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Value at Risk for Emerging Markets' Funds

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Abstract

Value at Risk is a commonly used risk measure which calculates the smallest losses you risk to lose from having an asset, given a certain risk level and time period. Even though Value at Risk is applicable to all different types of assets, some studies suggest that this risk measure is not suitable for developing countries/emerging markets. This is because these countries' assets generate very obscure or questionable return data. This essay applies some Value at Risk-models on top-performing funds from a number of low- and middle income countries in Africa, the Middle East and Latin America, and examines how well they fit these models. We calculate basic VaR for three confidence levels and two respective distributions (Normal distribution and Student's t-distribution), and compare these with GARCH and EGARCH models with the same distributions and confidence levels. We also calculate VaR with the historical simulation (HS) method. We calculate all values both with respect to short and long position. Our results indicate that no kind of model works significantly well for the countries' funds in general. The models applicable to most countries were of the basic VaR and HS kind. We also find that the highest confidence level, 99%, was the one generating most acceptable models.

Keywords: Value at Risk, Africa, the Middle East, Latin America, funds

Table of Contents

1. Introduction 5
 1.1 Background 5
 1.2 Purpose 5
 1.3 Motivation 6
 1.4 Limitations 6
 1.5 Outline 7
2. Theoretical framework 7
 2.1 Previous research 7
 2.2. Measure market risk with Value at Risk 10
  2.2.1. Advantages of VaR 11
  2.2.2. Disadvantages, criticisms and limitations of VaR 11
  2.2.3 Calculating returns 11
 2.3 Volatility estimation methods 12
  2.3.1 GARCH 12
  2.3.2 EGARCH 13
 2.4 Distributions 14
  2.4.1 Normal distribution 14
  2.4.2 t-distribution 14
 2.5 Backtesting 15
3. Method 16
 3.1 Outline 16
 3.2 Data 16
 3.3 Time periods 17
 3.4 Confidence levels 18

4. Results 19
4.1. Descriptive statistics 19
4.2. Sub-Saharan Africa 20
4.3. North Africa and the Middle East 23
4.4. Latin America 26
5. Discussion and analysis 29
5.1 Conclusions 29
5.2 Further research 30
6. References 31
Appendix 1 33

1. Introduction

1.1 Background

Value at Risk (VaR) is one of the most commonly used risk measure in the financial world. One outlined definition of VaR is:

$$VaR_\alpha L = \min\{\lambda : P(L>\lambda) \leq 1\text{-}\alpha\} \qquad (1)$$

where α is a chosen confidence level.[1] So the measure can be interpreted as the largest possible loss an investor faces for a certain asset, given a certain risk level and time period. The reason VaR is usually used is because it has a number of attractions; it is easy to use and interpret, and is applicable to all asset classes. There are also drawbacks: it does not tell anything about the size of a *possible* loss given a so-called tail event. That is, for a certain distribution, one is typically most interested in the left tail where the theoretical losses take place. One can estimate VaR for different risk levels, but the distribution of the tail events might be hard to estimate. Also, the reliability of the model depends crucially on the assumptions imposed on the loss distribution. The examined assets are typically assumed to be normally distributed. This has both attractions and drawbacks, and this will be discussed more later on. We have chosen to work with this and several other common distributions, and compare these in our special case.

This essay will focus on developing countries/emerging markets and their most successful funds, and applying VaR on these.

1.2 Purpose

The purpose of this thesis is to examine VaR and see how well it works for a number of funds situated in emerging markets, for different (available) time periods, all ending in April 2014. The thesis will focus on low and middle income economies that have a harder time following the development of the world. The goal is to check whether VaR is a suitable method to calculate presumably risked amounts of money for these countries' funds. The aim of the thesis is to try

[1] This formula is outlined (with slightly different notations) from out-handed lecture notes from the course NEKN83: Financial Valuation and Risk Management (Lund University, spring 2014).

answering the question "Is VaR a suitable method to measure risk for funds in/from low and middle income economies?".

1.3 Motivation

Not much has been written about developing countries' funds, in terms of Value at Risk. We would like to apply some theories and implications about stock market and portfolio theory to emerging markets' funds. We also want to discuss a bit about developing countries' problems and challenges regarding their financial systems. Here we basically look at the current situation, using data from the latest years. Several of the articles used here suggest that models often have to be specifically adjusted when dealing with emerging markets (examples will follow). We want to expand this suggestion further, and explore certain fields where it might need to be applied.

1.4 Limitations

We decided to look at three specific areas as grouped by the World Bank: Sub-Saharan Africa, North Africa with the Middle East, and Latin America.[2] These regions contain a large share of the world's developing countries. We decided to look at the one top-performing fund (no specific category) from each low- and middle income country in these groups. The gathering of fund data took place at the beginning of April 2014. We decided to calculate all returns/losses in US dollars, which is both a benefit and a limitation. As Gencay and Selcuk (2004, p. 301) put it: "An international portfolio holder might be interested in US dollar [...] returns." This "would make the returns comparable among different economies." This is written in the end of the article as a way of suggesting future research. At the same time, they write: "However, an analysis of stock market returns in dollar terms combines the dynamics of the stock return in the economy and the exchange rate and this complicates the analysis". We suppose the same thoughts are valid for fund returns. We chose a unified currency for basically the same reasons as they state. We did not expect to receive data for all countries, and this will be discussed more later on.

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[2] The last group was actually called Latin America and the Caribbean. We did however not find any data for any Caribbean countries. From the beginning we wanted to examine Africa and South America as continents alone, but it felt natural to use and include all the low- and middle-income countries in the mentioned groups (The World Bank, http://data.worldbank.org/country).

1.5 Outline

From here, we will start by outlining the previous research in the area that we have found. Thereafter we will outline and motivate the methods and models we are using. Then we will show our results, divided into sections of the three regions we are looking at. After that comes discussion and analysis, complemented with suggestions of further research.

