pricing various products. (Guerrero, 2015).

2. Literature review

Up to nowadays, an application of an FPGA architecture at the option price level has never occurred using a random number generator based only on the use of the central limit theorem. Sridharan et al. in 2012 introduced the FPGA implementation for the price of multi-asset barrier options. (Guerrero, 2015).

This project was directed toward Heston's more sophisticated model, a mathematical model that describes the evolution of a certain volatility of an underlying asset, which is the main difference. (Heston, 1993). Another is the level of organization in relation to the various threads or directions of products simulated in a single core, each having a glider in contrast, simulating a single product path, and all cores striking a glider. To produce randomly distributed numbers two random number generators based on inversion were used. (Cheung et al., 2007). In turn, this project was implemented by a FPGA Stratix IV E530 in Novo-G, which obtained a speed of 350 for a given product using four underlays. These results are uncertain to use in a comparison, since no exact parameter of the product is provided, as well as no absolute computing time. (Guerrero, 2015).

The authors Schryver et al. developed a pricing mechanism using the Heston model, but focused on a low power architecture. Pricing of a dual - barrier knockout option becomes zero if an upper or lower barrier is reached. Regarding this project to find a difference in the division of the pricing process between the FPCA and the computer, where the former only simulates the tariffs and sends the price of home path to the computer via USB. Here the Gaussian random number generator uses non-uniform random numbers based on inversion. (Schryver et al., 2010).

This mechanism in comparison with others proves to be more efficient in energy saving and at a higher speed, but since it has been only compared to a product, it is incorrect to draw conclusions if the FPGAs and / or the mechanisms CPU pruning benefit from failures caused by narrow barrier levels. (Guerrero, 2015).

Tian et al. 2008 explored the s option pricing models through the GARCH model, which is the condition of the existence of one or more data points for which the variance of the current error term or innovation is a function of the actual sizes of the error terms of the previous time slots. (Engle, 1995). They exploit the log-normal price movements and the Value-at-Risk calculations of the correlated assets. Like Schryver et al. they divide the path simulation into the FPGA and calculate the average or other operations for the host. Thus, its target accuracy was 0.01%. (Guerrero, 2015).

In general, we can say that the separation of the path simulation and processing of the data generated between the FPGA and the host is feasible if it allows high-speed communication and using a PCI connection. If this does not occur it leads to a loss of computation, because the FPGA would have to wait until all the data were read, along with the need for RAM to store the generated data. It is reasonable to apply this method if the pricing process consists of operation more complex than simply considering the average of all prices and contain costly operation as multiplications or divisions. (Guerrero, 2015).

Therefore, all this is considered difficult for the comparisons of different publications due to their differences and executions. Due to the numerous models for mu n the financial and the high volume of random numbers normally distributed, it is unlikely that publications have implementations with similar characteristics. It is worth to say that the compaction of the absolute time of computation with the use of the plate would allow a better comparison between the publications. (Guerrero, 2015).

3. Methodology

This dissertation was based on several methodologies that contributed to its development, the Black-Scholes model used to calculate the theoretical value of European-style options using current stock prices, expected dividends, option exercise price, expected interest rates, maturity to maturity and expected volatility. (Investopedia, 2019).

The previously described Heston model presents a stochastic volatility, modeled by a CIR process, based on geometric Brownian motion. In turn, these two models demonstrate a correlation that is generally considered negative. Due to the complexity of using the model, BS was used. (Guerrero, 2015).

To model the movement of the price of an asset in the BS model, the GBM was used because it is a stochastic process in which the logarithm of the randomly variable quality follows a Brownian with deviation. The Wiener process was used is a stochastic process of continuous time, but to obtain Wiener processes correlated to an active, to correlate n paths of simulation. Frequently, the methods used to produce RNs not evenly distributed from uniform RNs are the methods of transformation, rejection and inversion, the central limit theorem, which is limited to generating GRNs. (Guerrero, 2015).

A common method used as a Gaussian random number generator is in the Box-Muller transformation, it is a method of sampling pseudo-random numbers to generate pairs of independent, standard, normally distributed random numbers (zero expectation, unit variance) given a source of evenly distributed random numbers. (Raymond, 1934). This method has the advantage of using only one URN per GRN, but its implementation in hardware presents a high cost and a certain dependence on the bit width, making it impossible to have a small tail distribution with many subversions and vice versa. (Guerrero, 2015).

A method software implementation is ziggurat method, which generate a random a distribution point in a little more than desired and to test the generated point d is within the desired distribution. A disadvantage of this method is that not every RN input produces a GRN because certain samples are rejected, which requires special considerations for its use in a Monte Carlo simulation. (Guerrero, 2015).

The central boundary theorem (CLT) states that the arithmetic means of a sufficiently large number of independent and identically distributed random variables, each with a well-defined expected value and a well-defined variance, will be roughly distributed normally. CLT methods are, however, rarely used for applications that require normal high-precision distributions, since a large value n is required to obtain a good approximation of the bell curve. (Guerrero, 2015).

Surprisingly, the errors relating to the point of convergence were well below the desired one percent and the relative standard deviations are practically the same for all n values. We can say that a small error in the region of GRNG distribution tail is insignificant to the s prices regarding the barrier prior options. (Guerrero, 2015).

Est and design were considered two uniform generators of random numbers, first was the LFSR, which presents to be a shift register whose input bit is a linear function. Due to the operation factor in registration is deterministic, and the complete sequence generator for a given LFSR by its current state, this process generates pseudo-random numbers O rivers. When a new path simulation is started, the current prices of all underlying assets are defined as one, representing their relative initial value. A cycle is then started which, if not interrupted, is repeated until the product reaches maturity. (Guerrero, 2015). Through this we have the formula:

$$N = \text{time to maturity} / \Delta t$$

N must be integer, and delta t is determined from the pre-defined time to the expiration and the number of steps and not the other. (Guerrero, 2015).

All this sequence is immediately interrupted if at any stage of interaction any price of an asset falls below the predefined barrier level. When this happens, it is sending a lot l outage, which is the zero payoff for simulation of the current path and a new simulation is started. If this occurs, a new check is carried out, which tests whether the price of the poorer performing asset is at the default or below rated exercise price. Thus, if this happens, an interrupt signal is sent representing a zero payoff. If this does not, the simulated product has a payment that is then sent for further processing. However, to determine the actual price of the product, the average payment of all simulated paths, including zero payoffs, should be made. (Guerrero, 2015).

The main building block of the architecture presents 26 installations, each of which manages a potential price for the defined product, simulating its evolution later through the iteration formula derived from GBM model, each simulation step of three correlated underlays requires the generation of three correlated GRNS. The bit width of the signal level is used to determine the statistical evaluation, all other bit widths were identified by only way to quantify simulation parameters times. (Guerrero, 2015).

The core presents each nine Tausworthe generators as URNGs, three per GRNG, and contains three GRTGs of CLT, one for each asset price simulation. The correlating block performs the correlation of GRNs applying the Cholesky matrix to the three GRNs. The iteration block simulates the hypothetical evolution of the defined product, executing the predefined number of iteration stages of the GBM model, it is also possible to visualize three iteration cells, each one originated from a multiplier and two adders, a finite state machine denoted as FSM and logic to test payment scenarios. (Guerrero, 2015).

The FSM is responsible for verifying that a barrier event has occurred and that all iteration steps have been performed, manipulating the corresponding request, and recognizing signals, as well as sending the worst-performing asset price to the floating-point pipeline if the final price is above the strike price. After receiving an acknowledge signal, the FSM starts a new simulation. (Guerrero, 2015).

After recording all input parameters, the Controller block from the beginning to the cores and processes the handling of requests as well as confirmations. Break requests (signaling a barrier event) and normal requests (sent with a simulation price) are handled separately with their own counter. Both types of requests are added to have a total simulation count. When of the total count of the simulation to obtain a predetermined number, it carries out recording and withdrawal request in correspondents' registers. Through of the use of Tausworthe generators for the simulation of the pricing mechanism, it is possible to observe that the choice of the initial seeds for each generator is of extreme importance for the performance of Monte Carlo prices. When the first attempt was made to increase the initial seeds of each generator by a fixed number it showed a poor performance in relation to small increments, with the respective price being directed to a completely incorrect value. Thus, larger increments of each seed showed better results, but not satisfactory, hence the need to develop a more sophisticated method. (Guerrero, 2015).

To have an efficient execution, with low initial seeds and time saving, an integrated seed generation scheme was chosen. It preceded the modification of a URNG, wherein there equal URNGs were stacked similarly to GRNG block, making it necessary initial nine seeds. After the first URNs are generated, instead of continuing the sequence, two new seeds are introduced from the URNs generated by the two other URNGs for each URNG. (Guerrero, 2015).

To diagnose the results, two global counters were implemented, u m counter interrupts counting the broken paths for barrier events and worst performing assets ending below the exercise price and adding counter that counts the number of paths added. Subsequently, the required number of path simulation is added and compared, when it exceeds the total, 45 clock cycles are added to ensure that the floating-point pipeline is released. Because the interaction and growth counts increase when the nucleon sends the request, it is necessary to apply this technique because the price sent from a core must pass through the floating-point pipeline before the final price is updated. (Guerrero, 2015).

The floating-point pipeline consists of three Xilinx floating-point IP blocks. The processing system runs a C program with model simulation parameters and product information that is written and used a Matlab script.

At the level of the reproduction of a practical application, two change functionalities were implemented, one aimed at changing all the price parameters and one that changes only a single parameter, an already established barrier level was chosen, beyond the term until maturity, and exercise price, was to set a parameter by the issuer, also single parameter changes can be easily implemented. (Guerrero, 2015).

The PL generates seeds for the respective RNGs, the price parameters are distributed by several input words, since all parameters of the model have different optimized bit widths, thus, the last bit of the last word written as a completed bit, signaling to PL that all price parameters were recorded and that it can start the price calculation. Upon completion it reveals the result signal ready for a designated communication record. If other parameter sets are still left, the PS records a single or multiple parameter in the corresponding registers and a recognition signal in the communication register, acting as a starting signal for the PL to start a new price. (Guerrero, 2015).

4. Application

In this thesis a Zynq-7020 was implemented using Xilinx directed towards the speed. Through the result analysis, we affirm that when an architecture is complete, the number of cores is limited by the available units, by the fact of the subdivision in the correlator and in the interaction block. None of the absolute numbers of DSP usage can be provided in relation to these components. Since the correlator performs five multiplication and one interaction operations, albeit with a larger bit width, we assume that about 80% of the 8 DSP slices are used by the correlator. We can also say that control logic is not used through hardware overhead for pricing and that this is less than 5% of the available hardware resources. (Guerrero, 2015).

In relation to the evaluation of project accuracy, the points of convergence of the prices of six differentiated products executed by the FPGA were compared with the corresponding actual running prices, all this was determined by the Monte Carlo simulation in which it executed a total of 2 ^ 25 paths to 2 ^ 14 and 2 ^ 17 path prices. Compared to Black-Scholes, this differs by determining the analytical solution computed using the Matlab function. The worst barrier options ran a Matlab price script for a total of 2 ^ 24 paths. (Guerrero, 2015).

Because of its design constraints, architecture referencing cannot price a single asset call option. Regarding the test of analytical solutions of Black-Scholes pricing, design modifications required to ignore the output of the last two simulated active and barrier events. The calculation of price errors compared to pricings, we used 2 ^ 14 and 2 ^ 17 simulated paths. The simulation parameters were calculated from historical data, strike prices chosen at the 70% and 120% intervals from the initial price and each product configuration was evaluated with 6 different stocks forming to derive the mean error. (Guerrero, 2015).

When using 2 ^ 14 and 2 ^ 17 paths, it is worth to say that there is a tendency for greater error in relation to higher exercise prices, and that these will be the worst barrier option in relation to higher levels. Comparing road prices above 2 ^ 14 with lows of 2 ^ 17, we say that the same error is reduced to prices using more road simulations. (Guerrero, 2015).

Because the final price considers some simulated paths, such as high exercise prices and since most finishes below price and has a value of zero, the observation shows statistical defects in the Tausworthe combined generator. Reductions in the maturity times of short options lead to fewer simulation paths than the exercise price and increase the effect. (Guerrero, 2015).

Regarding the different average errors, we noticed a bigger error for the prices, in which only some ways of simulation contribute to the price, as we can observe with the Black-Scholes model. An example of this practice is the case of the higher barrier levels. Contrary to this model, the CP error is greater for longer time frames, since there is a longer duration to produce more barrier occurrences, reducing the number of simulations that contribute to the price of the product. Even using the generator and a Gaussian CLT distribution, the standard deviation performed by the FPGA and the software was considered almost equal. (Guerrero, 2015).

By the application of the studies, it was concluded that a certain error character was found in relation to the mean error, and that this is mainly due to the Tausworthe generator, and that shorter sequences of generated random numbers show stronger statistical defects. By applying the Matlab function, statistical defects are caused by the seeds generated. The simulations of the various models emphasize that even when using "ideal" seeds, the GRNG using three Tausworthe combined summing terms does not achieve the same precision in relation to one with random numbers of Matlab. Thus, a statistically optimal uniform distribution is highly important in a GRNG CLT. (Guerrero, 2015).

This study determined the acceleration by comparing the time the FPGA provided to determine the price of the product with the time needed for the Matlab script in a matching processor, at which clock frequency limited to 100MHz. (Guerrero, 2015).

With average CPU and FPGA computing times and accelerations relative to a specific group of products, the acceleration can be divided into two parts. First using a parallelism and a reduction of bit width achieving a speed increase of 550, which can be seen for very low barrier products, in which almost no barrier events occur. According to the optimized path simulation scheme it does not decrease time to continue the path simulation after a barrier event has occurred and immediately start a new simulation. This offers high barrier products of 80%, accelerations ranging from 850 to 1450, a product price of three years using 214 simulated paths requires less than 20ms, two years less than 13ms and a 7ms year. (Guerrero, 2015).

Due to a set of procedures, the resulting price has a smaller or larger standard deviation, so it is up to the issuer to choose the number of simulated paths needed to obtain an exact price. Since we obtain a linear correspondence of the calculation times and numbers of simulated paths, we can easily multiply by one factor to determine the calculation time for other numbers of simulated paths. (Guerrero, 2015).

5. Conclusion

It is possible to conclude from this project that the Gaussian distributions using the central limit theorem are correct about the pricing of multi-asset financial products by the Monte Carlo model. Even with a reduced number of three addition terms, it is possible to determine a correct price, reducing the need for hardware space. When using a combination of URNG with Tausworthe, it is worth to say that this approach is characterized by being a quick solution and requiring a specific choice of seeds, and that it cannot cause statistical defects in the GRNG of the CLT. With this combination, you can significantly reduce statistical defects, as software simulations have shown. (Guerrero, 2015).

The use of independent cores, which can be manipulated by a single control block and using a single floating-point pipeline, makes project tracking easier and code versatility facilitates manipulation of signal bit widths within the architecture. (Guerrero, 2015).

However, this project succeeded in achieving the desired accuracy and a point-of-convergence error relative to 1% or less, with possible improvement, eliminating the statistical defects of the Tausworthe combined generator, through more efficient seeds or another URNG. To improve accuracy an increase of input bit widths and internal signal should be applied. (Guerrero, 2015).

It was possible to observe the high potential of specialized architectures to accelerate the price of exotic financial products, since it becomes empty if the level of the barrier is reached. We can visualize this through the high speed achieved especially for high barrier options. The attain of an acceleration of 550 is surprisingly high even by this comparison being with a single CPU core because the design was run on an FPGA board with comparatively small hardware features and the greatest accelerations over three-year barrier products and 80% exceeded 1450. Thus, the project comprises the price of a product of three years in less than 20ms, two in less than 13ms and one in less than 7ms. (Guerrero, 2015).

In this thesis we could include the implementation of the Heston model or other more sophisticated ones. Considering that the exit process is handled by the controller, the model change was divided into change of block of iteration and change of the number of

GRNGs. Relative to the Heston model with variable volatility, three additional GRNGs would be required for each core. (Guerrero, 2015).

It was possible to achieve a further acceleration in the clock frequency of the architecture by introducing a second clock domain exclusively for the communication block. The application of the method of the antithetical variables, could contribute to the increase of the speed. For the already correlated GRNs could simply be reversed to gain a second set of GRNs, covering half of the area used by all central logic excluding the iteration block. To fully confirm its applicability, a thorough quantitative analysis of the negative impact on Monte Carlo pricing is recommended. (Guerrero, 2015).

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Chapter 3

The capital structure and its impact on firm value of JSE Securities Exchange listed companies - Article Summary[3]

Freitas, Emanuel and Santos, Miguel

Abstract

Modigliani and Miller (1958) were the first to introduce the capital structure theory, on which they argued that the capital structure of a firm is irrelevant to its value. So, using a panel of non-financial firms listed on the JSE Securities Exchange, it is investigated the importance of capital structure on the enterprise value and the capital structure of firms located in South Africa. After performing an analysis on the relevance of capital structure, the results indicated that there is no statistically significant relationship between firm value and its capital structure. On the other hand, the analysis of capital structure and its determinants made possible to conclude that South African firms might follow a pecking order theory. The results indicated that profitability, asset tangibility, tax shield and size have a statistically significant relationship to the capital structure of an organization. Also, and because it was investigated the capital structure of South African firms, it was possible to conclude that these might prefer to use long-term debt rather than short-term debt. Lastly, it was possible to understand that the leverage ratios were different between industries on this country, being the health care industry the one with the highest levels of leverage and the technology industry having the lowest levels of leverage.

[3] This paper is based on Mohohlo, N. R. (2013). The capital structure and its impact on firm value of JSE securities exchange listed companies (Master's Thesis). University of the Witwatersrand.

1. The capital structure and its impact on firm value of JSE Securities Exchange listed companies - Article Summary

There are many theories who try to provide better understanding of capital structure and its importance. Modigliani and Miller (1958), for example, defend that firm value isn't dependent on these ratios, and so, various types of structures of capital can be acceptable or rational. The trade-off theory, another perspective, consists on the proposition that enterprises are likely to use more debt, so that they can benefit from the tax shield offered by debt financing of investments. On another hand, the pecking order theory argues that firms will prefer internal funds rather than the external ones. And if the external capital may be required, the safest ones will be used first, for example, regular debt will be required first and equity only as last resort (Myers, 1984). But all of these have their own assumptions, their own weaknesses, limiting their applicability on the general environment. One thing is for sure: the growth of a firm is dependent of an effective capital budgeting that creates projects that add value to the company. It can be achieved, for example, with an estimation of cash flows from projects and costs of capital. So, if the company doesn't have a good understanding about the prevailing capital structure in the market, it won't have a good sense of what the appropriate cost of external capital should be, whether debt or equity. In this case, it's analyzed how well do south African firms comprehend the dominant capital structure on their respective sector and general economy (Mohohlo, 2013).