2. Theoretical framework

2.1 Previous research

The World Bank defines the income groups in terms of GNI per capita: low income, $1,035 or less; lower middle income, $1,036 - $4,085; upper middle income, $4,086 - $12,615; and high income,$12,616 or more, using 2012 currency values.[3] We downloaded price data for the top-performing fund in each country. All countries were not searchable, but we also did expect to get some fall-offs for the poorest countries. It is commonly known that poor countries have financial problems in general, not only in terms of low funds. There is also an issue with poor institutions and jurisdiction, and another concerning information and incentives among borrowers and lenders. Ray (1998) discusses the issues of finding which borrowers are safe and which are risky. Because of this, the banks set very high interest rates, which make only risky customers take loans, and hence a vicious circle is created. The problems with information and unstable jurisdiction also create moral hazard problems; the lender cannot fully observe the borrower's actions, so the latter might not have incentives to fulfill the actions. And in case of failure, the borrower might find a simple way to get away with it (see Ray (1998), ch 14). All of this would have negative effects on the financial market as a whole. Todaro and Smith (2011) mention that one of the biggest financial market failures in least developed countries (LDCs) are missing and incomplete markets. Our study could make a point of this; these countries could surely benefit from more developed fund markets.

Gencay and Selcuk (2004) examine VaR for daily stock market returns in nine emerging countries in Latin America and Asia. They do not state exactly how the countries and time

[3] The World Bank: "How we classify countries", http://data.worldbank.org/about/country-classifications .

periods have been chosen. Regarding the latter, this is in line with what we are doing (see further down). According to them, “[a]n emerging economy can be defined as a market economy with a small share of the world economy. [---] Also, political and economic stability in these economies are an exception rather than a rule”. They find that certain methods based on extreme value theory (EVT, which we will not address that much here) works better than a couple of more basic methods (Gencay and Selcuk 2004, p. 287, ft 2).

Ozun and Cifter (2007) look at VaR for equity markets in Mexico and Brazil. They mention that a proper VaR model should “capture the non-linear behaviors and extremes in the returns arising from the special features of the emerging markets”. They compare a time-varying copula model (this model is related to GARCH) with an EWMA model, and find that the former is more suitable in their special case (Ozun and Cifter 2007 p. 1916). Diamandis et al (2011) look at equity markets in three groups of countries: developed economies, Asia and Latin America, where the last consists of Argentina, Mexico and Brazil. They apply a skewed Student APARCH model and find that this improves VaR forecasts for both long and short trading positions. This is relevant for our study since we will be calculating both of these. They find that all the examined countries exhibit skewness, and most of them are negative. It is worth mentioning that both positive and negative skewness are present in all three groups. Just like in our study, they use varying time periods, based on availability (Diamandis et al 2011).

Maghyereh and Al-Zoubi (2006) study financial markets in MENA (Middle East and North Africa) countries. They find that their return distributions are fat-tailed and hence the normal distribution is not completely appropriate for computing VaR. They use APARCH (asymmetric power ARCH) with several distributions, and find that a skewed t-distributed ARCH model performs better than the respective normal distributed model (and in general all others used but certain extreme value models) for all markets. Most models clearly outperform the basic historical simulation. They write: “The [MENA] region has recently witnessed significant economic and financial development. [---] Many countries in this region have suffered wars, political turmoil or economic instability. Thus, [...] stock markets in the MENA are functions of different cultural, institutional, economic and political circumstances than those in the other emerging markets". They also mention that there have been problems with accurate legal systems and low transparency (Maghyereh and Al-Zoubi 2006, p. 155).

One of the MENA countries included in our study is Tunisia. Snoussi and El-Aroui (2011) have made a special study on this country, and mention that factors like "low liquidity, [...] asymmetric information and high volatility affect the risk market" in emerging economies. Also, non-integrated financial markets are common, and the information problem is a part of this. "Indeed, the non-integration leads to anomalies in the functioning of financial markets" here. Hence, the VaR models should be shaped with these factors in mind. Many models simply make too simple assumptions. The authors have in this case constructed relatively complex VaR models intended to adjust for some of the mentioned factors. Other aspects of non-integration are that there might be a lack of certain types of assets, and lack of diversification benefits. They find otherwise that many of the examined assets' distributions are skewed to the left; that is, very low values occur more often than very high ones (Snoussi and El-Aroui 2011, p. 86 and p. 89 resp.). So of course it becomes natural to use an asymmetric model here.

Todaro and Smith (2011) state that private portfolio investments have increased in many developing countries. They note however that "the middle-income countries have been the favored destination of these flows, with Sub-Saharan Africa all but neglected". They also mention that these markets are often very volatile (Todaro and Smith 2011, pp. 694-695). For Sub-Saharan Africa, most VaR-related studies seem to have been made on South Africa. One of these is made by McMillan and Thupayagale (2010), who also mention that South Africa is Africa's largest equity market. Hence this country has some economic magnitude in the region. According to them, these kinds of studies on Africa are not common, and they try to fill a gap with their article. They apply different models for calculating VaR using returns for a certain stock index from the same country. These models are EWMA and various GARCH models, and they find that EGARCH is one of the better-performing ones. EGARCH gives the best VaR estimations on the 95 % confidence level, while a modified EGARCH (fractionally integrated EGARCH, FIEGARCH) performs slightly better on higher levels. "We also find that the [EWMA] approach is consistently outperformed by all other models employed" (McMillan and Thupayagale 2010, p. 327). Seymour and Polakow (2003) have made an earlier similar study on this country however, and mention specifically that the VaR studies made on developed economies generally do not take the volatility in emerging markets into account. They find that volatility-updating methods (in this case, EWMA and GARCH) clearly outperform historical simulation here.

2.2. Measure market risk with Value at Risk [4]

Value at Risk is defined as the smallest loss λ, with the probability that a future portfolio loss L larger than the loss λ, is less or equal to $1-\alpha$, where α is a given risk level . This can be written mathematically as: $VaR_{\alpha}(\mathrm{L}) = \min\{\lambda\text{: } \mathrm{P}(\mathrm{L}>\lambda) \leq 1\text{-}\alpha\}$, as stated before. One can also say that Value at Risk is the quantile of the loss distribution. This means that if we have 1000 observations and a 99% confidence interval, we have 1000*(1-0.99) losses larger than $\mathrm{VaR}_{0,99}$ and the largest VaR estimate is our 1000*(1-0.99) + 1 largest loss. In this case, the 11th VaR estimate is our largest loss.

The standard confidence levels used for VaR are $\alpha = 0.99$ or $\alpha = 0.95$. We choose to use these levels, as well as $\alpha = 0.975$.