The literature on capital structure and its effect on firm value is still very thin in the African context. Most of it has been focused on developed capital markets, which are characterized by well-functioning, efficient stock markets and well-developed credit markets. On the other side, in Africa, the markets can be mainly characterized by its inefficiency. There's a huge gap between these two realities concerning the institutional infrastructure, so it's inappropriate to generalize the findings which come from developed economies studies to those from developing economies like the African context. This calls for more deliberation on the capital structure of firms in Africa (Mohohlo, 2013).

Apart from trying to shed enough light on the prevailing capital structure in South Africa, giving then continuation to the work that has been done by Gwatidzo and Ojah in 2009, and contribute to the literature on this matter, this investigation tries to understand what is the role of capital structure on enterprise valuation and the relevance of other market and economic variables on it.

This article summary is composed by the research literature review, reviewing authors who approached similar problems, methodology, describing the methods and data used in the work, study application, displaying and analyzing the findings from de empirical study, and finally its conclusions, revealing the conclusions that can be drawn from the investigation, its contributions to the field of studies and some suggestions for future research.

2. Literature Review

According to Firer et al., “capital structure decisions can have important implications for the value of the firm and its cost of capital” (as cited in Mohohlo, 2013, p.6). Firms are, however, generally at liberty to decide on any capital structure they wish to undertake since the capital structure decision can be made independently from the capital investment decision (Mohohlo, 2013).

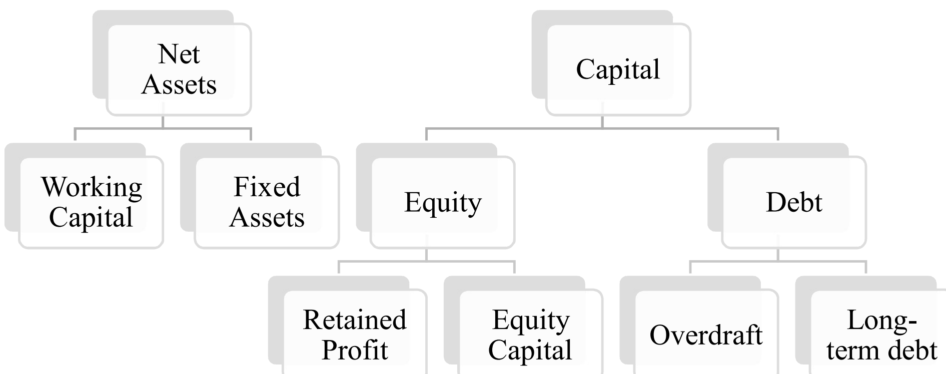

Figure 1: Application and sources of funding (An adoption from Ward and Price) Source: Mohohlo, 2013

As Dreyer affirms, the “departure point for virtually all discussions on capital structure theory is Modigliani and Miller’s capital structure irrelevance theory first published in 1958” (as cited in Mohohlo, 2013, p.10). Here, the type of financing doesn’t matter in perfect capital markets (Modigliani & Miller, 1958), because whatever may the proportions of debt and equity be, assuming that assets and growth opportunities on the left-hand side of the balance sheet are held constant, enterprise value keeps the same (Myers, 2001). And so, it argues that the value of a levered firm is equal to the value of an unlevered one, revealing not only the irrelevancy of capital structure, but also that the weighted average cost of capital remains the same no matter what combination of debt and equity is used to fund the company (Firer et al., 2008). But we can’t forget that this model relies on the assumption of a reality based on perfect capital markets, which imply, for example, homogeneous shares of different firms which are perfect substitutes of each other and the predictability of expected future returns on all shares by investors, thus opening the theory to multiple criticisms (Mohohlo, 2013).

Meanwhile, Modigliani and Miller delivered a correction of their 1958 seminal work, which states that the value of a levered firm is equal to the value of an unlevered firm plus the present value of the interest tax shield (Firer et al., 2008). This can be called the trade-off theory, and possesses two versions of itself, namely the static and the dynamic trade-off theory. The first advocates for an optimal level of debt that balances the advantages of adding one unit of debt against the cost of adding one unit of debt to the capital structure. It must, however, be of note that this theory version gives little or no indication of how this optimal debt-to-equity ratio is calculated. The dynamic trade-off theory, on the other hand, acclaims that firms consider the benefit of adjusting their capital structure against the adjustment cost and make debt adjustments only when the benefits are more than the costs (Mohohlo, 2013). This second version recognizes that, says Ovtchinnikov, "financing frictions make it suboptimal for firms to continuously adjust their leverage to the target" (as cited in Mohohlo, 2013, p.16).

If we look now at another perspective, the pecking order theory was first suggested by Donaldson in 1961 and it was modified by Stewart C. Myers and Nicolas Majluf in 1984. According to this, there is a financing hierarchy behavior in which firms tend to use firstly retained earnings, then cheap debt and only then, if under real pressure, will the enterprise use external equity to fund their investments. This idea is centered around adverse selection costs based on the superior case of information asymmetry (Mohohlo, 2013). There are also some valid opposing views to the pecking order theory, in which one of those states that firms might desire to maintain spare debt or preserve some funding capacity by first using debt, instead of retained earnings as acclaimed by the pecking order theory, but only if believed that this could be essential to fund profitable future investment opportunities (Ryen et al., 1997).

There's at least one more relevant and acceptable theory on the study of capital structures we should consider, which is the market timing theory, developed by Malcolm Baker and Jefrey Wurgler. Following their vision, market timing is the first order determinant of a corporation's capital structure use of debt and equity. In other words, firms generally don't care whether they finance with debt or equity, they just choose the form of financing which, at that point in time, seems to be more valued by financial markets. The idea here, says Baker and Wurgler, is that firms issue "shares at a high price (when their valuations are higher relative to book value and past market valuations) and repurchase them at low prices (when their market valuations are lower)" (as cited in Mohohlo, 2013, p.18). But some criticize this way of thinking, for example by the work of DeAngelo et al. (2010), in which the respective authors state that firms actually don't issue securities when they are overpriced. If we are to consider that the investor is rational, happens that he will most likely be able to recognize any attempts to sell off overvalued stocks, and as a result, this would reduce the price they are willing to pay for the stock. This would, then, imply that it's actually more difficult for firms to time the market than it really is, as it's alluded by the market timing theory (Mohohlo, 2013).

At last, we should keep in mind some empirical researches that have been conducted on different countries concerning the effects of capital structure on firm value.

In Australia, Oraluck and Mohamed found that "market reacts positively to announcements of financing events that lead to the firm's capital structure moving closer to their relative industry median debt equity ratio, while for firms changing the debt-equity ratios away from the median would lead to either less positive or negative abnormal returns. This indicates that the Australian market perceives the industry median as an appropriate capital structure benchmark" (as cited in Mohohlo, 2013, p.26).

In Pakistan, Muhammad et al. concluded, in a simple way, that "capital structure choice is an important determinant of financial performance of firms in that country" (as cited in Mohohlo, 2013, p.26).

In China, Ruan et al. found that "managerial ownership doesn't influence firm value significantly when capital structure is added into the equation. However, on the opposite side, managerial ownership significantly affects capital structure, which consequently affects corporate performance" (as cited in Mohohlo, 2013, p.26).

Regarding Nigeria, there exists two major studies. The first, by Iorpev and Kwanum, shows that, "statistically, capital structure is not a major determinant of firm performance for manufacturing companies in this country" (as cited in Mohohlo, 2013, p.26). On the second research, Ogbulu and Emeni found that "in an emerging economy such as Nigeria, as a component of capital structure, equity capital is irrelevant to the value of a firm, while long-term-debt was found to be a crucial determinant of firm value" (as cited in Mohohlo, 2013, p.26).

The last major research we should consider was done by Gwatidzo and Ojah, in which it concerns several African markets, namely in Ghana, Kenya, Nigeria, South Africa and Zimbabwe. Here, these authors tested for capital structure dependence on asset tangibility, corporate tax, profitability, size and firm age. In the end, the authors found that companies in these markets tend to follow a modified pecking order; that profitability is negatively related to leverage, which means that more profitable African firms tend to use retained earnings to finance their activities before borrowing; and that tangibility of assets is negatively correlated to debt for most of the sampled countries (Mohohlo, 2013, p.24).

However, despite all the literature evidence that can be presented, the question still remains on which pattern best describes the current situation in South Africa. In the continuation of the paper, the authors will try to provide a valid response to it.

3. Methodology

As previously said, this investigation centers around the matter of capital structure and its effects on the South African market. The population of application for this study, then, is all non-financial service companies that are listed on the main board of the JSE Securities Exchange (JSE), for the period 2002 – 2011 (a ten-year period of analysis) (Mohohlo, 2013).

The sample can be viewed as a suitability sample. As Dreyer and Zikmund defend, “firms are included or excluded based on whether they fulfilled the preferred criteria of the study. Industry analysis is also carried out, in an effort to detect capital structure contrasts between industries so the sample can be regarded as stratified, and because the number of firms in each industry is unequal, it becomes a disproportional stratified sample” (as cited in Mohohlo, 2013, p.31). Some of the exclusions include AltX listed companies, as there are significant differences between the AltX and JSE listing requirements which makes the caliber of companies listing in the respective exchanges vastly different; financial services companies, as their capital structure is different from that of a non-financial firm; and many other exclusions, which includes firms who did not have data covering the observed period. In the end, the research was done with data from a sample of 65 corporations (Mohohlo, 2013).

For the purpose of this study, only secondary data was employed. The primary source of the data employed for the investigation was Bloomberg, as it was the preferred all-encompassing data base for global information. Panel data was employed on this research study mainly because of its advantages. Going this way provides more observations which in turn leads to a larger sample status. Wang says that central limit theorem may apply where single dimensional time series or cross-sectional data sets fails making estimation and inference more efficient (as cited in Mohohlo, 2013, p.32). And as Wooldridge defends, this can allow for control of unobserved cross-section heterogeneity (as cited in Mohohlo, 2013, p.32).

In general, it’s used a quantitative analysis because it is a very important way of analyzing financial data. As Richard (1992) argues, quantitative techniques are regarded as an effective way of providing solutions to management problems, and so, diverse quantitative analysis techniques were employed.

One of them is descriptive statistics. Using them, Zikmund defends that we can “convert data into a format that is easier to analyze, interpret and understand” (as cited in Mohohlo, 2013, p.32). If we look in detail, there were used various types of descriptive statistics, like measures of central tendency, which includes the sample mean (the sum of all data observations divided by the number of the observations, widely known as the arithmetic average of the sample or observations), and the median (the observation in the middle of the data. For example, if the data set has an equal number of observations, then the median is calculated by averaging the two middle observations); measures of dispersion, like the minimum, maximum and the range (the minimum is the smallest observation in a data set, the maximum is the biggest value in a data set, and the difference between the smallest and largest observations is called the range); and measures of variability, with the variance (average of the squared deviations from the mean of the data set) and standard deviation (square root of the variance of the data set) (Mohohlo, 2013).

Another way to comprise the data and to draw conclusions from it, is with the use of a regression analysis. According to Sykes, this "is a statistical tool that is used for the investigation of relationships between variables, where the investigator assembles data on the underlying variables of interest and employs regression to estimate the quantitative effects of the causal variables upon the variable that they influence (as cited in Mohohlo, 2013, p.33). Part of this study seeks to establish whether the capital structure is irrelevant as stated by the first theory of Modigliani and Miller of 1958 (MM1), and the factors that determine the debt-equity structure divide. So, to effectively and efficiently achieve these objectives, a simple panel data regression analysis was adopted (Mohohlo, 2013).

To test the MM1 proposition and unravel the key determinants of a firm's capital structure, data was collected on different variables for each company from 2002 to 2011, for 65 companies. The desire for simplicity required that only a few variables were included in the model, but according to Koop, "a poorly specified model runs into the risk of misspecification and inadequate or meaningless regression" (as cited in Mohohlo, 2013, p.34). To mitigate such an unfavorable likelihood, it was adopted a panel data regression methodology that is acclaimed for being able to control individual heterogeneity, which helps to account for missing variables and reduce the possibility of multicollinearity that is prevalent in time series data (Mohohlo, 2013, p.34).

A basic representation of the study model can be represented as $Y_{it} = \alpha + X'_{it}\boldsymbol{\beta} + \varepsilon_{it}$. ***Y*** represents the dependent variable; ***X*** denotes a vector of explanatory variables; $\boldsymbol{\beta}$ is a vector of explanatory variables coefficients, ***E*** is the error term; ***i*** is the individual company subscript; and ***t*** is the time subscript. In the first case, this model seeks to estimate whether firm's performance, which is represented by EPS, has a significant relationship with debt-to-equity ratio, corporate tax shield ratio and asset tangibility. Consequently, ***X*** denotes a vector of debt-to-equity ratio, corporate tax shield ratio and asset tangibility, whereas ***Y*** represents the firm's performance. As can be seen, very few variables are included on the right side of the previous equation. This means that the error term will not meet the classic least square orthogonality requirements, since the effects of variables not covered in the study will all be captured by the variable ***Eit*** (Mohohlo, 2013, p.34).

In detail, $\varepsilon_{it} = d_i + \epsilon_{it}$. ***di*** is the individual specific effect which captures unobserved company-specific effects, and ***Eit*** represents the pure errors that are independent and identically distributed with a mean of zero and a constant variance. Assuming also that ***di*** is a fixed parameter for every company, independent of ***Eit*** for all ***i*** and ***t***, but highly correlated to ***Xit***, the new formed model is often called a fixed effect model (FEM). Actually, $Y_{it} = \alpha + X'_{it}\beta + d_i + \epsilon_{it}$, as it is common for such a model to be estimated using the dummy variables technique to represent each company, so that the intercept can vary between companies. This method is popularly known as the least square dummy variable approach. The number of dummies that is going to be introduced is, then, equal to the number of companies less one, being only 64 dummies used (Mohohlo, 2013, p.34).

For the purposes of addressing the research questions set out here, the dependent variables are the earnings per share (EPS - the net profit/earnings expressed on a per share basis), and the debt-to-equity (D/E) ratios. Because of the objectives of the study, EPS will be used as a proxy for firm value and the D/E ratio as a proxy for the firm's capital structure (Mohohlo, 2013, p.35).

The explanatory variables for the model used in the study are the debt-to-equity ratio, tax shield (expressed as a ratio of tax paid to net income), size (the ratio of market capitalization of the firm to the total industry capitalization), profitability (measured by the return on assets ratio), and the asset tangibility (calculated as a ratio of fixed assets to total assets) (Mohohlo, 2013, p.35-36).

Lastly, in this investigation is also used a test of hypothesis. As Zikmund appoints, the "theoretical hypothesis may be accepted or rejected by the application of appropriate statistical techniques to empirically observed data" (as cited in Mohohlo, 2013, p.36). So, it was first defined the null hypothesis (H0), then the alternative hypothesis (H1), then the level of significance (α = 0.05/95% - which establishes the level that is considered too low to support the null hypothesis), and only then it's rejected or accepted the null hypothesis, based on the level of significance (Mohohlo, 2013, p.36).

4. Application

Addressing the unit root test, a variable is said to have unit root when it is explosive. According to existing literature a variable can only be included in a model when it does not have unit root or is stationary. It was used the Levin, Lin and Chu test. As can be seen in figure 2, all variables exhibited stationarity and unit root was non-existent and were all suitable to include in the regression analysis (Mohohlo, 2013, p.38). All the figures here referenced are available in the annexes section, right after the references.

Starting with hypothesis one, the author investigated if the capital structure was irrelevant as per MM1. The results for the pooled companies across industries showed that none of the explanatory variables were significant at the 5% level of significance, however, asset tangibility showed significance at 10% level of significance. The debt to equity ratios of South African firms in this study were insignificant, which means that they had no explanatory power on EPS. The R squared value of 60% indicates that the model can explain 60% of the variance in the EPS. This is showed in figure 3. About the same matter but individualizing some of the industries, the industrial companies indicated asset tangibility as being the significant variable at the 5% level of significance, and the tax shield as significant at the 10% level of significance. The debt to equity ratio for this type of companies was found insignificant, meaning that they had no explanatory power on the dependent variable EPS. According to the R squared value, the model explained 63% of the variance in EPS. Addressing the basic material industries, only the asset tangibility was found significant at the 5% level of significance. Neither the debt to equity nor the tax shield were significant, which means that these two variables have no explanatory power over the dependent variable. The value of the R squared revealed that 53% of the variance in EPS is explained by the model. The consumer services showed the asset tangibility as being significant at the 5% level of significance, while the debt to equity ratio was insignificant meaning that the debt to equity ratio of these firms had no effect on their firm value. Due to the significance of the R squared at the 5% level of significance, the model explains 65% of the variation in EPS. The consumer goods firms experienced the same results as the consumer services, with the only difference being the fact that the significance of the R squared at the 5% level of significance showed that the model explained not 65% of the variation in EPS, but 83%. The results on the Health care industry showed that the tax shield was the only significant variable at the 5% level of significance. The debt to equity ratio, once again, had no effect on the firm value. The R squared being significant at the 5% level of significance indicated that the model explained 56% of the variation in EPS. The technology industries results showed that the asset tangibility was the only variable that was significant at the 5% level of significance, while the debt to equity ratio was, again, insignificant, meaning that it had no effect on firm value. The model explained 47% of the variation in EPS, according to the significance of the R squared at the 5% level of significance. These results can be seen in the figures 4,5,6,7,8 and 9, respectively (Mohohlo, 2013).

Summarizing, the debt to equity ratio had no explanatory power over EPS in any of the firms, meaning that there is no statistical relationship between firm value and the capital structure of firms in the south African context. The results were inconsistent with previous research in the South African context as those established a correlation between EPS and debt to equity ratio. For instance, Rayan (2008) found that there is a correlation between EPS and debt to equity ratio, however, he also found no significant correlation between EPS and the debt to equity ratio for the basic materials, consumer goods, health care, industrials and technology industries. To ensure robustness of the model, the author re-specified it and increased the number of firms in the sample to 82; to strip out the systematic and idiosyncratic effects on firm value he included the Alsi40 and EBITDA as control variables for systematic and idiosyncratic effects respectively. The debt to equity ratio was treated as an independent variable in this model. The results of the re-specified model are shown in figure 10. The results of the pooled companies across all industries showed that debt to equity is insignificant at the 5% level of significance, meaning that it has no explanatory power on market capitalization, whilst the two control variables have that explanatory power. The model explained 73% of the variation in market capitalization. It was carried further analysis of the MM I by segregating the data by market capitalization into large, medium and small firms (over R50 billion were classified as large firms, between R50 billion and R10 billion were classified as medium firms, and below R10 billion were classified as small firms), using the year 2007 as the base year. The large firms indicated that debt to equity ratio is insignificant at the 5% level of significance, meaning that the capital structure had no explanatory power over firm value. In these companies, the two control variables were significant at the 5% significance level. The model explained 83% of the variation in firm value. The results of the medium firms showed that, once again, debt to equity has no explanatory power over market capitalization. The two control variables were significant at 5% level of significance. The model explained 71% of the variation in firm value. Finally, the results on small firms showed that debt to equity has no explanatory power over firm value, while the two control variables had that power. The model explains 76% of the variation in firm value. These results are pictured in figures 11, 12 and 13. The re-specified model indicated that there is no statistically relevant relationship between firm value and the capital structure of a firm in South Africa. It can be concluded that the debt to equity ratio is insignificant at the 5% level of significance, meaning that the capital structure of a firm has no effect on firm value in South Africa (Mohohlo, 2013).

Now it’s addressed the second hypothesis, which tries to see if the debt to equity ratio differs among industries. As can be seen in figure 14, the health care industry had the highest level of debt to equity, followed by the industrial sector. On the opposite hand, the technological sector had the lowest level of debt to equity ratio. So, it is concluded that the debt to equity ratio of the different industries sampled for this study were heterogeneous (Mohohlo, 2013).

About the third hypothesis, which tries to investigate if the industry debt to equity ratio is persistent, it can be observed that the oil and gas industry´s debt to equity ratio declined drastically from 40% to 10% (figure 15); the firms of the technological sector had a debt to equity structure that varied over time, with a persistent increase from 2009 to 2011 (figure 16); the health care industry is highly leveraged, with great reliance on debt which makes the ratio of debt to equity of these firms the highest (figure 17); the debt to equity ratio of the telecommunications industry had a sharp decline from 49% to below 30% (after this decrease the ratio increased gradually until 2008) (figure 18); the consumer goods industry showed a variable pattern in this ratio, varying between 30% and 60% (figure 19); the consumer services industry showed a bound structure, and a sharp increase in 2006 followed by a decrease in 2007 (figure 20); the basic materials firms experienced a persistent decline between 2004 and 2011 (figure 21); the industrial sector had a ratio persistently over 60%, experienced an increase between 80% and 90% in 2006, declining gradually from there on (figure 22). From the results presented above, it can be concluded that the different industries have different capital structures and persistence patterns, which proves the heterogeneity of capital structure among these industries (Mohohlo, 2013).

Addressing the hypothesis four, which tries to analyze whether there is, or not, a relationship between debt to equity ratio and profitability, size, asset tangibility and tax shield, the regression results showed that the return on assets and asset tangibility were the only two variables that were significant, meaning that they have explanatory power over the dependent variable, the debt to equity ratio, as can be seen in figure 23. The industrial sector showed the return on asset as the only significant variable at the 5% level of significance, while market capitalization, tax shield and asset tangibility did not have explanatory power over the industrial´s firms capital structure (figure 24); the basic materials industry exposed market capitalization as being the only variable significant at the 5% level of significance, while return on assets, tax shield and asset tangibility had no explanatory power over the capital structure (figure 25); the industry of consumer services had return on assets, tax shield and asset tangibility as the significant variables at the 5% level of significance, with market capitalization having no explanatory power over the capital structure of these firms (figure 26); the consumer goods industry had no significant variable, meaning that none of the variables had explanatory power over the capital structure of firms (figure 27); and finally, the health care industry only had the return on asset as the significant variable at 5% significance level, and tax shield as significant at 10% level of significance, while market capitalization and asset tangibility were insignificant (figure 28). According to the results presented above, it can be concluded that return on asset and asset tangibility are the determinants of the capital structure of South African firms, with the relationship between capital structure and those two variables being negative, which means that the more profitable firms are, the less debt they use to finance their investments. The industrial sector shows a negative relationship between return on asset and debt to equity, the basic materials industry indicates a negative relationship between size and debt to equity, the consumer goods industry has two different relationships between the variables and debt to equity (with one of them being a negative relationship between return on asset and debt to equity, and the other being a positive relationship between tax shield, asset tangibility, and debt to equity), and finally, the health care industry shows that there is a negative relationship between return on asset and the debt to equity ratio. In general, this shows that there is a relationship between the debt to equity ratio of firms in South Africa and profitability, size, tax shield and asset tangibility (Mohohlo, 2013).

Lastly, it's addressed the fifth hypothesis, that tries to investigate if there is a difference among industries in terms of reliance on long-term debt. The oil and gas industry rely heavily on long-term borrowing as compared to short-term borrowing, as the long-term debt to total debt ratio has been above 70% from 2003 to 2011, and between 2003 and 2004 the company only had long-term debt (figure 29). The sector of technology had a variable level of long-term borrowing, which, between 2004 and 2006, was lower than short-term borrowing, reaching 65% in 2007, and from there on it gradually decreased (figure 30). The health care industry relied more on short-term borrowing between 2004 and 2005, after the level of long-term borrowing increased, which had been persistent from 2005 to 2011 (figure 31). The telecommunications industry had a variable long-term and short-term borrowing level, with the long-term borrowing experiencing a peak of more than 80% in 2004, which declined between 2005 and 2011 (figure 32). The consumer goods industry showed a bigger reliance on short-term borrowing, with the long-term borrowing having a peak of 50% in 2003 (figure 33). The consumer services clearly presented a higher reliance on long-term borrowing, ranging between 50% and 70% (figure 34). The basic materials industry relied more on long-term borrowing, with the same range as the consumer services industry (figure 35). Lastly, the industrial sector experienced an increase in the level of long-term borrowing from 40% to 60% (figure 36). Summarizing, the debt structure between long-term and short-term seemed to be heavily biased towards long-term debt, however, the reliance on this type of debt was very different among the different industries. This result contrasted with the finding of Gwatidzo and Ojah, which was that "firms in South Africa relied more on short-term debt" (as cited in Mohohlo, 2013, p.69). Hence, the debt structure in terms of funding between long-term and short-term is homogeneous among the sampled industries (Mohohlo, 2013).

5. Conclusion

This study sought to cover the questions: is capital structure irrelevant as per MM I? what is the capital structure of firms per industry in South Africa? How persistent is the debt to equity capital structure? What factors determine the debt to equity structure? What is the debt structure in terms of funding between long-term and short-term? How persistent is the log-term structure?

To establish whether capital structure was irrelevant, a panel data regression was done on all firms across industries and an industry specific analysis was also done to establish the behavior patterns and relationships within the industries. To establish the robustness of the model and to expand the analysis of MM I, it was conducted an analysis by firm size (Mohohlo, 2013).

The general pooled analysis found the model to be significant. Although none of the variables were significant at the 5% level of significance, asset tangibility was significant at the 10% level of significance. The industry specific analysis found all models to be significant. The re-specified model on all firms was significant at the 5% level of significance, however, debt to equity was still insignificant. The analysis by firm size also found all models to be significant at the 5% level of significance, with the debt to equity ratio being insignificant. These results show that there was no statistically significant relationship between firm value and capital structure of firms in South Africa. The findings of this study were also highly inconsistent with prominent literature, such as Sharma, who concluded that "there is a relationship between leverage and firm value" (as cited in Mohohlo, 2013, p.70).

To establish the capital structure of firms within the different industries listed on the JSE, a descriptive statistics analysis was carried out. The health care industry had the highest debt to equity ratio, meaning that firms in this industry used more debt than equity as their source of capital. The firms with the lowest debt to equity ratio were from the technological industry. This study implied that larger firms tend to use more debt than smaller ones, which may be explained by an easy access to debt from the larger firms. This finding was inconsistent with the result of the regression analysis which indicated pecking order behavior of South African firms. Such inconsistency may be caused by not including in this study other factors that might have driven the high debt to equity ratio of firms in the health care industry. Later, it was found that the capital structure patterns of the sampled firms varied over the observed period (Mohohlo, 2013).

Concerning the factors that affect the capital structure, it was indicated a negative significant relationship between profitability and the capital structure of a firm. This finding was supported by a research from Gwatidzo and Ojah, in which they found a negative significant relationship between these two variables (Mohohlo, 2013, p.71).

It was also possible to conclude that most of the sampled industries relied more on long-term borrowing than short-term. This finding, as already explained, contrasts with what Gwatidzo and Ojah found in their study (Mohohlo, 2013, p.72).

Lastly, the results presented along the study are mostly inconsistent with recent literature and economic theory from across the world. This concurs with Myers, who stated that "there is no universal theory of capital structure" (as cited in Mohohlo, 2013, p.72). It can be said that there can be factors significant in one context but insignificant in another. As a suggestion, future research should find possible explanations for these contrasting results, starting with verifying differences in test variables proxy and testing techniques used in these studies.

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Annexes

Panel unit root test: Summary
Sample: 2002 2011
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	
Null: Unit root (assumes common unit root process)				
AT	-325.366	0.0000	65	520
Debt-to-Equity Ratio	-5.66143	0.0000	65	520
EPS	-4.34689	0.0000	65	520
PE	-12.4399	0.0000	65	520
TS	-215.158	0.0000	65	520
ROA	-17.2426	0.0000	65	519
Market Capitalization Ratio	-12.6915	0.0000	65	520

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Note: EPS stands for Earnings Per Share, PE stands for price per earnings ratio, TS stands for tax shield ratio, AT stands for asset tangibility ratio, ROA stands for return on assets

Figure 2: Unit root test (Source: Mohohlo, 2013)

Dependent Variable: EPS
Method: Panel Least Squares
Sample: 2002 2011
Periods included: 10
Cross-sections included: 65
Total panel (balanced) observations: 650

Variable	Coefficient	Std. Error	t-Statistic	
C	4.451460	0.387097	11.49959	0.0000
D2E	-0.002138	0.002996	-0.713499	0.4758
TS	0.001515	0.001110	1.365001	0.1728
AT	-0.011029	0.006351	-1.736578	0.0830

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.595398	Mean dependent var	3.860712
Adjusted R-squared	0.548820	S.D. dependent var	5.475059
S.E. of regression	3.677593	Akaike info criterion	5.541123
Sum squared resid	7871.369	Schwarz criterion	6.009483
Log likelihood	-1732.865	Hannan-Quinn criter.	5.722788
F-statistic	12.78285	Durbin-Watson stat	1.078609
Prob(F-statistic)	0.000000		

Note: C stands for the common intercept, D2E stands for debt-to-equity ratio, TS stands for tax shield ratio, AT stands for asset tangibility ratio, S.E stands for standard error, S.D is the standard deviation and F-statistic stands for Fischer statistic

Figure 3: FEM regression of all companies - firm value as dependent (Source: Mohohlo, 2013)

Dependent Variable: EPS
Method: Panel Least Squares
Sample: 2002 2011
Periods included: 10
Cross-sections included: 18
Total panel (balanced) observations: 180

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.963874	0.884506	7.873177	0.0000
D2E	0.000194	0.003570	0.054303	0.9568
TS	0.001590	0.000847	1.877088	0.0623
AT	-0.068269	0.023086	-2.957164	0.0036

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.625761	Mean dependent var	4.463009
Adjusted R-squared	0.578687	S.D. dependent var	4.162982
S.E. of regression	2.702134	Akaike info criterion	4.935242
Sum squared resid	1160.943	Schwarz criterion	5.307753
Log likelihood	-423.1717	Hannan-Quinn criter.	5.086279
F-statistic	13.29312	Durbin-Watson stat	0.807361
Prob(F-statistic)	0.000000		

Note: C stands for the common intercept, D2E stands for debt-to-equity ratio, TS stands for tax shield ratio, AT stands for asset tangibility ratio, S.E stands for standard error, S.D is the standard deviation and F-statistic stands for Fischer statistic

Figure 4: FEM regression of industrial companies - firm value as dependent (Source: Mohohlo, 2013)

Dependent Variable: EPS
Method: Panel Least Squares
Sample: 2002 2011
Periods included: 10
Cross-sections included: 12
Total panel (balanced) observations: 120

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	15.62170	4.001696	3.903768	0.0002
D2E	-0.045150	0.044473	-1.015218	0.3123
TS	0.006028	0.017290	0.348669	0.7280
AT	-0.105043	0.049307	-2.130406	0.0355

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.538854	Mean dependent var	6.229901
Adjusted R-squared	0.477368	S.D. dependent var	10.03394
S.E. of regression	7.253866	Akaike info criterion	6.917415
Sum squared resid	5524.950	Schwarz criterion	7.265851
Log likelihood	-400.0449	Hannan-Quinn criter.	7.058916
F-statistic	8.763828	Durbin-Watson stat	1.185977
Prob(F-statistic)	0.000000		

Note: C stands for the common intercept, D2E stands for debt-to-equity ratio, TS stands for tax shield ratio, AT stands for asset tangibility ratio, S.E stands for standard error, S.D is the standard deviation and F-statistic stands for Fischer statistic

Figure 5: FEM regression of basic materials companies - firm value as dependent (Source: Mohohlo, 2013)

Dependent Variable: EPS
Method: Panel Least Squares
Sample: 2002 2011
Periods included: 10
Cross-sections included: 17
Total panel (balanced) observations: 170

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.926782	0.931943	5.286572	0.0000
D2E	0.000183	0.003172	0.057712	0.9541
TS	-0.003598	0.005218	-0.689529	0.4916
AT	-0.044045	0.020753	-2.122396	0.0354

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.647460	Mean dependent var	2.884656
Adjusted R-squared	0.602805	S.D. dependent var	2.654892
S.E. of regression	1.673203	Akaike info criterion	3.977488
Sum squared resid	419.9414	Schwarz criterion	4.346405
Log likelihood	-318.0865	Hannan-Quinn criter.	4.127190
F-statistic	14.49915	Durbin-Watson stat	0.569593
Prob(F-statistic)	0.000000		

Note: C stands for the common intercept, D2E stands for debt-to-equity ratio, TS stands for tax shield ratio, AT stands for asset tangibility ratio, S.E stands for standard error, S.D is the standard deviation and F-statistic stands for Fischer statistic

Figure 6: FEM regression of consumer services companies - firm value as dependent (Source: Mohohlo, 2013)

Dependent Variable: EPS
Method: Panel Least Squares
Sample: 2002 2011
Periods included: 10
Cross-sections included: 11
Total panel (balanced) observations: 110

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.100045	1.272217	0.864668	0.3894
D2E	-0.003253	0.005113	-0.636205	0.5262
TS	-0.002381	0.002751	-0.865349	0.3890
AT	0.047942	0.023476	2.042156	0.0439

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.831334	Mean dependent var	3.332155
Adjusted R-squared	0.808494	S.D. dependent var	3.915189
S.E. of regression	1.713343	Akaike info criterion	4.033184
Sum squared resid	281.8124	Schwarz criterion	4.376881
Log likelihood	-207.8251	Hannan-Quinn criter.	4.172589
F-statistic	36.39780	Durbin-Watson stat	0.892084
Prob(F-statistic)	0.000000		

Note: C stands for the common intercept, D2E stands for debt-to-equity ratio, TS stands for tax shield ratio, AT stands for asset tangibility ratio, S.E stands for standard error, S.D is the standard deviation and F-statistic stands for Fischer statistic

Figure 7: FEM regression of consumer goods companies - firm value as dependent (Source: Mohohlo, 2013)

Dependent Variable: EPS
Method: Panel Least Squares
Sample: 2002 2011
Periods included: 10
Cross-sections included: 3
Total panel (balanced) observations: 30

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.805106	0.593117	4.729431	0.0001
D2E	0.000402	0.001673	0.240129	0.8123
TS	-0.026596	0.009360	-2.841362	0.0090
AT	-0.001995	0.002149	-0.928016	0.3626

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.556607	Mean dependent var	1.634580
Adjusted R-squared	0.464233	S.D. dependent var	1.512952
S.E. of regression	1.107422	Akaike info criterion	3.218802
Sum squared resid	29.43318	Schwarz criterion	3.499042
Log likelihood	-42.28204	Hannan-Quinn criter.	3.308453
F-statistic	6.025608	Durbin-Watson stat	0.595468
Prob(F-statistic)	0.000952		

Note: C stands for the common intercept, D2E stands for debt-to-equity ratio, TS stands for tax shield ratio, AT stands for asset tangibility ratio, S.E stands for standard error, S.D is the standard deviation and F-statistic stands for Fischer statistic

Figure 8: FEM regression of health care companies - firm value as dependent (Source: Mohohlo, 2013)

Dependent Variable: EPS
Method: Panel Least Squares
Sample: 2002 2011
Periods included: 10
Cross-sections included: 4
Total panel (balanced) observations: 40

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.733536	0.909980	-1.905028	0.0655
D2E	0.001082	0.015802	0.068483	0.9458
TS	-0.005117	0.006036	-0.847837	0.4026
AT	0.191378	0.056131	3.409503	0.0017

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.468932	Mean dependent var	1.314178
Adjusted R-squared	0.372374	S.D. dependent var	1.629320
S.E. of regression	1.290794	Akaike info criterion	3.506020
Sum squared resid	54.98292	Schwarz criterion	3.801574
Log likelihood	-63.12040	Hannan-Quinn criter.	3.612883
F-statistic	4.856481	Durbin-Watson stat	1.805290
Prob(F-statistic)	0.001181		

Note: C stands for the common intercept, D2E stands for debt-to-equity ratio, TS stands for tax shield ratio, AT stands for asset tangibility ratio, S.E stands for standard error, S.D is the standard deviation and F-statistic stands for Fischer statistic

Figure 9: FEM regression of technology companies - firm value as dependent (Source: Mohohlo, 2013)

Panel unit root test: Summary
Sample: 2002 2011
Exogenous variables: Individual effects
User specified lags at: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
ALSI40	-7.56325	0.0000	82	653
DEBT_EQUITY	-17.9186	0.0000	82	641
EBITDA	-10.0099	0.0000	82	641
MKT_CAP	-6.58019	0.0000	82	653

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

Figure 10: Unit root test (re-specified model) (Source: Mohohlo, 2013)