Because gains are equal to minus losses ($\mathrm{G} = -\mathrm{L}$) we can also write Value at Risk in terms of gains:

$$-VaR_{\alpha}(\mathrm{G}) = \max\{\mathrm{g}\text{: } \mathrm{P}(\mathrm{G} < \mathrm{g}) \leq 1\text{- }\alpha\} \qquad (2)$$

where VaR is the largest gain g, such that probability of future portfolio gain G, smaller than gain g, is less or equal to $1-\alpha$.

Either way, calculating Value at Risk based of loss or gain distribution gives the same result: $VaR_{\alpha}(\mathrm{L})=VaR_{\alpha}(\mathrm{G})$.

[4] The theory here at the beginning is outlined from out-handed lecture notes from the course NEKN83: Financial Valuation and Risk Management (Lund University, spring 2014).

2.2.1. Advantages of VaR

The main reasons to use Value at Risk are that it is applicable to all asset classes and relatively simple to interpret. VaR focuses on "bad" outcomes and aggregates risk instead of looking at one risk at a time. It is probabilistic and expressed in a simple unit, money (Dowd 2005, pp. 11-13).

2.2.2. Disadvantages, criticisms and limitations of VaR

The model has been criticized concerning whether it's mathematical and statistical implications are applicable to financial returns, which depend heavily on social and other underlying factors. VaR depends both on the model's specific form and *how* it is implemented, and hence there is so called implementation risk. There is also a matter of what happens if all financial market participants use VaR - this could make certain risks become more correlated than before, and hence destabilize the system. Also, risk is endogenous; it is hard to tell how the market will respond to VaR estimates (Dowd 2005, pp. 13-14). What furthermore is worth to mention is that VaR only states how much is at risk if a tail event does *not* occur. If a tail event does occur, one really has no idea how much is at stake. Dowd describes this state like this: "[W]here VaR is reliable, we don't need it; and where we do need it, it isn't reliable" (Dowd 2005, p. 32). In an earlier publication by Dowd, he also mentions the fact that VaR is backward-looking: it estimates future losses using past data. The question is if all the past data is relevant at all times (Dowd 1998, p. 44).

2.2.3 Calculating returns

There are typically two ways to calculate asset returns: arithmetically (simple division) and geometrically (assuming exponential returns). According to Jorion (2001, pp. 99-100), the latter is more commonly used for long horizons, and could be more meaningful in economic terms. For ease of calculation, one can use logarithmic values for these. So here the returns are expressed as:

$$R_t = \ln\left(\frac{P_t + D_t}{P_{t-1}}\right), \tag{3}$$

where R_t is the (logarithmic) return for period t, P_t and $P_{t-1}$are the asset prices for the respective periods, and D_t is the possible dividend for period t. Two benefits of this calculation model are that it does not accept prices to be negative, because of the logarithmic form, and that it is easy to extend into multiple periods. That is, the geometric return after a number of periods is simply the sum of the returns of the individual periods. This calculation is not as easy for the arithmetic model. When returns are small the two models give approximately equal results. “This may not be true, however, in markets with large moves such as emerging markets” (Jorion 2001, pp. 100-101). We set D_t= 0 for all the fund returns here due to lack of relevant information.

2.3 Volatility estimation methods

There are several ARCH models that can be used for calculating VaR. However, we will focus on GARCH and EGARCH, which take relative factors for our cases into account. The main reason for choosing GARCH and EGARCH is that they are two models widely used in finance. The GARCH model helps finding a volatility measure to forecast residuals in our model. A popular implementation for GARCH(1,1) is Value at Risk, which gives us another reason for choosing this model. EGARCH is one of many variant of the GARCH model. The EGARCH model is a better model for some market mechanics, because it considers the fact that negative shocks tend to impact volatility more than positive shocks (Engel, 2001).

2.3.1 GARCH

The GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model originates from ARCH (Autoregressive Conditional Heteroscedasticity) models. The latter ones are assumed to have a constant long-run variance, but goes through periods of higher or lower ones. This makes ARCH attractive for financial assets which experience up- and downgoing periods, but still might (and are often assumed to) have a constant variance. So the ARCH process has a conditional variance in the sense that its error terms are functions of its own lagged (squared) terms. The GARCH model outlines the variance as an ARMA (autoregressive moving average) process. Here, the error terms are defined as:

$$\varepsilon_t = v_t\sqrt{h_t}\,, \tag{4}$$

where v_t is a white-noise process with variance equal to 1, and

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \quad . \tag{5}$$

This is the ARMA(p,q)-process in question[5] (note that $h_t = E(\varepsilon_t^2)$) (Enders 2010, p. 131). The GARCH model is an extension/alternative to the commonly used EWMA model.[6] One drawback of EWMA in comparison is that it uses a constant parameter λ which determines the coefficients for both the error term and the lagged variance (Dowd 2005, pp. 129-132).

In this thesis, we will use GARCH(1,1) which is the most simple GARCH-model. The reason for this is that GARCH(1,1) was statistically significant for all countries with a p-value of 0.000.[7]

2.3.2 EGARCH

EGARCH is short for Exponential GARCH. Matlab defines EGARCH(p,q) as:

$$\log \sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum_{i=1}^{p} \alpha_i \left(\left|\frac{\epsilon_{t-i}}{\sigma_{t-i}}\right| - E\left(\left|\frac{\epsilon_{t-i}}{\sigma_{t-i}}\right|\right)\right) + \sum_{k=1}^{p} \gamma_k \left(\frac{\epsilon_{t-k}}{\sigma_{t-k}}\right) \tag{6}$$

.[8] There are several advantages of using EGARCH instead of pure GARCH. Since the logarithm of σ_t^2 is modelled, σ_t^2 will be positive, even if the parameters are negative. It is worth to mention that EGARCH is asymmetric; it treats up- and downgoing periods differently. This makes it convenient for financial assets, because these have often been found to be more volatile in downgoing periods than in upgoing ones. This effect is referred to as the leverage effect (Enders 2010, pp. 155-157). This contrasts to the standard GARCH which is symmetric.

For EGARCH, we will also use the most simple model, EGARCH(1,1).

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[5] Where the requirements $\alpha_0>0$, $\alpha_1>0$, $\beta>0$ need to be fulfilled.