Dependent Variable: MKT_CAP
Method: Panel Least Squares
Sample: 2002 2011
Periods included: 10
Cross-sections included: 14
Total panel (balanced) observations: 140

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.51E+10	1.70E+10	-0.886430	0.3771
DEBT_EQUITY	2.98E+09	8.34E+09	0.356941	0.7217
ALSI40	6199926.	790222.1	7.845802	0.0000
EBITDA	2387.307	739.6243	3.227729	0.0016

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.832195	Mean dependent var	1.34E+11
Adjusted R-squared	0.810367	S.D. dependent var	1.32E+11
S.E. of regression	5.76E+10	Akaike info criterion	52.50400
Sum squared resid	4.08E+23	Schwarz criterion	52.86120
Log likelihood	-3658.280	Hannan-Quinn criter.	52.64915
F-statistic	38.12474	Durbin-Watson stat	0.756377
Prob(F-statistic)	0.000000		

Note: C stands for the common intercept, DEBT_EQUITY stands for debt-to-equity ratio, ALSI40 stands for Top 40 all share index, EBITDA stands for earnings before interest, tax, depreciation and amortisation, S.E stands for standard error, S.D is the standard deviation and F-statistic stands for Fischer statistic

Figure 11: FEM regression of large firms - firm value as dependent (Source: Mohohlo, 2013)

Dependent Variable: MKT_CAP
Method: Panel Least Squares
Sample: 2002 2011
Periods included: 10
Cross-sections included: 26
Total panel (balanced) observations: 260

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.92E+08	1.23E+09	-0.237689	0.8123
DEBT_EQUITY	-76079960	1.14E+08	-0.667469	0.5051
ALSI40	759995.5	65950.82	11.52367	0.0000
EBITDA	1410.480	324.1809	4.350904	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.708183	Mean dependent var	1.77E+10
Adjusted R-squared	0.672812	S.D. dependent var	1.20E+10
S.E. of regression	6.87E+09	Akaike info criterion	48.24467
Sum squared resid	1.09E+22	Schwarz criterion	48.64183
Log likelihood	-6242.808	Hannan-Quinn criter.	48.40434
F-statistic	20.02118	Durbin-Watson stat	0.854069
Prob(F-statistic)	0.000000		

Note: C stands for the common intercept, DEBT_EQUITY stands for debt-to-equity ratio, ALSI40 stands for Top 40 all share index, EBITDA stands for earnings before interest, tax, depreciation and amortisation, S.E stands for standard error, S.D is the standard deviation and F-statistic stands for Fischer statistic

Figure 12: FEM regression of medium firms - firm value as dependent (Source: Mohohlo, 2013)

Dependent Variable: MKT_CAP
Method: Panel Least Squares
Sample: 2002 2011
Periods included: 10
Cross-sections included: 42
Total panel (unbalanced) observations: 416

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.08E+08	2.45E+08	-0.847309	0.3974
DEBT_EQUITY	-37849379	43908164	-0.862012	0.3892
ALSI40	149148.2	12338.50	12.08804	0.0000
EBITDA	1159.603	221.5937	5.233012	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.761047	Mean dependent var	3.29E+09
Adjusted R-squared	0.732708	S.D. dependent var	3.26E+09
S.E. of regression	1.69E+09	Akaike info criterion	45.43027
Sum squared resid	1.05E+21	Schwarz criterion	45.86629
Log likelihood	-9404.497	Hannan-Quinn criter.	45.60267
F-statistic	26.85469	Durbin-Watson stat	0.828664
Prob(F-statistic)	0.000000		

Note: C stands for the common intercept, DEBT_EQUITY stands for debt-to-equity ratio, ALSI40 stands for Top 40 all share index, EBITDA stands for earnings before interest, tax, depreciation and amortisation, S.E stands for standard error, S.D is the standard deviation and F-statistic stands for Fischer statistic

Figure 13: FEM regression of small firms - firm value as dependent (Source: Mohohlo, 2013)

Ratio (%)	Industrials	Basic materials	Consumer services	Consumer goods	Telecoms	Health care	Technology	Oil&Gas
2002/12/31	63	41	31	44	49	30	15	42
2003/12/31	69	43	29	34	38	32	15	26
2004/12/31	61	63	36	33	26	43	13	29
2005/12/30	71	52	30	41	29	53	32	34
2006/12/29	85	45	29	38	37	194	14	31
2007/12/31	80	36	53	48	41	210	19	25
2008/12/31	78	37	40	61	42	278	18	21
2009/12/31	75	37	35	43	34	238	10	15
2010/12/31	70	32	32	54	31	228	17	13
2011/12/30	69	29	32	44	38	214	38	10
Average ratio	**72**	**42**	**35**	**44**	**37**	**152**	**19**	**25**

Figure 14: Debt-to-equity ratios by industry (Source: Mohohlo, 2013)

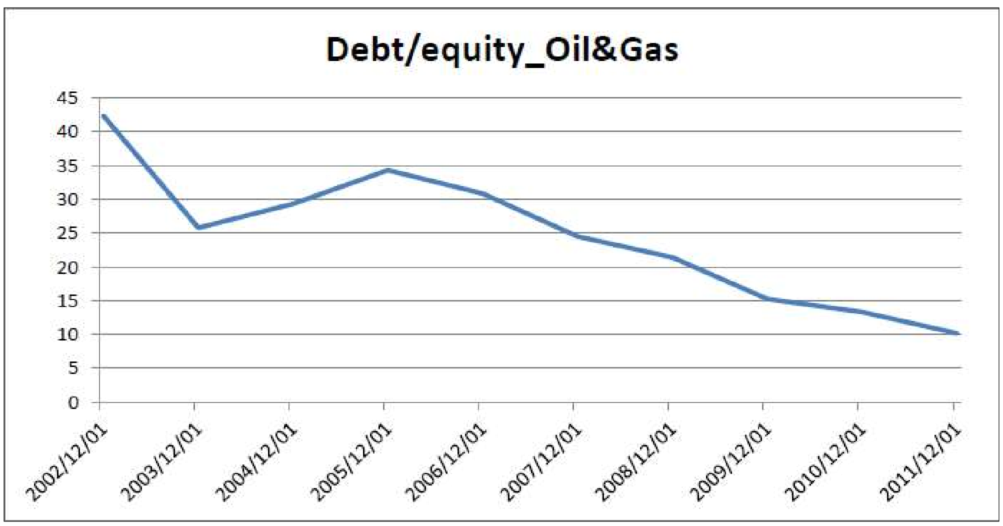

Figure 15: Debt-to-equity ratio OIL&GAS (Source: Mohohlo, 2013)

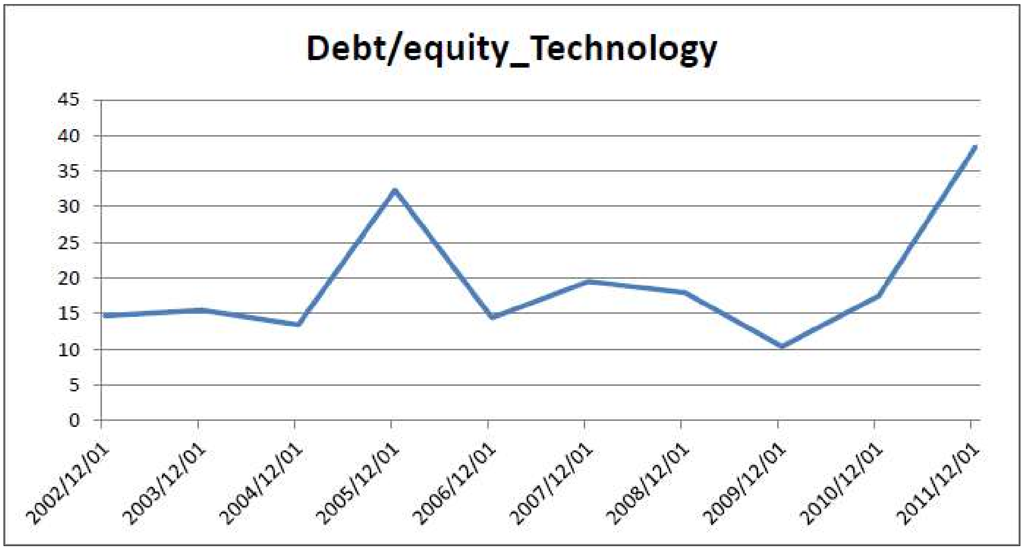

Figure 16: Debt-to-equity ratio Technology (Source: Mohohlo, 2013)

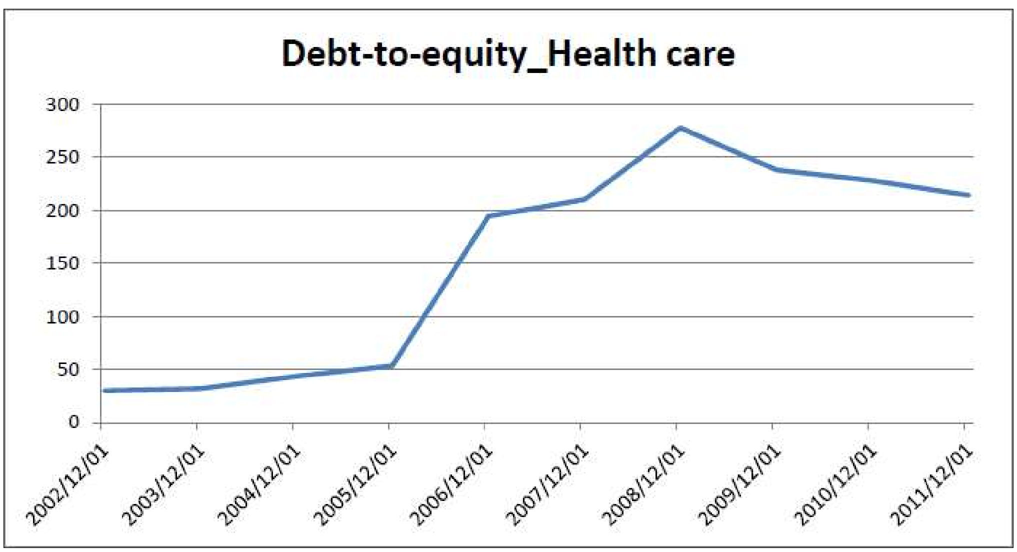

Figure 17: Debt-to-equity ratio Health Care (Source: Mohohlo, 2013)

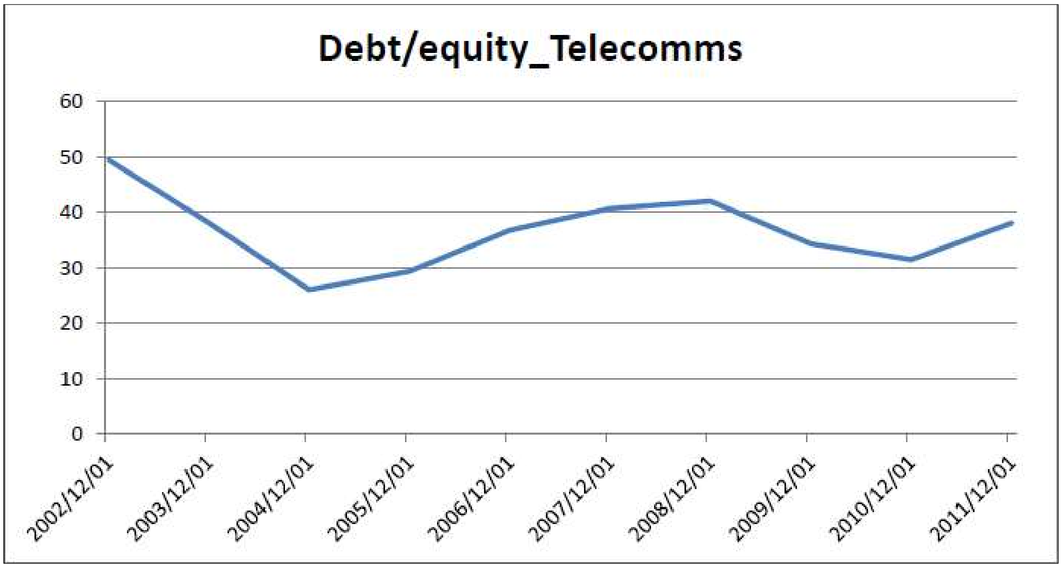

Figure 18: Debt-to-equity ratio Telecommunications (Source: Mohohlo, 2013)

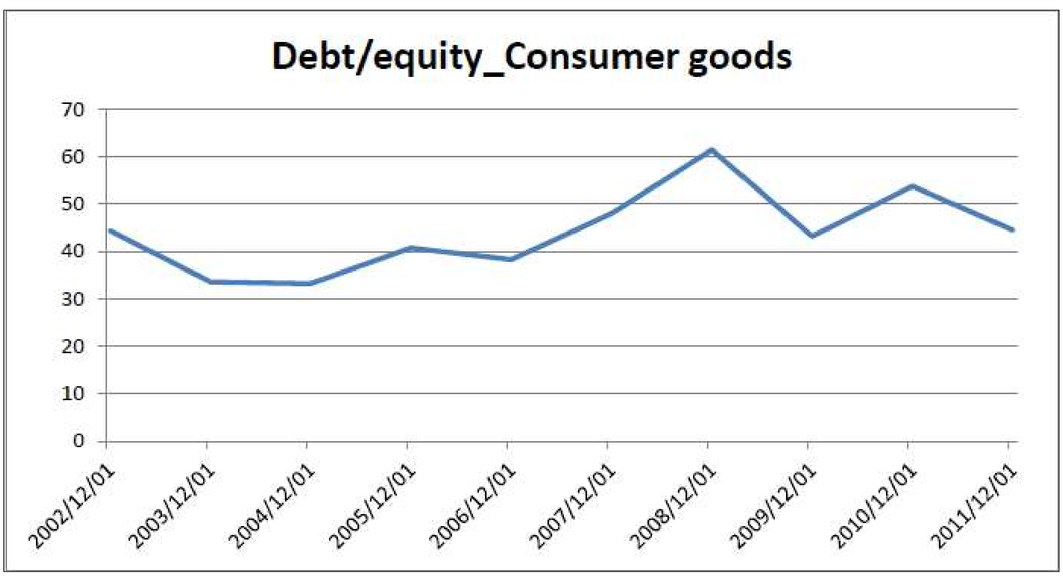

Figure 19: Debt-to-equity ratio Consumer Goods (Source: Mohohlo, 2013)

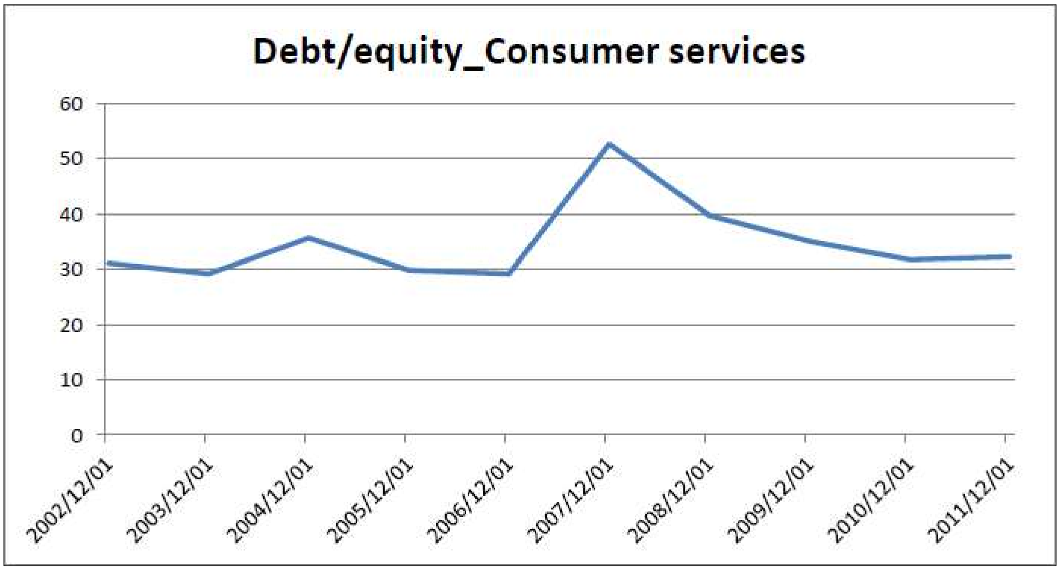

Figure 20: Debt-to-equity ratio Consumer Services (Source: Mohohlo, 2013)

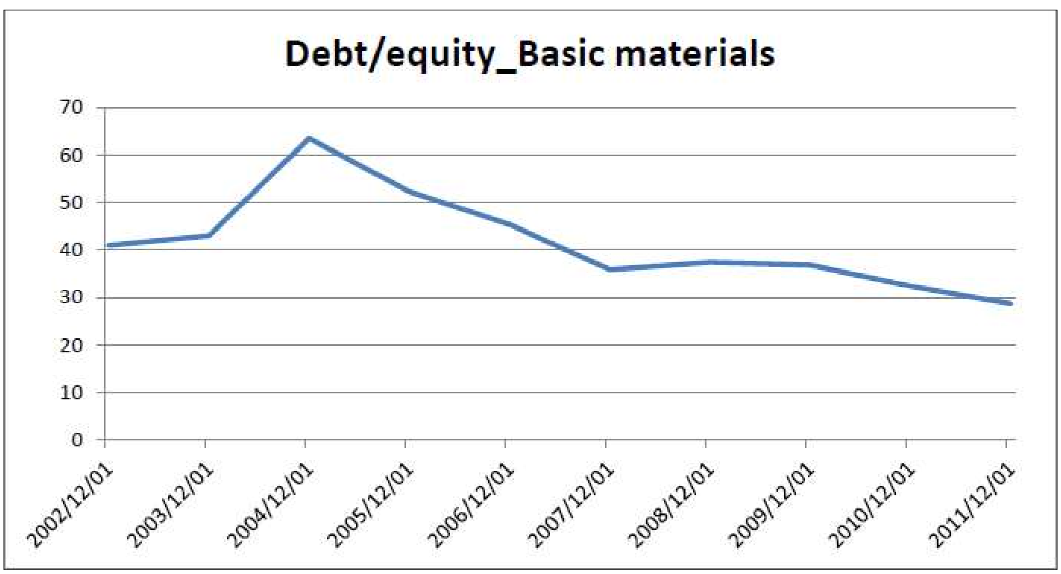

Figure 21: Debt-to-equity ratio Basic Materials (Source: Mohohlo, 2013)