[6] In the EWMA model, the variance is approximated as:

$$\sigma_t^2=\lambda\sigma_{t-1}^2 + (1-\lambda)x_{t-1}^2,$$

where x is the return for a certain period (in some cases x is replaced by the error term, e).

[7] For more descriptive statistics, see Table 2.

[8] See Mathworks, http://www.mathworks.se/help/econ/specify-egarch-models-using-egarch.html (note that we have named the parameters and indexes differently).

2.4 Distributions

The models above will be tested with both normal distribution and t-distribution. We have chosen the normal distribution because it is the most common distribution. The t-distribution is used due to uncertainty about the distribution and as it puts more weights on unlikely events.

2.4.1 Normal distribution

When estimating Value at risk under the normal distribution we use the following equation:

$$\mathrm{VaR}_{\alpha}(L) = \mu + \sigma z_{\alpha} \tag{7}$$

where z_{α}denotes the α-quantile for the standard normal distribution. This is a common distribution when estimating VaR, but it is not always believed to be the most appropriate one (this relates a bit to the criticisms towards VaR mentioned earlier). This is not the least because financial asset returns often have been found to imply distributions with fatter tails than the normal distribution (Dowd (1998), pp. 87-88). “In fact, normality is rarely an adequate assumption in finance” say Ozun and Cifter (Ozun and Cifter (2007), p. 1916). Also, the normal distribution is unskewed, and portfolio returns have often been found to be negatively skewed - that is, a larger portion of the probability mass is distributed in the loss area. “If we assume normality, we should always run checks to satisfy ourselves that normality is an adequate description of the particular portfolio at hand” [Dowd, ibid]. So it’s natural that we use more than one distribution here.

2.4.2 t-distribution

As an alternative to the normal distribution, we use the Student’s t-distribution:

$$\mathrm{VaR}_{\alpha}(L) = \mu + \sqrt{\frac{v-2}{v}} * \sigma t_{\alpha,v} \tag{8}$$

where $t_{\alpha,v}$ is the t-quantile for a certain confidence level α and a number of degrees of freedom v. The number of degrees of freedom is given by:

$$v = \frac{4k-6}{k-3} \tag{9}$$

where k is the kurtosis for the relevant loss observations (calculated in Excel by KURT()+3). If we want a relatively high excess kurtosis, we should choose a relatively low value of v, and vice versa (Dowd 2005, pp. 77-78). A higher kurtosis is equivalent to fatter tails, and that is why the t-distribution is useful here. According to Dowd, the fatter tails of this distribution contains more information and therefore captures more uncertainty of, for example, portfolio standard deviation (Dowd 1998, p. 44).

2.5 Backtesting

To test if one assumed model is good, one uses backtesting. The principle behind this is to test how many actual values (in this case, losses) that exceed the estimated value for VaR. We will use a common and simple backtest which Dowd refers to as "The Basic Frequency Backtest", which is a binomial test, invented by Kupiec in 1995.This is outlined as follows:

$$P(x|n,p) = \left(\frac{n!}{x!(n-x)!}\right) p^x (1-p)^{n-x}, \tag{10}$$

where p is the stated probability of a tail event x, and n is the total number of observations. So p can be interpreted as 1 minus the confidence level, or 1-α (Dowd 2005, pp. 324-325).

To count the number of VaR violations, produced by each of the VaR models for the test period, we do a logical IF() statement in Excel. This statement will return 0 (zero) if there is no VaR violation a given day, and return 1 (one) if there is a VaR violation that day.

The approximate number of violations that should be observed in the data is N*(1-α).[9] Here, N is the number of observations in the test period and α is the confidence level. We will compare the actual value to the estimated value of violations.

[9] For exact number of violations that should be observed within the different countries, see Appendix 1.

To interpret the violations we need the lower and upper limits for the different confidence intervals based on Kupiec's binomial test. In Excel, we do this by the function BINOM.INV().[10] We calculate one interval for each confidence level which in our case means we need three intervals with an upper and lower limit.

3. Method

3.1 Outline

We start with the normal distribution as our standard where we calculate daily VaR for a long and short position. VaR is then tested using GARCH and EGARCH, both with normal- and t-distribution. To see how the results differ with different significant levels, we calculate VaR at 95, 97.5 and 99% confidence levels.

To test how well the VaR model fits the data for the different countries, we calculate the expected violations of VaR, and perform a binomial Kupiec test. By calculating the expected number of violations (both in terms of pure probability, and as a confidence interval) we can see which models that pass and fail the Kupiec test, and by that see how applicable the VaR models are for the different countries in our test.

To backtest the models, Matlab was used to estimate parameters for each day in the test period, our out-of-sample data.

3.2 Data

The thesis focuses on Africa, the Middle East and Latin America and the data contains values of the closing prices for funds from low and middle income countries in the chosen areas. The fund data was collected from Thomson Reuters Eikon. Here we picked the top performing fund for each country, and collected daily data from each one. For Africa and the Middle East, 62 countries are classified as low and middle income economies, and for Latin America, the number

[10] Within the brackets, you need data for number of trials, the probability and the confidence interval.

of countries is 27.[11] When searching in Eikon we found that just 14 of all these countries had available data. These countries were Argentina, Brazil, Egypt, Jordan, Lebanon, Mauritius, Mexico, Morocco, Panama, Paraguay, Peru, Swaziland, South Africa and Tunisia. However, we chose to exclude Brazil, Jordan, Mexico and Panama, due to clear weaknesses in the data. This gives us 10 countries to work with.

When picking the funds, some limitations occurred. Paraguay was included as a low income country, but only one fund was available in Eikon. Therefore, there was not much to choose from for this country, but otherwise this did not cause any problem here. It is just a bit striking. There were also some gaps in the daily data for Tunisia and South Africa. Tunisia were missing values for the dates 2013-04-30 and 2011-05-31 and South Africa were missing values for 2014-01-02, 2013-07-01, 2013-01-02, 2012-07-02 and 2012-01-03.

3.3 Time periods

The time periods picked were very dependent on the available data for the countries, which gives us a different number of observations for each country. These are shown in Table 1. When choosing the sample periods, we take into consideration the large differences in number of data points for the different countries. A common guideline is to choose ⅔ of the data as the in-sample period and ⅓ as the out-of-sample period. We choose to follow this guideline and the respective in- and out-of-sample periods are also shown in Table 1.