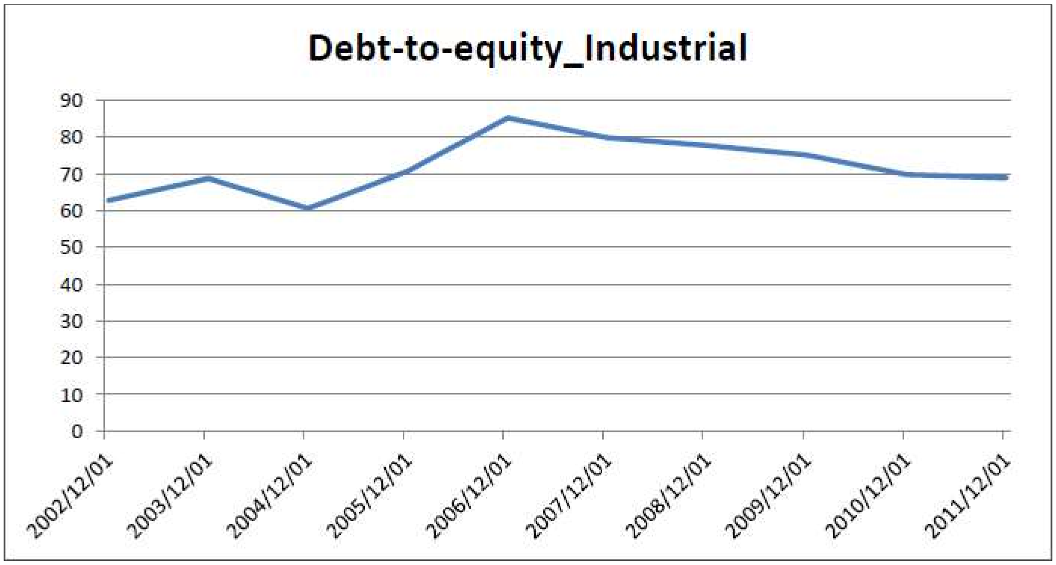

Figure 22: Debt-to-equity ratio Industrials (Source: Mohohlo, 2013)

Dependent Variable: D2E
Method: Panel Least Squares
Sample: 2002 2011
Periods included: 10
Cross-sections included: 65
Total panel (balanced) observations: 650

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	68.56153	6.892333	9.947508	0.0000
MCAP	-0.574213	0.492695	-1.165453	0.2443
ROA	-0.226823	0.101865	-2.226697	0.0264
TS	0.001885	0.015285	0.123351	0.9019
AT	-0.215968	0.087574	-2.466129	0.0139

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.544307	Mean dependent var	50.18922
Adjusted R-squared	0.490972	S.D. dependent var	70.97957
S.E. of regression	50.64120	Akaike info criterion	10.78749
Sum squared resid	1489993.	Schwarz criterion	11.26274
Log likelihood	-3436.936	Hannan-Quinn criter.	10.97183
F-statistic	10.20559	Durbin-Watson stat	0.910026
Prob(F-statistic)	0.000000		

Note: C stands for the common intercept, D2E stands for debt-to-equity ratio, MCAP stands for market capitalisation, ROA stands for return on asset, TS stands for tax shield ratio, AT stands for asset tangibility ratio, S.E stands for standard error, S.D is the standard deviation and F-statistic stands for Fischer statistic

Figure 23: FEM regression of all companies and industries - capital structure as dependent (Source: Mohohlo, 2013)

Dependent Variable: D2E
Method: Panel Least Squares
Sample: 2002 2011
Periods included: 10
Cross-sections included: 18
Total panel (balanced) observations: 180

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	63.52329	24.12477	2.633115	0.0093
MCAP	-1.005274	2.144806	-0.468702	0.6399
ROA	-1.737170	0.612976	-2.833994	0.0052
TS	0.004596	0.018565	0.247556	0.8048
AT	0.667979	0.501177	1.332820	0.1845

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.436653	Mean dependent var	67.15041
Adjusted R-squared	0.361777	S.D. dependent var	73.49036
S.E. of regression	58.71060	Akaike info criterion	11.09720
Sum squared resid	544615.6	Schwarz criterion	11.48745
Log likelihood	-976.7480	Hannan-Quinn criter.	11.25543
F-statistic	5.831731	Durbin-Watson stat	0.803002
Prob(F-statistic)	0.000000		

Note: C stands for the common intercept, D2E stands for debt-to-equity ratio, MCAP stands for market capitalisation, ROA stands for return on asset, TS stands for tax shield ratio, AT stands for asset tangibility ratio, S.E stands for standard error, S.D is the standard deviation and F-statistic stands for Fischer statistic

Figure 24: FEM regression of industrial companies - capital structure as dependent (Source: Mohohlo, 2013)

Dependent Variable: D2E
Method: Panel Least Squares
Sample: 2002 2011
Periods included: 10
Cross-sections included: 12
Total panel (balanced) observations: 120

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	38.19706	10.01638	3.813459	0.0002
MCAP	-0.569989	0.282368	-2.018605	0.0461
ROA	-0.018499	0.036035	-0.513364	0.6088
TS	0.046972	0.037455	1.254074	0.2126
AT	0.013184	0.119018	0.110771	0.9120

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.861123	Mean dependent var	35.95127
Adjusted R-squared	0.841093	S.D. dependent var	39.33392
S.E. of regression	15.67976	Akaike info criterion	8.466184
Sum squared resid	25568.90	Schwarz criterion	8.837850
Log likelihood	-491.9710	Hannan-Quinn criter.	8.617119
F-statistic	42.99090	Durbin-Watson stat	1.287387
Prob(F-statistic)	0.000000		

Note: C stands for the common intercept, D2E stands for debt-to-equity ratio, MCAP stands for market capitalisation, ROA stands for return on asset, TS stands for tax shield ratio, AT stands for asset tangibility ratio, S.E stands for standard error, S.D is the standard deviation and F-statistic stands for Fischer statistic

Figure 25: FEM regression of basic materials companies - capital structure as dependent (Source: Mohohlo, 2013)

Dependent Variable: D2E
Method: Panel Least Squares
Sample: 2002 2011
Periods included: 10
Cross-sections included: 17
Total panel (balanced) observations: 170

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-48.62539	28.44569	-1.709412	0.0895
MCAP	1.598333	1.507378	1.060340	0.2907
ROA	-1.737781	0.502196	-3.460362	0.0007
TS	0.425092	0.125283	3.393055	0.0009
AT	1.825408	0.528354	3.454899	0.0007

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.596871	Mean dependent var	35.50554
Adjusted R-squared	0.542760	S.D. dependent var	61.29674
S.E. of regression	41.44858	Akaike info criterion	10.40199
Sum squared resid	255979.8	Schwarz criterion	10.78935
Log likelihood	-863.1693	Hannan-Quinn criter.	10.55918
F-statistic	11.03043	Durbin-Watson stat	1.519763
Prob(F-statistic)	0.000000		

Note: C stands for the common intercept, D2E stands for debt-to-equity ratio, MCAP stands for market capitalisation, ROA stands for return on asset, TS stands for tax shield ratio, AT stands for asset tangibility ratio, S.E stands for standard error, S.D is the standard deviation and F-statistic stands for Fischer statistic

Figure 26: FEM regression of consumer services companies - capital structure as dependent (Source: Mohohlo, 2013)

Dependent Variable: D2E
Method: Panel Least Squares
Sample: 2002 2011
Periods included: 10
Cross-sections included: 11
Total panel (balanced) observations: 110

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	88.72528	30.11890	2.945834	0.0041
MCAP	-0.068998	1.536023	-0.044920	0.9643
ROA	-1.092647	0.657300	-1.662327	0.0997
TS	-0.019803	0.054726	-0.361864	0.7183
AT	-0.615712	0.463234	-1.329160	0.1870

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.665984	Mean dependent var	44.08492
Adjusted R-squared	0.616760	S.D. dependent var	54.74102
S.E. of regression	33.88818	Akaike info criterion	10.01013
Sum squared resid	109098.9	Schwarz criterion	10.37838
Log likelihood	-535.5574	Hannan-Quinn criter.	10.15950
F-statistic	13.52979	Durbin-Watson stat	0.820708
Prob(F-statistic)	0.000000		

Note: C stands for the common intercept, D2E stands for debt-to-equity ratio, MCAP stands for market capitalisation, ROA stands for return on asset, TS stands for tax shield ratio, AT stands for asset tangibility ratio, S.E stands for standard error, S.D is the standard deviation and F-statistic stands for Fischer statistic

Figure 27: FEM regression of consumer goods companies - capital structure as dependent (Source: Mohohlo, 2013)

Dependent Variable: D2E
Method: Panel Least Squares
Sample: 2002 2011
Periods included: 10
Cross-sections included: 3
Total panel (balanced) observations: 30

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	453.6803	75.11458	6.039844	0.0000
MCAP	-1.858029	1.808227	-1.027542	0.3149
ROA	-21.77118	2.966142	-7.339898	0.0000
TS	-1.099116	0.631393	-1.740779	0.0951
AT	0.026219	0.148385	0.176698	0.8613

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.812315	Mean dependent var	152.0290
Adjusted R-squared	0.763354	S.D. dependent var	153.5209
S.E. of regression	74.68219	Akaike info criterion	11.66532
Sum squared resid	128280.9	Schwarz criterion	11.99227
Log likelihood	-167.9799	Hannan-Quinn criter.	11.76992
F-statistic	16.59100	Durbin-Watson stat	2.036564
Prob(F-statistic)	0.000000		

Note: C stands for the common intercept, D2E stands for debt-to-equity ratio, MCAP stands for market capitalisation, ROA stands for return on asset, TS stands for tax shield ratio, AT stands for asset tangibility ratio, S.E stands for standard error, S.D is the standard deviation and F-statistic stands for Fischer statistic

Figure 28: FEM regression of health care companies - capital structure as dependent (Source: Mohohlo, 2013)

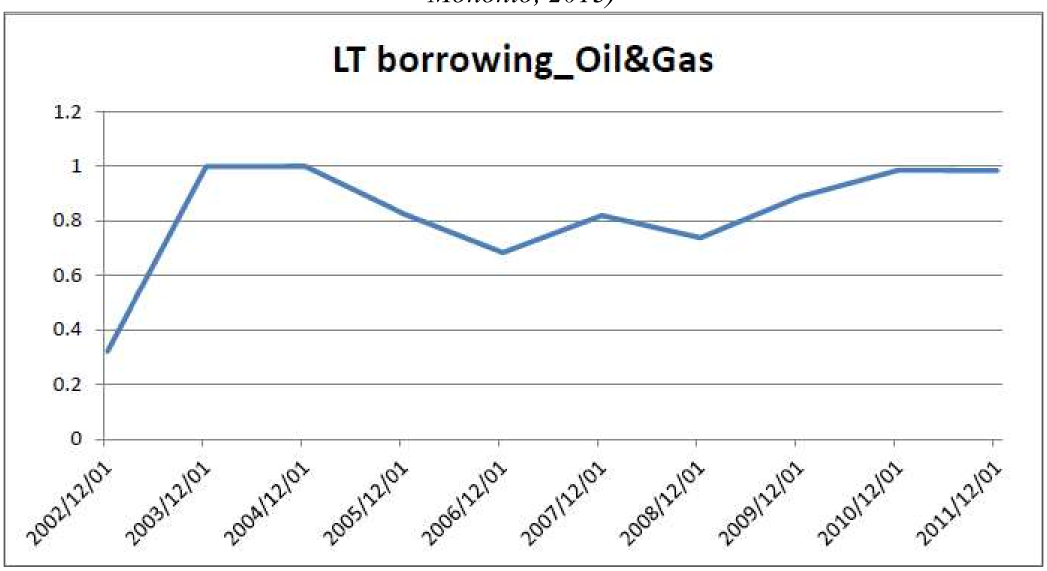

Figure 29: Long-term borrowing Oil&Gas (Source: Mohohlo, 2013)

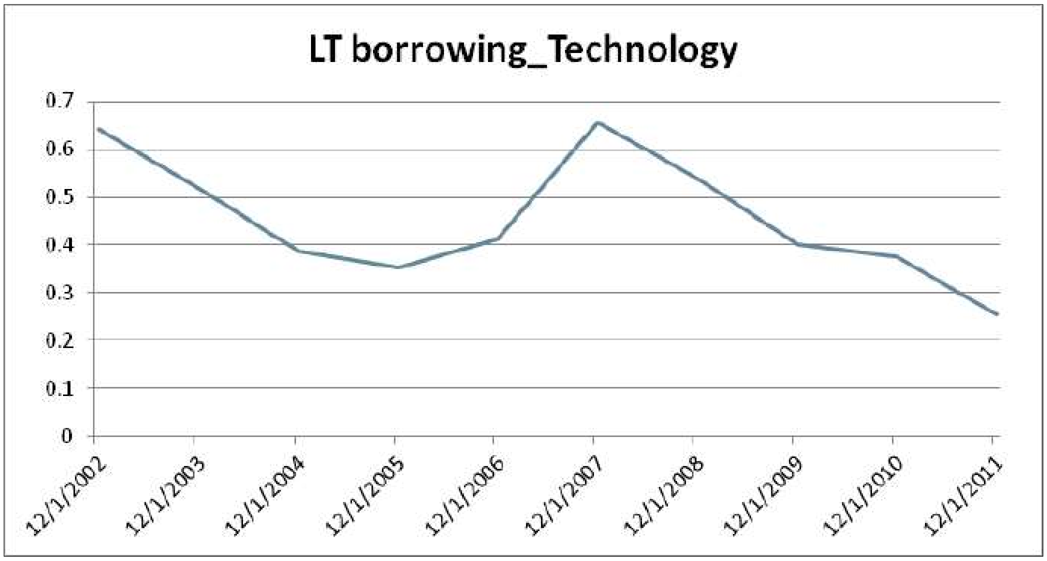

Figure 30: Long-term borrowing Technology (Source: Mohohlo, 2013)

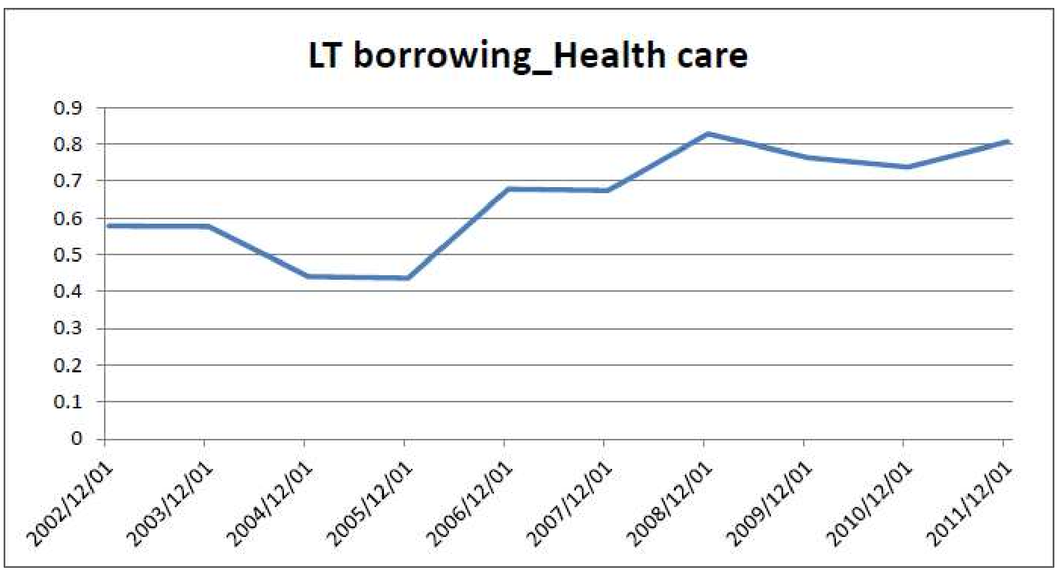

Figure 31: Long-term borrowing Health Care (Source: Mohohlo, 2013)

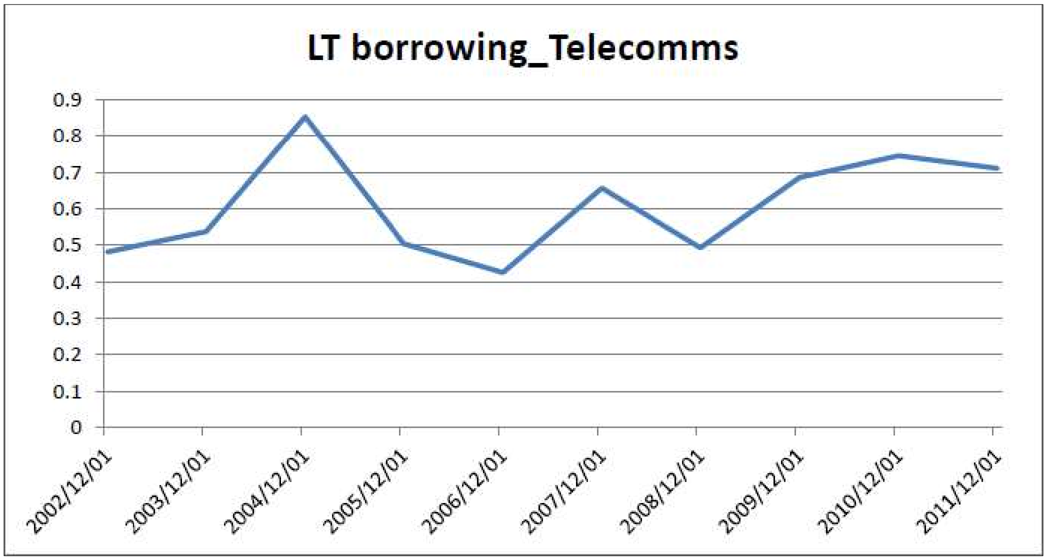

Figure 32: Long-term borrowing Telecommunications (Source: Mohohlo, 2013)

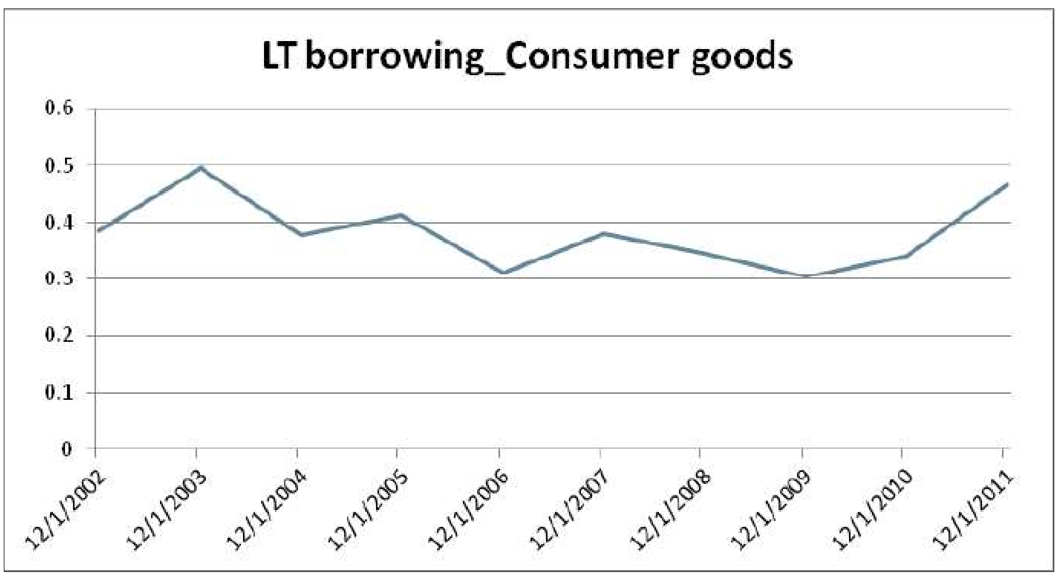

Figure 33: Long-term borrowing Consumer Goods (Source: Mohohlo, 2013)

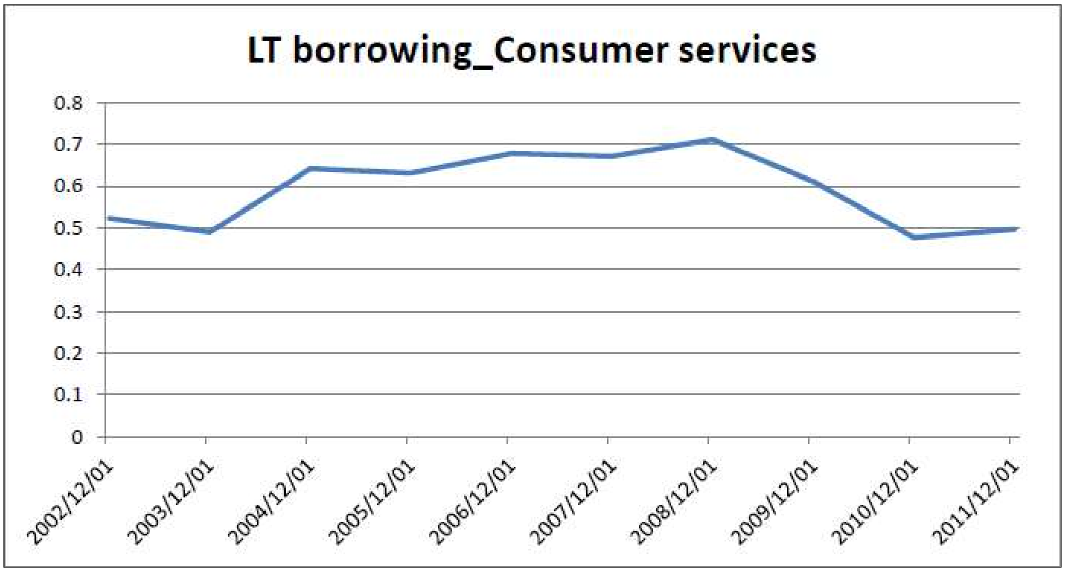

Figure 34: Long-term borrowing Consumer Services (Source: Mohohlo, 2013)

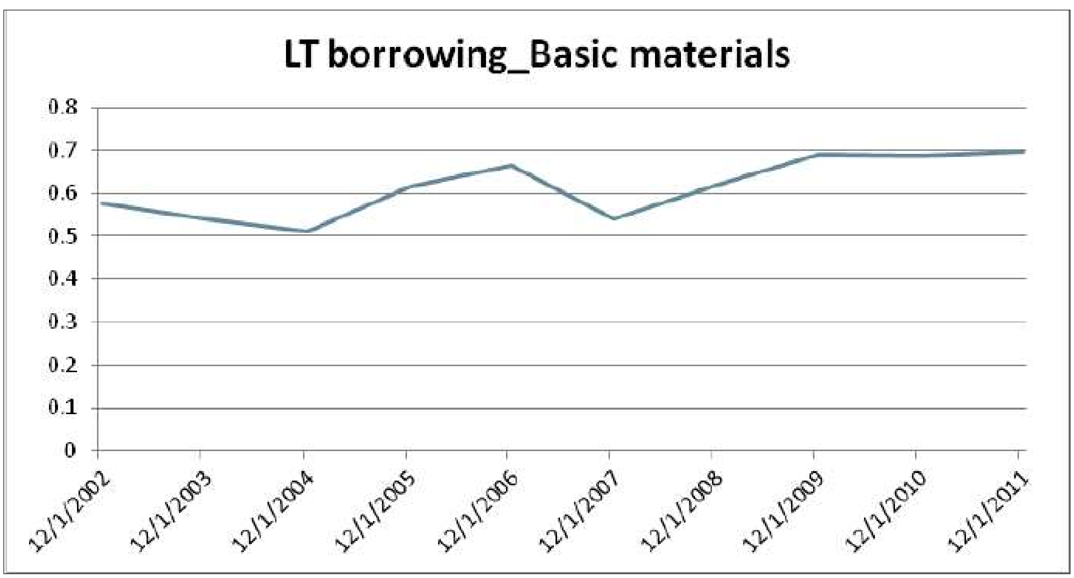

Figure 35: Long-term borrowing Basic Materials (Source: Mohohlo, 2013)

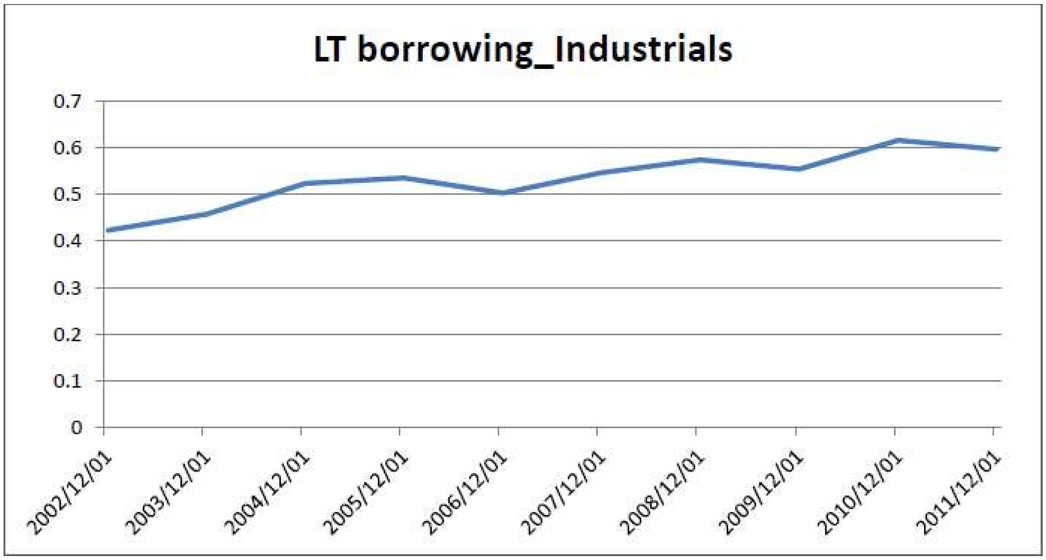

Figure 36: Long-term borrowing Industrial (Source: Mohohlo, 2013)

Chapter 4

Enterprise Risk Management Analysis with Suggestions for Improvements for the Selected Company [4]

Gomes, Cristopher and Freitas, Daniel

Abstract

Organizations face uncertainty while making business in different countries, leaving an open door to unanticipated or negative variation that can affect outcome variables. Therefore, one important task of managers is to manage risk the best way possible, because if managed efficiently, it can become a competitive advantage for the company. For example, companies may gain power enough to intimidate, allocate more diversity and reduce risk management costs better than competition. To help, Enterprise Risk Management can be used in the company. It is a process which enables the identification and assessment of risks that might impact the company, incorporating the following steps: risk identification, risk assessment and risk response. In the Slovene subsidiary of the selected company, the predefined assessment criteria was built for qualitative risk assessment. But, apart from being a uniform rule for risk assessment, the senior management team was having difficulties using it and getting into consensus with other teams. The objective of the ERM improvement process was to increase the abilities of the senior management team in the identification and assessment of risks, but since the risk managing process and risk mitigation planning was already part of the regular activity of the organization, the improved ERM looked more like a documented process and a unattractive area (Ferkolj, 2010).

Keywords: Risk, Enterprise Risk Management, Monte Carlo simulation

[4]This paper is based on Ferkolj, A. (2010). Enterprise risk management analysis with suggestions for improvements for the selected company (Master's thesis). University of Ljubljana.

1. Introduction

Nowadays, the enterprise world is found in a process of globalization, connected to a complexity of interrelationships between firms that can be linked to risks that are specific to multinational firms (Ferkolj, 2010). They, however, should not be managed individually. Instead, and because of its impact, they should be managed having into account the total organization, needing, for this, to have practical ways to deal with risks, instead of just statistical and analytical ways, like drawing future scenarios and planning (Jolly, 2003). For this task, companies can use Enterprise Risk Management (ERM), that lets companies elaborate a comprehensive view of risk and risk management, processing it in a holistic manner and analysing the correlation between them (Ferkolj, 2010). It is essential that companies do that, because, if well managed, risks can become a competitive advantage for the company (Davenport & Bradley, 2000).

Meanwhile, Ferkolj was nominated as Risk advisor for the Slovene subsidiary of a multinational company, that made non-alcoholic beverages, with the task to improve the ERM process. Therefore, Ferkolj searched for to encourage managers to adopt an integrated risk management approach and elevate risk to the senior management team, by pushing them to the participation in risk identification and assessment. The objectives of the research made by Ferkolj were the introduction of ERM, the definition of the current situation of it in the company and the proposal of ways for the selected company to improve the ERM process used (Ferkolj, 2010).

The article begins with an overview of the relevant literature and theoretical findings of ERM, accompanied with the main difficulties that companies face when implementing it. Subsequently, a review of the ERM implementation and performance in the selected company is made, using the initial targets as a basis. In the end, it is proposed suggestions for improvements in the selected company (Ferkolj, 2010).

2. Literature review

Risk management is constantly evolving. Risk deals with uncertainty, having them negative or positive impacts. Despite that, risk is treated differently depending on the area that it is serving (Ferkolj, 2010). For example, strategic management uses risk in relation to unforeseen or negative variations in the business earning variables (March & Shapira, 1987). In another hand, finance refers to risk as the likelihood that a return on an investment will deviate from its expected value, which is usually calculated using the standard deviation (Clark & Marois, 1996).

Operating internationally lets the organizations reach new markets. The technology tends to be used even more and making internal business just gets easier by time (Czinkota, Ronkainen, & Moffett, 2005). Some markets have become deregulated with the reductions of barriers of trade, creating multiple opportunities for trading (Brooks, Weatherston, &

Wilkinson, 2004). When an organization creates a subsidiary, they transfer their own resources to the unit, but that doesn't grant full control of it. Some important decisions are generally made by the subsidiaries, being them an essential piece on the company structure (Hilmi, Ihsen, & Safa, 2007).

Overall, the risks that multinational companies may face can be divided in three major risk categories: country-specific risk, firm-specific risk and systematic risk (Ferkolj, 2010).

The first, country-specific risk, refers to the volatility of international trade returns caused by country-specific events, associated to economic, financial, currency or political risk, being them all interactive, meaning that changes in one of them affects the others (Clark & Marois, 1996; Ferkolj, 2010). First, economic risk refers to the volatility of macroeconomic performance (Clark & Marois, 1996). Secondly, financial risk concerns to the volatility related to the ability of a country economy to generate sufficient foreign exchange to be able to pay payments of foreign debt (Ferkolj, 2010). Thirdly, currency risk points to the volatility of the exchange rates and its consequences on the output and consumption of a country (Clark & Marois, 1996). And lastly but not least, political risk relates to the volatility of the preferences of political leaders, parties and factions, and their ability to execute policies when facing internal and external challenges (PricewaterhouseCoopers & Eurasia Group, 2006).

The second, firm-specific risk, refers to risks associated with operating uncertainties, which include labour, input supply and production uncertainties; liability uncertainties, that relates to product liability and emission of pollutants; research and development uncertainties, like the uncertain from their activities; credit uncertainties, such as problems with collectibles; and behavioural uncertainties, referring to the managerial or employee self-interested behaviour (Miller, 1992).

And the last, systematic risk, is the overall risk to which a multinational is exposed when operating in different markets. The more diversified a multinational company is, the less the returns of the company will be correlated with the market and its systemic risk may increase. It is also stated that additional foreign exchange risk and political risk can also increase the level of systematic risk (Ferkolj, 2010).

Enterprise Risk Management (ERM) enables a company to manage risk from all sources, focusing on a comprehensive view of risk and risk management, rather than managing them separately, in order to increase the value of the organization to the stakeholders (Casualty Actuarial Society, 2003; Ferkolj, 2010). All companies face uncertainty and management has to figure out how much of uncertainty to take on. The risks diversity must be treated holistically and in correlation between them (Ferkolj, 2010).

ERM involves the align of risk appetite and strategy, the enhance of risk-response decisions, the decrease of operational surprises and losses, the identification and management of multiple and cross-enterprise risks, the seize of opportunities and the better deploy of capital (Ferkolj, 2010).

Therefore, risk management should be the responsibility of senior managements, because, if companies understand their risks better than their competitors, the organizations stay in a good position to take on risks and gain a competitive advantage (Davenport & Bradley, 2000).

In this way, is probably better to manage risk than just transfer risk, like generally is done, either by insurance or other financial product (Ferkolj, 2010).

The risks, that can be hazard, financial, operational, and strategic, should be managed considering the following steps: establish context, identify risks, quantify risks, integrate risks, prioritize risks, exploit risks, and monitor and review (Casualty Actuarial Society, 2003). There are some techniques for identifying the various events that create risk that include review of prior internal audit reports, brainstorming or risk questionnaires (Ferkolj, 2010). Also, risks in the ERM can be presented through a cumulative probability in order to determine the incremental impact of alternative strategies or decisions (Casualty Actuarial Society, 2003).

The main relevant risk measures to determine volatility around expected results are the variance, the standard deviation, the semi variance and downside standard deviation, and the below target risk (Ferkolj, 2010).

The measure of risk that focus on the adverse tail of the probability distribution is Value at Risk. It only takes into consideration the negative deviations from expected results and has three elements: a high level of confidence, a period of time and an estimate of the loss of an investment. There is also three methods for calculating it: the historical method, which reorganizes historical returns; the variance-covariance method, that says that stock returns are normally distributed; and the Monte Carlo simulation method, which runs several hypothetical alternatives (Harper, 2004).

The risk model points to the models and methods used to evaluate risk and performance measures (DecisionCraft, 2005). The main ones used are structural financial models and probabilistic risk models. Structural financial models describe the expected outcomes of a given set of inputs in a deterministic way, being the method that is usually used by companies. Probabilistic risk models include probabilities of results that are above or below the expected values, prevailing two main classes: analytical risk models and simulation models (Ferkolj, 2010).

Analytical risk models require a series of restrictive assumptions and mathematical tractable probability distributions (Ferkolj, 2010). They are fast, replicable and can use publicly available data (Casualty Actuarial Society, 2003). Simulation models (or Monte Carlo models) require a large number of computer-generated trials to approximate a response (Ferkolj, 2010). It is flexible and allows the review of scenario drivers (Casualty Actuarial Society, 2003).

There are some ERM frameworks already created and used on business environment which includes the Association of Insurance and Risk Managers, The National Forum for Risk Management in the Public Sector and The Committee of Sponsoring Organizations of the Treadway Commission's. The last one referred is the most commonly used (Ferkolj, 2010). It sets the key components, proposes a common language and guides ERM clearly. It also sets the objectives of an entity in four categories: strategic, operations, reporting and compliance, and considers the activities division, business and subsidiary levels. A relation between ERM components, objectives and entities levels is described in a three-dimensional matrix, like the one presented in Figure 1. With it is possible to focus on the company ERM at its fullness or by category, component, entity unit or another subset (COSO, 2004).

If the ERM implementation is going to be successful, it is important that the Board directs the implementation, with internal auditors having a key role in training the Board members about risk and control (Ferkolj, 2010). All members on an enterprise must also be responsible for managing certain risk factors (Schanfield & Helming, 2008). When the ERM is implemented, a risk glossary should be made to make sure that risk definitions are understood by all members of an organization, in order to standardize interpretations and save time (Ferkolj, 2010).

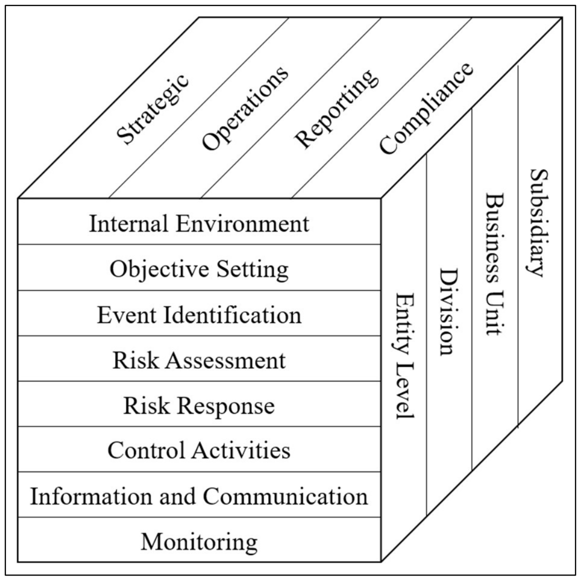

Figure 1. COSO ERM Framework. Adapted from Enterprise Risk Management — Integrated Framework (p. 5), by The Committee of Sponsoring Organizations of the Treadway Commission, 2004.

The Sarbanes-Oxley Act introduced strict new rules in order to protect investors by increasing the accuracy of information provided by organization in accordance with the securities laws (Sarbanes-Oxley, 2002). The adoption of these rules are sufficient for an ERM implementation, but, despite that, Sarbanes-Oxley centres attentions to the control of transactions, while ERM has its focus on risks associated with events, needing, this way, an evaluation of the last ones if it is wanted a facilitation of the Sarbanes-Oxley effort (Ferkolj, 2010).