Country	**Time period (number of observations)**	**In-sample period**	**Out-of-sample period**
Argentina	2004-08-26 -- 2014-04-02 (2504)	2004-08-26 -- 2011-01-19 (1669)	2011-01-20 -- 2014-04-02 (834)
Egypt	2010-02-25 -- 2014-04-02 (1063)	2010-02-25 -- 2012-11-22 (709)	2012-11-23 -- 2014-04-02 (353)
Lebanon	2007-09-27 -- 2014-04-02 (2380)	2007-09-27 -- 2012-01-31 (1587)	2012-02-01 -- 2014-04-02 (793)

[11] The World Bank: http://data.worldbank.org/country .

Mauritius	2006-02-03 -- 2014-04-02 (2128)	2006-02-03 -- 2011-07-15 (1419)	2011-07-18 -- 2014-04-02 (709)
Morocco	2008-09-12 -- 2014-04-02 (1448)	2008-09-12 -- 2012-05-28 (965)	2012-05-29 -- 2014-04-02 (483)
Paraguay	2009-10-14 -- 2014-04-02 (1165)	2009-10-14 -- 2012-10-08 (777)	2012-10-09 -- 2014-04-02 (388)
Peru	2009-11-10 -- 2014-04-02 (1147)	2009-11-10 -- 2012-10-16 (765)	2012-10-17 -- 2014-04-02 (382)
South Africa	2007-07-02 -- 2014-04-02 (1762)	2007-07-02 -- 2012-01-03 (1175)	2012-01-04 -- 2014-04-02 (587)
Swaziland	2009-06-30 -- 2014-04-02 (1242)	2009-06-30 -- 2012-08-31 (828)	2012-09-03 -- 2014-04-02 (414)
Tunisia	2007-01-02 -- 2014-04-02 (1891)	2007-01-02 -- 2011-11-03 (1261)	2011-11-04 -- 2014-04-02 (630)

Table 1. List of chosen countries and their respective time periods, and number of available observations.

As seen in Table 1 the time periods differ a lot. Argentina has available data way back to 2004 while the data for Egypt starts in 2010. We simply wanted to use all available data for each case.

3.4 Confidence levels

We have chosen to use three common levels of significance: 5%, 2.5% and 1%. This is partly because there is always a trade-off between so-called Type I-errors and Type II-errors. The first one refers to rejecting a correct null hypothesis, the latter to accept an incorrect null hypothesis (Verbeek 2012, p. 31). According to theory mentioned above, the standard confidence levels used with VaR are $\alpha = 0.99$ and $\alpha = 0.95$. We therefore choose these levels, and we also choose to include $\alpha = 0.975$.

It is of interest for this thesis to calculate VaR for both the long and short position. Therefore, we will include the corresponding α's for the long position as well. These are $\alpha = 0.01$; $\alpha = 0.05$ and $\alpha = 0.025$, respectively.

4. Results

4.1. Descriptive statistics

In Table 2 below we have gathered descriptive statistics for all of our chosen countries. With a p-value of 0.00, we can conclude that the country data is statistically significant. From the standard deviation we can determine which of the countries that is the most volatile. From our calculations we see that South Africa is the most volatile country followed by Mauritius with a slightly lower volatility. The least volatile country is Tunisia.

With a negative skewness, the left tail (negative returns) is longer, which means that there are more extreme losses. In our data, there are only two countries with positive skewness, indicating that most of our tested countries have very extreme losses, some more extreme than others.

Kurtosis is a measure of the probability for the more extreme outcomes in a given distribution. A Kurtosis distribution larger than 3 is characterized by a high, small peak around the mean with fat tails. The probability of extreme losses is than high compared to the normal distribution (Holton, 2003). From Table 2 we can see that this interpretation matches all of our countries. We see that Morocco has the highest probability of extreme losses with a kurtosis far higher than the country with the second highest kurtosis.

	Mean	Std. Dev.	Skewness	Kurtosis	P-value
Argentina	0.0278	1.448	-0.3202	8.632	0.00
Egypt	0.02	1.079	0.865	28.627	0.00
Lebanon	0.0168	1.072	-3.668	72.536	0.00
Mauritius	0.0003	2.227	0.2081	8.257	0.00
Morocco	-0.0089	1.246	-4.737	86.96	0.00
Paraguay	0.0262	1.03	-0.587	6.391	0.00
Peru	-0.0008	0.0247	-0.311	4.7896	0.00
South Africa	-0.036	2.363	0.0243	36.147	0.00
Swaziland	0.0263	0.435	-1.103	35.867	0.00
Tunisia	0,00010	0.0083	-0.426	33.01	0.00

Table 2. Descriptive statistics for all countries.

We have divided our results into three regions, in line with how the sample is based and in line with the World Bank's division: Sub-Saharan Africa (3 countries), North Africa and the Middle East (4 countries), and Latin America (3 countries). This will outline the results more clearly and give us the possibility to compare the results within the different regions where countries usually display similarities.

4.2. Sub-Saharan Africa

The result in Table 3, shows that all the Basic VaR models, except for one case in South Africa, give lower failure rates (that is, rate of violations) than expected here. The same goes for historical simulation (HS). Hence these models overestimate the risk. The GARCH models generally give higher failure rates than expected, except for in Swaziland. The normally distributed ones give higher values than the t-distributed ones, except for in Swaziland. For EGARCH, all failure rates are equal to 0 for Swaziland. For the other two, all failure rates are lower than expected in Mauritius, while they are all higher in South Africa. The EGARCH t-values in the latter country are much higher than expected.

When analyzing Table 4, we find a few models which are accepted for all 3 countries here: basic VaR Nd 99 % (both positions), basic VaR t 99% (long), HS 99 % (both positions) and HS 95% (long). For Mauritius and South Africa, a few more models are accepted: basic VaR Nd 97.5%, basic VaR t 97.5%, and HS 97.5%, all only for short position. In all other cases, the models are accepted for none or only one country. In the cases when a model is accepted for only one country, this country is mainly Mauritius.

Failure rates						
	0,05		0,025		0,01	
	short	long	short	long	short	long
Mauritius						
Basic VaR						
Normal	0,0254	0,0226	0,0155	0,0099	0,0099	0,0056
t-dist	0,0268	0,0282	0,0155	0,0099	0,0042	0,0042
HS	0,0282	0,0353	0,0155	0,0112	0,0042	0,0042
GARCH						
Normal	0,1185	0,1579	0,0917	0,1298	0,0748	0,1058
t-dist	0,0494	0,0564	0,0282	0,0395	0,0183	0,0226
EGARCH						
Normal	0,0028	0,0042	0,0014	0,0028	0,0014	0,0028
t-dist	0,0056	0,0127	0,0042	0,0099	0	0,0056
South Africa						
Basic VaR						
Normal	0,0239	0,0187	0,0136	0,0119	0,0085	0,0051
t-dist	0,0273	0,2044	0,0119	0,0102	0,0051	0,0051
HS	0,0307	0,0375	0,0204	0,0136	0,0068	0,0085
GARCH						
Normal	0,1857	0,1874	0,1618	0,1601	0,1431	0,1431
t-dist	0,1567	0,1516	0,1209	0,1226	0,0954	0,0886
EGARCH						
Normal	0,0630	0,0716	0,0477	0,0477	0,0375	0,0375
t-dist	0,1721	0,1618	0,1499	0,1363	0,1397	0,1260
Swaziland						
Basic VaR						
Normal	0,0073	0,0266	0,0073	0,0073	0,0024	0,0048
t-dist	0,0073	0,0266	0,0024	0,0073	0	0,0024
HS	0,0145	0,0314	0,0073	0,0097	0,0024	0,0024
GARCH						
Normal	0,0024	0,0024	0,0024	0	0	0
t-dist	0,1232	0,1111	0,0604	0,0845	0,03382	0,0435
EGARCH						
Normal	0	0	0	0	0	0
t-dist	0	0	0	0	0	0

Table 3. The failure rates in Sub-Saharan Africa using different intervals. The models are tested on both long and short position. The sample periods are given in Table 1. HS = historical simulation.

Violations of VaR												
	0,05				0,025				0,01			
		Result				Result				Result		
	Min	short	long	Max	Min	short	long	Max	Min	short	long	Max
Mauritius	25			47	10			26	2			13
Basic VaR												
Normal		18	16			11*	7			7*	4*	
t-dist		19	20			11*	7			3*	3*	
HS		20	25*			11*	8			3*	3*	
GARCH												
Normal		84	112			65	92			53	75	
t-dist		35*	40*			20*	28			13*	16	
EGARCH												
Normal		2	3			1	2			1	2*	
t-dist		4	9			3	7			0	4*	
South Africa	19			40	8			23	2			11
Basic VaR												
Normal		14	11			8*	7			5*	3*	
t-dist		16	12			7	6			3*	3*	
HS		18	22*			12*	8*			4*	5*	
GARCH												
Normal		109	110			95	94			84	84	
t-dist		92	89			71	72			56	52	
EGARCH												
Normal		37*	42			28	28			22	22	
t-dist		101	95			88	80			82	74	
Swaziland	12			30	5			17	1			9
Basic VaR												
Normal		3	11			3	3			1*	2*	
t-dist		3	11			1	3			0	1*	
HS		6	13*			3	4			1*	1*	
GARCH												
Normal		1	1			0	1			0	0	
t-dist		51	46			25	35			14	18	
EGARCH												
Normal		0	0			0	0			0	0	
t-dist		0	0			0	0			0	0	

Table 4. Number of violations in Sub-Saharan Africa using different calculations and interval. The violations denoted with a * is within the given confidence interval and in these cases, the model should be accepted. The models are tested on both long and short position. The sample periods are given in Table 1.

4.3. North Africa and the Middle East

From Table 5, one can see that for basic VaR, all failure rates were smaller than expected at the 5% (risk) level. For the two other levels this varies a bit more, but the majority is smaller than expected. For HS, a few values at the 5% and the 2.5% levels are higher than expected, otherwise they are lower. For the GARCH models, the majority of the failure rates are smaller than expected as well. For the EGARCH models, all failure rates are smaller than expected at the 5% level. At the 2.5% level most are smaller than expected, but at the 1% level most are actually larger than expected. So EGARCH overestimates the risk in the first two cases, and underestimates it in the last one.

Following Table 6, none of the VaR models was accepted for all four countries in this region, at any confidence level or position. For 3 of the 4 countries, the following were accepted: basic VaR Nd 99% (both positions), basic VaR Nd 97.5% (long), basic VaR t 99% (long), basic VaR t 97.5% (long), HS 95% (short), HS 97.5% (short) and GARCH Nd 95% (short). The country not making it was mainly Lebanon or Tunisia. The majority of the models/cases were acceptable for at least 2 of the 4 countries. In 7 cases, the model was only accepted for 1 country; this country was Morocco in 5 of those.

Failure rates						
	0,05		0,025		0,01	
	short	long	short	long	short	long
Egypt						
Basic VaR						
Normal	0,0368	0,0227	0,0368	0,0142	0,0339	0,0142
t-dist	0,0397	0,0227	0,0339	0,0142	0,0227	0,0085
HS	0,0595	0,0339	0,0311	0,0198	0,0057	0,0029
GARCH						
Normal	0,0284	0,0113	0,0198	0,0057	0,0397	0,0057
t-dist	0,0170	0,0085	0,0113	0,0057	0,0057	0,0028
EGARCH						
Normal	0,0425	0,0227	0,0425	0,0142	0,0425	0,0142
t-dist	0,0368	0,0085	0,0339	0,0057	0,0283	0,0057
Lebanon						
Basic VaR						
Normal	0,0239	0,0076	0,0139	0,0050	0,0088	0,0025
t-dist	0,0265	0,0076	0,0101	0,0038	0,0025	0,0025
HS	0,0618	0,0114	0,0177	0,0038	0,0013	0,0025
GARCH						
Normal	0,0517	0,0139	0,0404	0,0101	0,0239	0,0063
t-dist	0,0227	0,0114	0,0114	0,0076	0,0063	0,0063
EGARCH						
Normal	0,0015	0,0038	0,0101	0,0025	0,0101	0,0025
t-dist	0,0164	0,0038	0,0050	0,0038	0,0013	0,0013
Morocco						
Basic VaR						
Normal	0,0311	0,0228	0,0249	0,0186	0,0186	0,0166
t-dist	0,0352	0,0228	0,0249	0,0186	0,0145	0,0166
HS	0,0600	0,0393	0,0393	0,0331	0,0228	0,0228
GARCH						
Normal	0,0704	0,0476	0,0538	0,0414	0,0435	0,0352
t-dist	0,0249	0,0186	0,0186	0,0166	0,0145	0,0166
EGARCH						
Normal	0,0249	0,0166	0,0228	0,0145	0,0166	0,0145
t-dist	0,0363	0,0331	0,0269	0,0249	0,0228	0,0186
Tunisia						
Basic VaR						
Normal	0,0127	0,0191	0,0064	0,0143	0,0031	0,0111
t-dist	0,0127	0,0207	0,0064	0,0143	0,0016	0,0064
HS	0,0254	0	0,0095	0	0,0032	0,0064
GARCH						
Normal	0	0,0016	0	0,0016	0	0,0016
t-dist	0	0,0016	0	0,0016	0	0,0016
EGARCH						
Normal	0	0	0	0	0	0
t-dist	0	0	0	0	0	0