3. Methodology

The selected company in analysis had a license to produce, sell and distribute some non-alcoholic beverages. It started its activities in 2000 and had as main shareholders Kar-Tess Holding S.A. and The Coca-Cola Company. Most of the beverages are The Coca-Cola Company trademarks, being the last one who gives the concentrates and does the marketing.

The company was located in Athens, had operations in 28 countries and employed more than 44,000 workers in 2009. Net revenues were 6,544 million euros, in that year, and earnings before interest and taxes (EBIT) summed 651 million euros (Ferkolj, 2010).

The Operating Committee was the executive management group of the company and had various functions, which included the development of the strategy of the group; the approval of the annual objectives for each country and for each corporate function; the demand and the acceptance of the strategic business plan; the evaluation of the operating performance of countries and corporate functions, and the establishment of corrective actions; and the implementation of better practices from other organizations and industries. Apart from these roles, it was also designated to manage the most important staff and processes. Every function had a country-level and a group-level structure, that allowed functional operations to be as near possible to the customer and enabled the company to achieve significant scale benefits in areas like procurement savings, knowledge sharing, investment planning and operations practices (Ferkolj, 2010).

The corporate finance office was tasked for overall risk management that included protecting the company's assets to minimize the financial loss risk and evolve risk management capacities in order to improve the decision making. The Risk and Insurance department and the Treasury department of the corporate finance office worked principally with the risk dealing (Ferkolj, 2010).

The corporate risk and insurance department handled three main areas which were the group insurance and risk financing, property loss prevention and integrated risk management. Group insurance and risk financing purposes were the protection of the company against insurable risk, using tools like insurance protection or self-funding arrangements; the make of cost-effective global insurance policies for the company where it could be made; the formation of cost-effective local protection in regions where was not possible through global insurance; and the management of efficient and effective insurance relationships with the global and local insurers. The insurances needed to protect the company from events like property damage, product recall, terrorism, director and officer liability, personal accident and travel, special contingency and crime (Ferkolj, 2010).

Property loss prevention (PLP) handled the development of a culture of loss prevention, since it was an important aspect of business decisions; the guarantee that the assets of the company had protection, with the help of PLP guidelines; the evaluation of the exposure of the manufacturing places, also with the use of PLP guidelines and other standards; the actions to minimise emerging risks, by looking for the threats and doing advices to improve the risk; the monitoring of risk improvement and risk quality; and the supply of guidance and train in PLP for all levels of the company (Ferkolj, 2010).

Integrated risk management was a recognized need in the company, so the subsidiaries had to manage the best way they could the risk than emerged from their business activities. In the case of this company, the implementation process started in 2005, but it was insufficient, since it considered principally financial sources of risk. So, in 2009, the corporate Risk and Insurance Department started a project with the goal of increase the involvement of subsidiaries in risk assessment, having each one to nominate a Risk advisor who was given the responsibility for the ERM implementation on them. In the Slovene subsidiary, that task was given to Ferkolj (Ferkolj, 2010).

In relation to the Treasury Department, there was a commitment from the Board of Directors of the company that the organization had to own a good system for financial control. For this, the Board defined a Chart of Authority for the company, setting financial and other authorisation limits, and defining procedures for the approval of capital and investment expense. It also approved strategic and financial plans, and annual budgets with the duration of three years. After that, and at every month, it evaluated if the goals were being reached. The objective of these actions was to ensure the earning stream and the management of the cash flows. In this case, the treasury function was to control the financial risk following the policies approved by the Board of the company. The treasury policy and the Chart of Authority provided the framework to manage all the tasks related to the treasury. The treasury policies also included the hedging transactional exposures, to decrease risk and volatility; and an investment policy to reduce counterparty risks and guarantee a good return of excess cash positions (Ferkolj, 2010).

In what concerns the interest rate risk management, it was used mainly interest rates swaps and options. In relation to the foreign risk management, it was crucial for the company to keep attention to it, since this type of exposure could emerge from unexpected changes in exchange rates. Exposures of this type could bring some problems like the followings: raw material acquired in foreign currency could make a higher cost of sales and consequentially reducing the margins of profit, devaluation of foreign currency in association to inflation could decrease sales; and operations done with foreign currencies could affect the company’s income statement and balance sheets. The Treasury department had a policy that enforced a hedging of forecast of transactional exposures during a year, with minimum coverage level of 25% and maximum of 80%. In the case that forecasted transactions were very probable, it could be hedged further than the established year period. Some ways that could be used for hedging the variation of market prices for raw materials were commodity futures, option contracts and supplier agreements, and could be used for a period of up to three years. The forecasted transaction exposures could be hedged with the use of currency forward and option contracts. For the exposures of transactions, they were only hedged if it was involved loans between companies or dividends transactions inside the group. For this case, it was commonly used forward contracts (Ferkolj, 2010).

4. Application

In 2005, the risk department began with risk assessment every year with every business plan, starting the implementation of the Enterprise Risk Management (ERM). The main objective of this framework was not only to reduce the company’s vulnerability to unexpected events but as well to provide the tools needed to management to make easier the identification of risks. ERM had two major objectives. The first one, was the compilation and maintenance of an updated risk portfolio of the company, and the second one, was the constant and replicable risks identification, management and escalation of the identified risks. These objectives should be achieved by a monthly risk review by the country senior management to check the progress of the risk exposure management, an escalation of significant operational risks together with progress on agreed management actions to the regional directory every quarter, and a two time yearly communication of cumulative regional risk exposure (Ferkolj, 2010).

Since the frequency of the ERM process was not enough, the company made efforts to improve it. So, subsidiaries needed to nominate a risk advisor which was responsible for the risk management process implementation. Ferkolj was trained to implement the ERM process in the Slovene subsidiary. By introducing the ERM concept to the senior management team, he assured that they participated frequently in the identification and assessment of risks. He was also responsible for the escalation of significant operational risks with the progress on agreed management actions (Ferkolj, 2010).

The ERM process in the selected company had three tasks: the risk identification, the risk assessment and the risk response. The risk identification was when the company defined the relevant risks that should be taken in consideration by the subsidiaries when identifying risks. These risks could be separated in five types which were people assets, product and market assets, infrastructure assets, information assets and finance assets. In Table 3 it is presented the risk types common on the subsidiaries (Ferkolj, 2010).

Table 1

Every occurrence that could difficult the enterprise to achieve its objectives was seen as risk. For this task, the risks were identified by brainstorming, interviews and analysation of historical data and, when they were agreed, then, they were put on the risk register (Ferkolj, 2010).

The risk register was a document created by the management team that was reviewed and adapted constantly, which made it the backbone of the risk management study. The goal of it was to register all the risks that might had impact on the business activity, to capture their qualitative assessment, and to write the detailed management information, like risks owner, response plans and management target dates. It used a methodology that was commonly used as the best way of dealing with risk management process, independently of industry or task (Ferkolj, 2010).

The risk assessment consists in getting the opinion from those who identified the risks that were found before. In order to access the qualitative risk, it was needed two main factors: the likelihood that the risk would occur and the consequences that it may had on the company if it happens. The probability scale was defined in the current business planning period. Then, the risks were assessed in terms of how likely they could occur within a certain timeframe. An exemplification of the assessment is shown in Table 1 (Ferkolj, 2010).

Table 1

Qualitative probability assessment of identified risks in the selected company

Probability of occurrence	Probability assessment
Highly unlikely (1-10%)	1
Remote (10-25%)	2
Possible (25-50%)	3
Probable (50-85%)	4
Highly probable (>85%)	5

Note. Adapted from "Enterprise risk management analysis with suggestions for improvements for the selected company," by A. Ferkolj, 2010, University of Ljubljana, Slovenia, p. 32.

Subsequently, an evolution of the impact that the risk could potentially have was made, by investigating the following impact categories: EBIT; company reputation; health, safety and environment; management effort; and quality. If the risk impacted more than two categories, then the two highest categories should have to be chosen. The criteria used for the impact assessment in every subsidiary is shown in Table 4 (Ferkolj, 2010).

Table 3

In Table 5, a description of the identified risk likelihood and the impact of those assessed, according to the assessment criteria defined in Table 4, is shown (Ferkolj, 2010).

Table 4

Once the risks were given a score, they were automatically ranked with the formula: probability score X (impact A score + impact B score) = total impact (Ferkolj, 2010).

The main reason to rank the risks was to focus the attention of management efforts onto those risks that showed greatest potential to have a negative impact (Ferkolj, 2010).

The top ranked risks in the Slovene subsidiary were direct sales distribution disruption, Slovene gross domestic product will be below the forecasted, increased competition by competitor Piovarna Lasko Group, plastic deposit, increased outstanding debts and people retention due to implementation of enterprise resource system SAP (Ferkolj, 2010).

The top 10 risks were shown on the heat map page which was part of the business register. The heat map had four colours, the dark red area, risks that had a high probability and high potential impact; the red area, risks that needed constant management effort; the amber area, risks that were worthy of regular review and consistent management update, and, finally, the green area, risks that needed to be evaluated constantly to see if they matched the resources that were being used. The critical risks needed to be quickly reported to the Risk director of the company. The heat map of the Slovene subsidiary is shown in Figure 2 (Ferkolj, 2010).

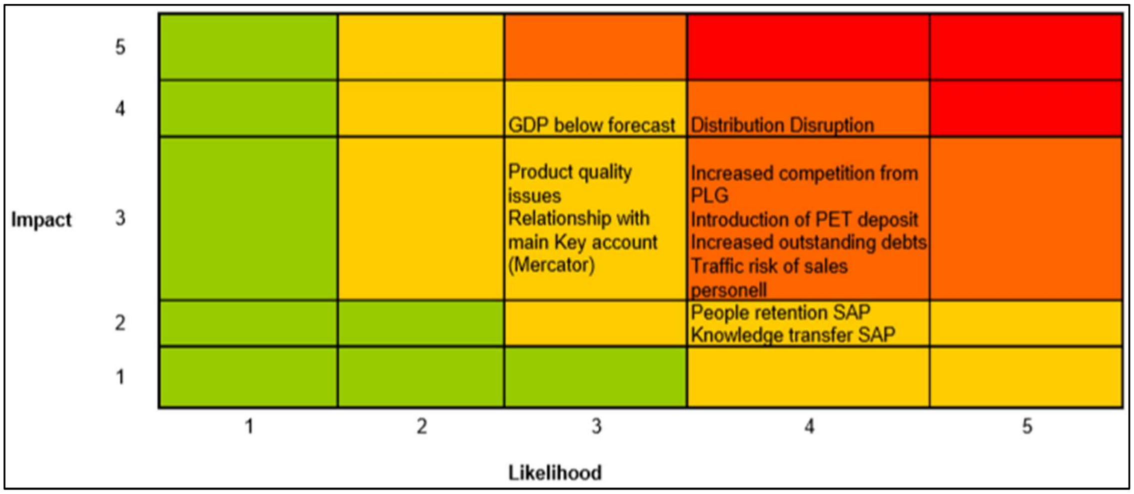

Figure 2. Top 10 risks heat map of the Slovene subsidiary of the selected company. Adapted from "Enterprise risk management analysis with suggestions for improvements for the selected company," by A. Ferkolj, 2010, University of Ljubljana, Slovenia, p. 36.

The last task of the ERM process was the risk response and consists in three options: decrease the likelihood of the risk happening, decrease the impact of it occurring and decrease simultaneously the likelihood and the impact of it. For every risk identified, it was designated a person that became responsible to deliver the risk response plans in time. The risk response plans for the Slovene subsidiary are listed in Table 6 (Ferkolj, 2010).

Table 5

In order to quantify the risks, it was made a quantitative risk analysis by using empirical data or by quantifying qualitative assessments. The Monte Carlo simulation was one way of quantifying risks by representing the uncertainties inputs with values obtained with probabilities distribution. This way, it was possible to give a value associated to a certain probability. The probability distributions most used are normal, lognormal, uniform, triangular, PERT and discrete. In this company, only PERT distribution was used (Ferkolj, 2010). With the Monte Carlo simulation, inputs probability distributions are iterated, and the outcomes are registered. This simulation is made thousands of times which make possible to obtain a comprehensive view of what is possible to occur (Palisade, 2010).

The advantage of using the Monte Carlo simulation are the probabilistic results, graphical results, sensitivity analysis, scenario analysis and correlation of inputs that it can provide (Ferkolj, 2010).

The company in study had a @Risk Software to run Monte Carlo simulation. To run this software, it was needed to set up a risk model and run a risk simulation. To set up a risk model it was needed data like risk likelihood in percentage; minimum; maximum; if possible, most likely cost of risk; and probability distribution of the risk. In Table 7 it is exhibited the risk model of the Slovene subsidiary (Ferkolj, 2010).

Table 6

Then, the software put together all the outcomes reached in a graph known as cumulative probability curve or “S” curve, that can be seen in Figure 3 (Ferkolj, 2010).

From the curve was possible to extract different percentiles like the percentile 5 (P5) which had the result of 862 thousand euros, the P25 had 872 thousand euros, the P75 had 1,150 thousand euros and the P95 had 1,651 thousand euros. This way was possible to know the maximum cumulative impact of risks. In this case, there was a 95% probability of the cumulative impact not being higher than 528,404 euros. On another hand, there was a 5% probability that the cumulative impact would not be higher than 42,003 euros. With this, it was possible to conclude that there was a 90% likelihood that the cumulative costs would be between 42,003 euros and 528,404 euros (Ferkolj, 2010).

Apart from the cumulative probability curve, there was another important output from the risk simulation, the sensitivity analysis, which told what risks influenced the most according to their impact on the cumulative risk. The risk model sensitivity analysis can be checked in Figure 4 (Ferkolj, 2010).

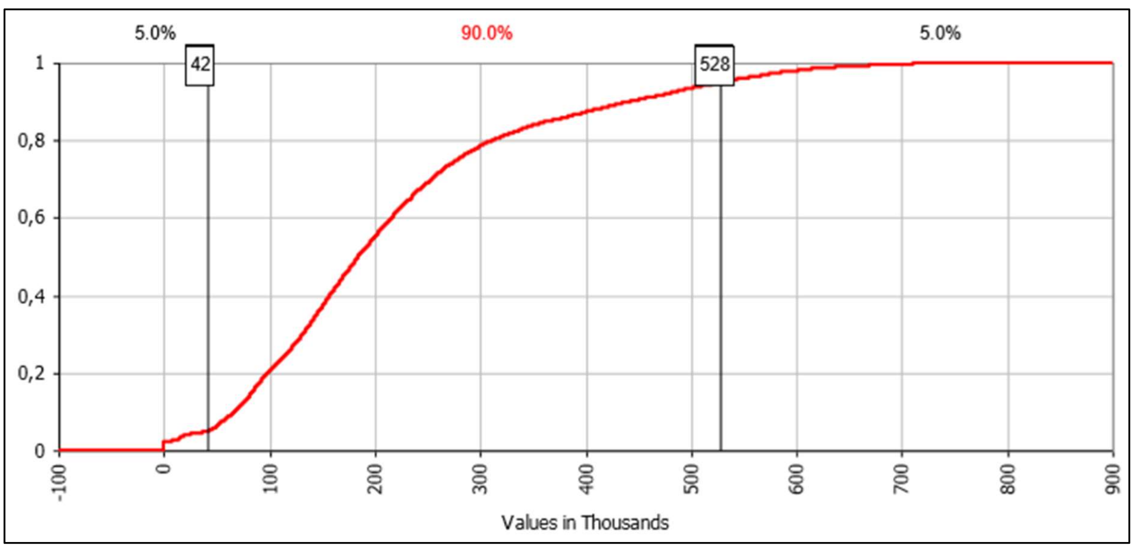

Figure 3. S Probability Curve for the Slovene subsidiary of the selected company according to the risk review in March 2010. Adapted from “Enterprise risk management analysis with suggestions for improvements for the selected company,” by A. Ferkolj, 2010, University of Ljubljana, Slovenia, p. 41.

With the graph presented in Figure 4, it was possible to check that the identified risk number 2 had the most impact to the selected company, by having a regression coefficient of

0.78. Then followed the risk 1 with 0.29, and risk 11 with 0.26. This type of information organization was beneficial for the company since it enabled the enterprise to provide the most resources to the risks with more impact, reducing the company overall risk exposure (Ferkolj, 2010).

In the past, the company was reporting the risk fragmentedly, or in other words, the risks were being reported separately to the Board of the organization. The most important risks were being administrated from various departments and, therefore, having pour communication and cooperation, putting the senior management of the subsidiary on a difficult situation, since it was unable to know the risk environment in a holistic manner (Ferkolj, 2010).

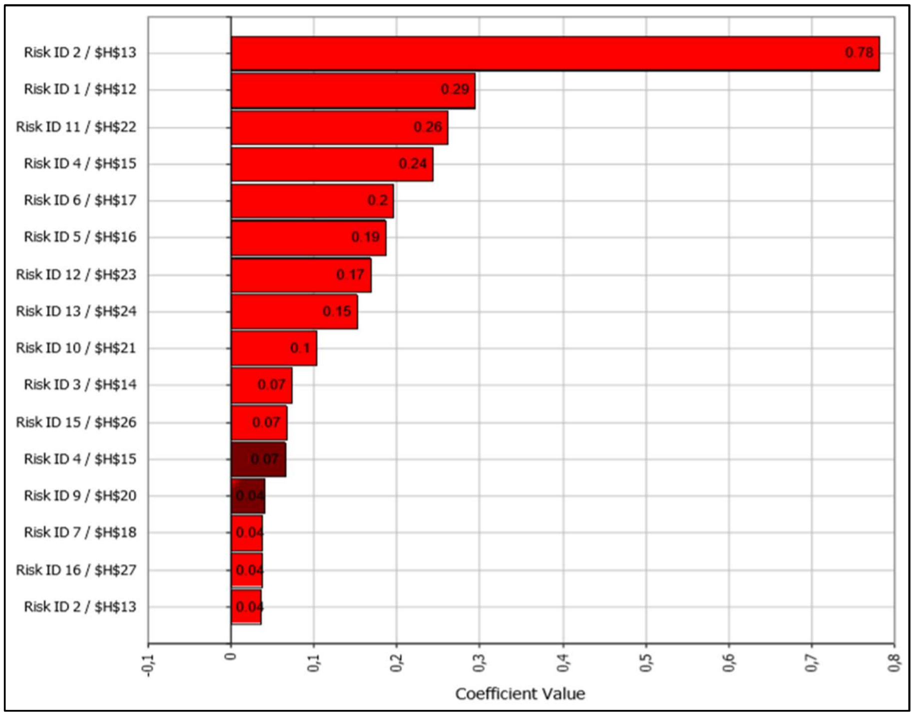

Figure 4. Risk Model Sensitivity analysis for the Slovene subsidiary of the selected company according to the risk review in March 2010. Adapted from "Enterprise risk management analysis with suggestions for improvements for the selected company," by A. Ferkolj, 2010, University of Ljubljana, Slovenia, p. 43.