Table 5. Shows the failure rates in North Africa and the Middle East using different intervals. The models are tested on both long and short position. The sample periods are given in Table 1.

Violations of VaR												
	0,05				0,025				0,01			
	Result				Result				Result			
	Min	short	long	Max	Min	short	long	Max	Min	short	long	Max
Egypt	30			54	13			30	3			14
Basic VaR												
Normal		18	26			11	20*			7*	11*	
t-dist		36*	42*			12	20*			3*	6*	
HS		25	31*			11	14*			4*	6*	
GARCH												
Normal		32*	43*			13*	29*			5*	15	
t-dist		53*	59			16*	31			2	4*	
EGARCH												
Normal		0	0			0	0			0	0	
t-dist		5	3			0	0			0	0	
Lebanon	11			28	4			16	1			8
Basic VaR												
Normal		2	7			1	4*			0	2*	
t-dist		3	7			0	3			1*	8*	
HS		3	5			1	2			0	1*	
GARCH												
Normal		10	13*			5*	9*			2*	5*	
t-dist		16*	14*			1	6*			0	2*	
EGARCH												
Normal		0	0			0	1			0	1*	
t-dist		0	2			0	1			0	1*	
Morocco	11			28	4			16	1			8
Basic VaR												
Normal		26*	23*			16*	13*			8*	8*	
t-dist		36	61			16*	25			1*	6*	
HS		26*	23*			16*	13*			7*	6*	
GARCH												
Normal		22*	25*			12*	12*			7*	7*	
t-dist		44	44			17	24			1*	5*	
EGARCH												
Normal		9	11*			4*	7*			3*	2*	
t-dist		19*	27*			7*	13*			1*	2*	
Tunisia	11			28	4			16	1			8
Basic VaR												
Normal		8	12*			4*	9*			2*	7*	
t-dist		8	13*			4*	9*			1*	4*	
HS		16*	0			6*	0			2*	4*	
GARCH												
Normal		0	1			0	1			0	1*	
t-dist		0	1			0	1			0	1*	
EGARCH												
Normal		0	0			0	0			0	0	
t-dist		0	0			0	0			0	0	

Table 6. Number of violations in North Africa and the Middle East using different calculations and intervals. The violations denoted with a * is within the given confidence interval and in these cases, the model should be accepted. The models are tested on both long and short position. The sample periods are given in Table 1.

4.4. Latin America

When analyzing Table 7, we find that for basic VaR, most failure rates are lower than expected for both distributions and positions, and for all confidence levels. We note that at the 2.5% value, all values for Peru are larger than expected while all others are lower. For GARCH, most failure rates are larger than expected at the 5% and the 2.5% levels but lower at the 1% level. So the first two failure rates seem to underestimate the risk, while the last one overestimates it. For EGARCH, we got many zero values for Argentina and Paraguay (and hence overestimation of the risk), but the few values larger than zero were lower than expected. For Peru on the other hand, all EGARCH values are larger than zero. Here we got one failure rate higher than expected each at the 5% and the 2.5% level, and both are at the long position. All other failure rates are lower than expected.

From Table 8, one can see that for Latin America, the following models were accepted for all three countries here: three basic VaR models (all at 99 or 97,5% level, all for long position only), HS 99% (long), the three GARCH Nd models (for different positions) and GARCH t 99% (long). Otherwise, the vast majority of the models were applicable to at least one of the countries, no matter which position. The only exception is EGARCH Nd 95% (short).

Failure Rates						
	0,05		0,025		0,01	
	short	long	short	long	short	long
Argentina						
Basic VaR						
Normal	0,0216	0,0311	0,0132	0,0239	0,0084	0,0132
t-dist	0,0431	0,0503	0,0144	0,0239	0,0036	0,0072
HS	0,0371	0,0299	0,0132	0,0168	0,0048	0,0072
GARCH						
Normal	0,0383	0,0515	0,0155	0,0347	0,0059	0,0179
t-dist	0,0635	0,0707	0,0192	0,0371	0,0024	0,0048
EGARCH						
Normal	0	0	0	0	0	0
t-dist	0,0059	0,0036	0	0	0	0
Paraguay						
Basic VaR						
Normal	0,0052	0,0180	0,0026	0,0103	0	0,0052
t-dist	0,0077	0,0180	0	0,0077	0	0,0026
HS	0,0026	0,0052	0,0077	0,0129	0	0,0026
GARCH						
Normal	0,0129	0,0232	0,0258	0,0335	0,0052	0,0129
t-dist	0,0412	0,0361	0,0025	0,0155	0	0,0052
EGARCH						
Normal	0	0	0	0,0026	0	0,0026
t-dist	0	0,0052	0	0,0026	0	0,0026
Peru						
Basic VaR						
Normal	0,0681	0,0602	0,0419	0,0340	0,0209	0,0209
t-dist	0,1204	0,1414	0,0498	0,0602	0,0026	0,0157
HS	0,0681	0,0628	0,0419	0,0340	0,0183	0,0157
GARCH						
Normal	0,0576	0,0654	0,0314	0,0314	0,0183	0,0183
t-dist	0,1152	0,1152	0,0445	0,0628	0,0026	0,0131
EGARCH						
Normal	0,0236	0,0288	0,0105	0,0183	0,0079	0,0052
t-dist	0,0498	0,0706	0,0183	0,0340	0,0026	0,0052

Table 7. Shows the failure rates in Latin America using different intervals. The models are tested on both long and short position. The sample periods are given in Table 1.