In order to see risks in a holistic perspective, the organization had to overcome some obstacles, but to be successful, it was required a leadership. In the company case, it was initiated in 2009 by the Risk Department, which the major objective was to increase the paper that the senior management team had in risk assessment. To help this task, there were nominated risk advisers, whose job was to improve the senior management team in risk assessment in the subsidiaries (Ferkolj, 2010).

Ferkolj, being the one responsible for the ERM process in the Slovene subsidiary, had encountered no obstacles improving the senior management team in risk assessment on March

2010. On that period, Ferkolj introduced the principal changes that had to be done about the risk management process in order to obtain a comprehensive view of risks. This work was benefited by a good starting point of the ERM process that included a clear ERM glossary, in order to make sure that everyone in the company understood the risk definitions (Ferkolj, 2010).

The risks identified by the group were useful on the Slovene subsidiary to identify risks and let the senior management team to focus broadly, not only on financial sources of risk (Ferkolj, 2010).

The predefined assessment criteria brought an advantage by helping the group assessing risks faster in a uniform way, but sometimes the senior management team suffered difficulties. To make a qualitative risk assessment there would have to be chosen two of five impact categories: EBIT; company reputation; health, safety and environment; management effort; and quality. However, sometimes it was difficult to get a consensus, either because it was difficult to know which two had the more impact, or either because certain risks could link to more than two categories (Ferkolj, 2010).

Risk response plans were useful, because this way the senior management team could quickly define a risk response plan, a person responsible for the risk and a due date to disseminate the risk. Ferkolj also noted that the managers of the company were already aware of the risks identified during the ERM process and the risk response were already part of the regular activities of the company (Ferkolj, 2010).

The response plan for the risk that had more impact, the distribution disruption, was efficiently carried out. With this response, it was able to reduce significantly the risk and decrease cumulative risk exposure. For example, the P95 of the risk in question was in March 2010 584,000 euros and in June 2010, the same P95, was 456,796 euros, proving the effective reduction of this risk. The comparison of percentiles for the cumulative impact of the risks identified is shown in Table 2 (Ferkolj, 2010).

Table 2

Comparison of percentiles for the cumulative impact of identified risks for the Slovene subsidiary of the selected company according to the risk reviews in March and June 2010

	March 2010	June 2010
P05	42,003 €	0 €
P25	116,452 €	59,076 €
P50	184,225 €	116,426 €
P75	278,097 €	199,356 €
P95	528,404 €	456,796 €

Note. Adapted from “Enterprise risk management analysis with suggestions for improvements for the selected company,” by A. Ferkolj, 2010, University of Ljubljana, Slovenia, p. 45.

Apart from this effective plan, it required from the senior management team the quantification of risks which, even with the efforts of Ferkolj, remained an unattractive area. Overall, the team were more interested in the risk response plans (Ferkolj, 2010).

The risk model used for risk quantification in the company only required the cumulative probability and costs of the identified risks. Apart from not being possible to get the likelihood of different outcomes, the @Risk software computed the risk based on the probability of different possible outcomes. In this model, PERT was the only distribution used (Ferkolj, 2010).

With the time, the cooperation of the senior management team in risk assessment got worse in every review made. In the first one, the senior management team identified 16 risks, and, in the following ones, they didn't identify any additional ones. Also, in the first one, the senior management team had an active participation in risk assessment, and, in the next ones, the team only adjusted their initial assessments (Ferkolj, 2010).

In Table 8, it is shown comparisons between the likelihood and the most likely costs of identified risks according to the risk assessment in March and June of 2010 (Ferkolj, 2010).

Table 8

At the same time, the senior management team could not relate the percentiles for cumulative impact of the identified risks computed with the @Risk software with the EBIT, used as a key performance indicator. One cause for this, is that each subsidiary submits monthly the profit and loss account plans for the current year according to the market situation and internal information from different functions of the subsidiary. Because the identified risks were already incorporated in profit and loss planning and, with that, in the planned EBIT, it was difficult to define the relationship between the risk model output and the subsidiary's EBIT (Ferkolj, 2010).

Ferkolj suggested an increase of the participation of the senior management team in the ERM process. There was a lack of motivation on the team, because it believed that the risks were already incorporated in the regular activities. Also, they found out the process an additional, and too bureaucratic, process (Ferkolj, 2010).

In the Slovene subsidiary, the cumulative risk exposure, using the P95 from cumulative probability distribution, had decreased by a result of an effective response plan for the major risks (Ferkolj, 2010).

Since March 2010 no additional risks were identified and the likelihood of initially identified risks decreased in general, the effectiveness of the cumulative probability distribution was questionable. It could be because of two causes: because the cumulative risk exposure of the subsidiary decreased with an effective response plan, or because senior management team, since they were not motivated and had not found a linkage between risk model output and the key performance indicator EBIT, important risks could have been left out from the risk analysis (Ferkolj, 2010).

It was suggested that the company upgrade the ERM process in order to establish a linkage between the ERM model output and EBIT (Ferkolj, 2010).

The company had a risk software, but because the company tended to standardize the risk register, it did not take the full use that the software could give. One of the things was to perform risk analysis according to defined probabilities for different possible outcomes for each identified risk. It would be an advantage for the company to use that feature, since, at that moment, it was disabled (Ferkolj, 2010).

Overall, the ERM process could be upgraded. The selected company was highly aware of risk. They efficiently implemented risk response strategies and continuously tried to decrease the likelihood of risks from happening. Risk management was already an important part of the activities. It was required by the shareholder The Coca-Cola Company, who helped by sharing their risk management practises and tools (Ferkolj, 2010).

It was recommended to the subsidiary to continuously and collectively identify and assess risks, because it was the area that needed the most upgrades. The predefined risk assessment criteria must be reviewed and adapted to the needs of the subsidiaries. In order to improve the involvement of the management teams in the subsidiaries in the risk assessment, a direct linkage should be made between the ERM model output and EBIT (Ferkolj, 2010).

5. Conclusions

In a way, multinational companies that are operating or operated on different markets than their own are facing a period of uncertainty. This uncertainty lead eventually to negative and unexpected variations on business outcomes like revenues, costs or profits (Ferkolj, 2010).

An important activity of management is to manage risks efficiently, so companies that understand better their own risks than their competitors can gain a competitive advantage. The more you know about risks the better, because it delivers the ability to deal with risks which intimidates in a way the competitors, to have a better adversity than competitors and to manage risks at the lowest costs possible (Ferkolj, 2010).

Ferkolj introduced the concept of Enterprise Risk Management (ERM) which later analysed its performance on a Slovene subsidiary. ERM is a process that identifies which risks are affecting negatively or positively the performance of the enterprise and needs the involvement of all from the management team. There are lot of different risks and each one should be treated in a holistic manner and have their correlation analysed. It can be deliberated by defining which types of risk are included and the steps needed for it (Ferkolj, 2010).

ERM when presented and analysed in the selected company consisted on three standard steps: risk identification, risk assessment and risk response (Ferkolj, 2010).

The selected company had described their main risks areas that were important to be considered in the risk identification phase. Using the predefined risk universe, the Slovene subsidiary of the selected company was helped a lot in terms of risk identification and facilitated the senior management team to not only focus in financial sources of risk (Ferkolj, 2010).

In terms of the predefined assessment criteria, it was developed for qualitative risk assessment. These criteria brought rules that were used in a uniform way in risk assessment, but the senior management team had a lot of difficulties using them, because it was hard to achieve consensus amongst the members (Ferkolj, 2010).

The selected company used @Risk software to analyse risk using the Monte Carlo simulation, but to run this analysis it was needed to set up a risk model and run a risk simulation. The risk model was set by deciding the risk likelihood in percentage; the minimum; the maximum; if possible, the most likely costs of risks; and the probability distribution of risk (Ferkolj, 2010).

The @Risk software computed the risk model thousands of times, and each time it didn't, the @Risk sampled random values from the function that was on the risk model and recorded the results. When the Risk software gathered all the outcomes, it generated a graph called cumulative probability curve or "S" curve (Ferkolj, 2010).

The management team couldn't hook up the percentiles for the cumulative impact of the risks identified by the @Risk software with EBIT, causing this way a big impact in terms of team motivation for future risks assessments (Ferkolj, 2010).

On the first half of the year 2010 of the selected company, the risks plan used by Ferkolj were settled to be very efficient. The big problem was the disruption in distribution which was caused by a major distributor that was facing liquidity problems. Later, this risk was efficiently well managed and made the overall risk exposure decrease in terms of risk probability distribution (Ferkolj, 2010).

The main ambition of using the ERM process was to involve the senior management teams in identifying the risks and its assessment. With an efficient perspective of this process it would increase their awareness in risks that could highly affect the performance of their subsidiaries (Ferkolj, 2010).

Since the company was improving in their risk's management capabilities, because the establishment and risk mitigation was part, not only of the managements, but as well by the employees, the management team found out that they could use the ERM in a more documented process, which meant they could deal with risk and implement risk mitigation exercises on a daily basis (Ferkolj, 2010).

Finally, to improve the involvement between the senior management teams and the ERM process, a direct linkage between the ERM model output and EBIT should be settled (Ferkolj, 2010).

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Table 3

Risk universe of the selected company

Risk area	Risk type
People assets	Availability of talented people Inappropriate employee behaviour Safe and healthy workplace Security
Product and market assets	Consumer/marketplace trends Malicious product attacks Manufacturing process/quality Trademark erosion Relationship management Marketing and promotions New product commercialisation
Infrastructure assets	Business disruption Government actions Legal liability issues Security environment Supply chain
Information assets	Lack of information for decision making Loss of access to information Unauthorised access to information
Finance assets	Currency/interest rates Financial controls Financial misstatements Forecasting/budgeting Commodity pricing Counterparty default Inventory theft/fraud

Note. Adapted from “Enterprise risk management analysis with suggestions for improvements for the selected company,” by A. Ferkolj, 2010, University of Ljubljana, Slovenia, p. 30.

Table 4

Impact assessment of identified risks in the selected company

Risk impact area	Impact description	Impact assessment
EBIT	<3% of EBIT	1
	Approx. 3% of EBIT	2
	3-7% of EBIT	3
	7-10% of EBIT	4
	>10% of EBIT	5
Company reputation	Insignificant damage to reputation Unlikely to attract regional media attention No brand impact expected	1
	Minor damage to reputation Unlikely to attract regional media attention No brand impact expected	2
	Moderate damage to reputation Regional media attention lasting 1-2 weeks Brand recovery expected in 1-2 weeks	3
	Severe damage to reputation Adverse national media coverage Brand recovery expected in 2-8 weeks	4
	Critical damage to reputation Adverse multi-national media coverage Brand recovery expected in 8-24 weeks	5
Health, safety and environment	Internally reportable incident managed locally leading to < 3 days absence	1
	Internally reportable incident managed locally leading to 3-5 days absence	2
	Internally reportable incident managed locally leading to 5-10 days absence	3
	Incident managed locally leading to major injury/loss of limb or sight	4
	Fatality	5
Management effort	No management involvement required	1
	Management input required to limit impact	2
	Dedicated management effort required	3
	External management report required for less than 28 weeks	4
	External management report required for more than 28 weeks	5
Quality	Isolated single event in breach of quality standards	1
	Multiple complaints in breach of quality standards	2
	Multiple incident in breach of local regulatory quality standards	3
	Silent recall of product line	4
	Public recall of product line Closure of production facility	5

Note. Adapted from “Enterprise risk management analysis with suggestions for improvements for the selected company,” by A. Ferkolj, 2010, University of Ljubljana, Slovenia, pp. 32-33.

Table 5

Qualitative risk assessment of the Slovene subsidiary of the selected company performed in March 2010

ID	Risk description	Consequence	Likelihood (1 -5)	Impact (1 - 5) EBIT	Reputation/perception	H, S & E	Management effort	Quality
1	Direct sales distribution disruption	Goods not delivered	4	4	0	0	3	0
2	GDP below forecast	Lower consumption	3	5	0	0	3	0
3	Increased competition – PLG will increase activities in AFB	Decreased market share	4	3	0	0	3	0
4	Introduction of PET deposit	Lower sales	4	3	0	0	3	0
5	Increased outstanding debts	Loss	4	4	0	0	2	0
6	People retention SAP	Business disruption	3	4	0	0	4	0
7	Product quality issues still drinks-Nestea	Unsatisfied consumers	3	0	0	0	3	4
8	Traffic risk of sales personnel	Absenteeism, bad company reputation	4	0	0	3	2	0
9	Knowledge transfer SAP	Employees not trained properly	4	1	0	0	4	0
10	Relationship with main key account (Mercator)	Decrease in sales	3	3	0	0	3	0
11	Waste packaging regulation change	Increase of packaging fee	3	4	0	0	2	0
12	Slovenian customers buying from foreign CCH countries	Lower sales	3	3	0	0	3	0
13	External supply point dependency	Lost sales	2	2	0	0	3	0
14	Promotional mechanics	Penalty or recall	3	1	0	0	2	0
15	Employee strike	Work disruption	1	0	3	0	3	0
16	Changed labelling from GDA to traffic	Sales decrease	1	3	3	0	0	0

Table 6

Risk response plans for the identified risks in the Slovene subsidiary of the selected company in March 2010

ID	Risk description	Risk response plans	Risk owner	Response plan to be completed by
1	Direct sales distribution disruption	Identify alternative services providers	Supply chain manager	April 2010
2	GDP below forecast	Marketing mix adjustment	Commercial manager	Ongoing
3	PLG will increase activities in AFB	Marketing mix adjustment	Commercial manager	Ongoing
4	Introduction of pet deposit	Negotiations with government	Public affairs manager	June 2010
5	Increased outstanding debts	Update of accounts receivables policy, weekly monitoring	Finance manager	April 2010
6	People retention sap	Following sap recruitment policy	Public affairs manager	April 2010
7	Product quality issues still drinks-Nestea	Increased visual incoming goods inspections on critical SKUs	Supply chain manager	April 2010
8	Traffic risk of sales personnel	Training on safety driving	Supply chain manager	June 2010
9	Knowledge transfer sap	Close monitoring of sap implementation process	Public affairs manager	Ongoing
10	Relationship with main key account (Mercator)	Extensive monitoring of Mercator's performance improved relationship with other key accounts	Commercial manager	April 2010
11	Waste packaging regulation change	Negotiations with government	Public affairs manager	Ongoing
12	Slovenian customers buying from foreign subsidiaries	Review of commercial policy	Commercial manager	June 2010
13	External supply point dependency	Prepare proper contingency plans	Supply chain manager	April 2010
14	Promotional mechanics	Legal check of promotional practice, use of legal services	Commercial manager	April 2010
15	Employee strike	Negotiations with union	HR manager	April 2010
16	Changed labelling from GDA to traffic light system	Not able to influence		

Note. Adapted from "Enterprise risk management analysis with suggestions for improvements for the selected company," by A. Ferkolj, 2010, University of Ljubljana, Slovenia, pp. 37-38.

Table 7

Risk model of the Slovene subsidiary of the selected company according to the risk review in March 2010

	Risk Model					
Risk description	ID	Likelihood	Min	ML	Max	Distribution
Direct sales distribution disruption	1	30%	50,000 €	100,000 €	110,000 €	p
GDP below forecast	2	15%	250,000 €	300,000 €	450,000 €	p
Increased competition - PLG will increase activities in AFB	3	10%	10,000 €	40,000 €	50,000 €	p
Introduction of PET deposit	4	60%	10,000 €	80,000 €	100,000 €	p
Increased outstanding debts	5	10%	70,000 €	80,000 €	150,000 €	p
People retention SAP	6	10%	50,000 €	100,000 €	120,000 €	p
Product quality issues still drinks-Nestea	7	20%	10,000 €	15,000 €	17,000 €	p
Traffic risk of sales personnel	8	20%	5,000 €	8,000 €	9,000 €	p
Knowledge transfer SAP	9	10%	10,000 €	20,000 €	32,000 €	p
Relationship with main key account (Mercator)	10	10%	40,000 €	50,000 €	60,000 €	p
Waste packaging regulation change	11	40%	50,000 €	80,000 €	90,000 €	p
Slovenian customers buying from foreign CCH countries	12	40%	40,000 €	50,000 €	60,000 €	p
External supply point dependency	13	15%	40,000 €	65,000 €	70,000 €	p

Table 8

Comparisons between likelihood and most likely costs of the identified risks according to the risk assessment in March and June 2010

ID	Risk description	March 2010		June 2010	
		Likelihood	Most likely costs	Likelihood	Most likely costs
1	Direct sales distribution disruption	30%	100,000 €	10%	30,000 €
2	GDP below forecast	15%	300,000 €	15%	300,000 €
3	Increased competition - PLG will increase activities in AFB	10%	40,000 €	20%	40,000 €
4	Introduction of PET deposit	60%	80,000 €	10%	80,000 €
5	Increased outstanding debts	10%	80,000 €	20%	80,000 €
6	People retention SAP	10%	100,000 €	10%	100,000 €
7	Product quality issues still drinks-Nestea	20%	15,000 €	20%	15,000 €
8	Traffic risk of sales personnel	20%	8,000 €	20%	8,000 €
9	Knowledge transfer SAP	10%	20,000 €	10%	20,000 €
10	Relationship with main key account (Mercator)	10%	50,000 €	10%	50,000 €
11	Waste packaging regulation change	40%	80,000 €	30%	80,000 €
12	Slovenian customers buying from foreign CCH countries	40%	50,000 €	40%	50,000 €
13	External supply point dependency	15%	65,000 €	15%	65,000 €
14	Promotional mechanics	5%	20,000 €	5%	20,000 €
15	Employee strike	5%	50,000 €		

Note. Adapted from “Enterprise risk management analysis with suggestions for improvements for the selected company,” by A. Ferkolj, 2010, University of Ljubljana, Slovenia, pp. 46-47.