Violations of VaR												
	0,05				0,025				0,01			
	Result				Result				Result			
	Min	short	long	Max	Min	short	long	Max	Min	short	long	Max
Argentina	30			54	13			30	3			14
Basic VaR												
Normal		18	26			11	20			7*	11*	
t-dist		36*	42*			12	20*			3*	6*	
HS		25	31*			11	14*			4*	6*	
GARCH												
Normal		32*	43*			13*	29*			5*	15	
t-dist		53*	59			16*	31			2	4*	
EGARCH												
Normal		0	0			0	0			0	0	
t-dist		5	3			0	0			0	0	
Paraguay	11			28	4			16	1			8
Basic VaR												
Normal		2	7			1	4*			0	2*	
t-dist		3	7			0	3			1*	8*	
HS		3	5			1	2			0	1*	
GARCH												
Normal		10	13*			5*	9*			2*	5*	
t-dist		16*	14*			1	6*			0	2*	
EGARCH												
Normal		0	0			0	1			0	1*	
t-dist		0	2			0	1			0	1*	
Peru	11			28	4			16	1			8
Basic VaR												
Normal		26*	23*			16*	13*			8*	8*	
t-dist		36	61			16*	25			1*	6*	
HS		26*	23*			16*	13*			7*	6*	
GARCH												
Normal		22*	25*			12*	12*			7*	7*	
t-dist		44	44			17	24			1*	5*	
EGARCH												
Normal		9	11*			4*	7*			3*	2*	
t-dist		19*	27*			7*	13*			1*	2*	

Table 8. Number of violations in Latin America using different calculations and intervals. The violations denoted with a * is within the given confidence interval and in these cases, the model should be accepted. The models are tested on both long and short position. The sample periods are given in Table 1.

5. Discussion and analysis

5.1 Conclusions

The most accepted models are at a confidence level of $\alpha = 0.99$, which also makes this level the most suitable for calculating Value at Risk for funds from these regions. For the other confidence levels, there was no clear correlation between the countries. Unfortunately, there is no clear pattern within the fails and passes of the models.

Peru was the country where most models passed the Kupiec test. It passed all except one model for the normal distribution. For the t-distribution it passed about half of the tested models. This makes Peru the country most fitted for calculating risk with the Value at Risk method.

Mexico, Tunisia and Swaziland had no violations in EGARCH, neither in the normal distribution nor in the t-distribution. The results were the same for all three confidence levels. With zero violations they all fail Kupiec for EGARCH. In Appendix 1, we see that these countries should have at least some violation at every confidence level, which makes it hard to trust the models. Hence, EGARCH is not appropriate for calculating Value at Risk in these three countries.

Some of the countries failed almost every test. For these countries, VaR is not a good risk measure. Although many models failed the test, at least we were able to make the calculations for VaR and Kupiec in every case. The models accepted for most countries were actually of basic VaR and historical simulation kind. What does this say about the data? Does it really need more complex models, or does it simply have to be adjusted or updated more carefully?

This result confirms our suspicion. For the developing countries and emerging markets that were tested in the thesis, Value at Risk is not a completely suitable method for measuring risk. Following the thoughts of Snoussi and El-Aroui (2011), this could be simply because of the countries' individual matters. There might be factors simply making it too hard to find a reasonable model, and fit it correctly. We did not find that our more advanced models (GARCH and EGARCH) performed significantly better than the basic ones (basic VaR and HS) in general.

But it is worth to mention that in many cases, different GARCH and EGARCH models worked fairly well for individual countries (e.g. EGARCH t 99% for Mauritius and South Africa, and GARCH t 99% for Egypt, Lebanon and Morocco). Hence, it seems one really has to take individual matters into account when dealing with these markets.

One common error for emerging markets' data mentioned by Snoussi and El-Aroui is zero returns. This is highly interesting here since we experienced this ourselves in some of our data. We discovered that some fund data was not updated or adjusted for weekends, public holidays etc. We tried to adjust the data somewhat for countries with a high number of zero returns (one or two countries were excluded from our study because of this problem). The mentioned authors also point out that the Tunisian market is lowly correlated to the world market, and this is a lot because of unstable institutions, asymmetric information and non-integration.

All of these factors might give rise to very special kinds of return data. Perhaps in some cases, one has to find the optimal risk model for each specific country one wants to invest in. Snoussi and El-Aroui also suggest that improved integration improves liquidity, which makes it easier for foreign agents to invest (Snoussi and El-Aroui, 2011). Hopefully, the countries we have studied struggle to improve their financial institutions, because they would most likely benefit from it. How, if and when this will be solved remains to be seen.

5.2 Further research

We have limited this study to three specific regions in the world. First of all, one could make a similar study for other regions/continents. Second of all, one could try to find data for more, if not all, of the countries in the chosen region/continent. This could not be made in this thesis due to lack of data access. One could also make a study for a specific time period for all countries. One also has to bear in mind that there are other and more complex VaR models that could be more or less suitable here.

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The World Bank: http://data.worldbank.org/about/country-classifications, downloaded 2014-04-10.

The World Bank: http://data.worldbank.org/country, downloaded 2014-04-10.

Appendix 1

Violations: N*(1-α)		Number of violations at:		
Country	**Observations out-of-Sample**	**α = 0,95**	**α=0,975**	**α=0,99**
Argentina	834	41,7	20,85	8,34
Egypt	353	17,65	8,825	3,53
Lebanon	793	39,65	19,825	7,93
Mauritius	709	35,45	17,725	7,09
Mexico	424	21,2	10,6	4,24
Morocco	483	24,15	12,075	4,83
Paraguay	388	19,4	9,7	3,88
Peru	382	19,1	9,55	3,82
South Africa	587	29,35	14,675	5,87
Swaziland	414	20,7	10,35	4,14
Tunisia	630	31,5	15,75	6,30

Table 9. Number of violations that we should observe within every country at different confidence levels.