VALUE AT RISK
- A comparison of Value at Risk models during the 2007/2008 financial crisis

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ABSTRACT

The financial crisis of 2007/2008 brought about a debate concerning the quality of risk management models, such as Value at Risk (VaR) models. Several studies have tried to make conclusions about multiple VaR models in periods around the crisis. The conclusions differ, but the Extreme Value Theory (EVT) is considered to be a good prediction model in times of unstable financial markets. In this thesis, the VaR for six financial instruments; the OMXS 30, the OMX Stockholm Financials PI, the OMX Stockholm Materials PI and the currencies USD/SEK, GBP/SEK and EUR/SEK are estimated with the Historical Simulation, the Monte Carlo Simulation and the Variance-Covariance Method, with a 95 percent confidence interval. The risk is estimated both for single instruments as well as portfolios in times before, during and after the crisis with the purpose of concluding which of the VaR models more accurately predict risk for specific instruments/portfolios in different time periods of the crisis.

No direct conclusions can be made about the accuracy of the models before, during or after the crisis. The only clear conclusion can be drawn for the single instruments regarding the EUR. All methods predict more accurate results for this instrument compared to the other instruments. The clearest conclusion for the portfolios is that portfolios holding larger weights of indexes show on larger VaR estimations. Also, the modified Monte Carlo Simulation and the Variance-Covariance Method estimate lower risk in general than the Historical Simulation.

Keywords: Value at Risk, financial crisis, Historical Simulation, Monte Carlo Simulation, Variance-Covariance Method, individual financial instrument, portfolios, OMXS 30, OMX Stockholm Financials PI, OMX Stockholm Materials PI, USD/SEK, GBP/SEK, EUR/SEK
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1. INTRODUCTION

First, the background describes the stepping stone of the financial crisis and the debates around the possible causes to its origin and whether or not it could have been predicted. Next, the problem, purpose and delimitations will be presented.

1.1 BACKGROUND

Many debates and speculations about what caused the financial crisis of 2007/2008 have been discussed in the past years. Implications, stating the problem laid in declines of asset valuations, government interventions and larger corporations, but maybe most significantly, the declining activity in the economic markets. The start of the crisis was the overvaluation of houses in the United States. This housing bubble, triggered by low credits and the thought that housing prices always incline, finally burst and financial institutions all over the world were affected. This was the case as many of these institutions had exposed risk to the housing market. In 2008 the crisis saw its peak. (Chang, 2010)

Another debate about what caused the financial crisis concerns the risk prediction models; was it their fault? (Gillani and Masri, 2010) In 2009, a hearing was held regarding risk models and their role in the crisis. The testimony of several witnesses blamed risk models, particularly Value at Risk (VaR) models, for the financial instability that followed with the crisis. The models cannot be held responsible for the crisis as they are designed to reflect reality. All risk models have strengths and weaknesses, which is why it is important not to solely rely on one single model. Gillani and Masri (2010) argue that the models are not good estimators for risk in times of financial crises. Rowe (2010) adds that risk managers themselves must bear the responsibility for losses. Subsequently, one of the lessons of the financial crisis, according to Varma (2009), is the importance of using several high-quality risk management models.

Voinea and Anton (2009) describe that a considerable amount of studies with the focus on risk management during the crisis has been made. The main conclusions of these studies have been underestimations and misleading calculations of risk performed by financial institutions.

According to Berman (2009), the financial crisis of 2007/2008 was not impossible to predict. It is therefore uncertain if it can be classified as a fat-tailed event. Berman tries to attempt the question of why Value at Risk models did not foretell the crisis. His conclusion was that when market conditions changed, the behavior of securities was incorrectly predicted by private investors as well as financial institutions. VaR models master short-term volatilities, while crises have long-term volatility trends, an explanation to why the models could not produce correct estimations. Value at risk (VaR) is a measure for the potential market risk. For a 95 percent confidence level the potential loss should equal or exceed estimations of VaR on one day out of 20 (Linsmeier and Pearson, 1996). It was first used by financial firms in the latter part of the 1980’s to measure risk on portfolios (Linsmeier and Pearson, 1996). VaR is further described in the section for Value at Risk.
1.2 PROBLEM
Risk is generally more volatile for financial instruments in times of crises, compared to times when financial markets are considered stable. Investors may therefore lose more than expected on invested capital. Even though VaR models do not capture the changes in the market, it is important that financial institutions provide accurate information about the financial market. Risk managers bring this information into the models. A problem can be caused when models cannot fully capture the changes of the market, as it could lead to underestimations in risk.

In the last decades multiple simulations with VaR models have been applied to different crises in order to estimate the VaR. The models have shown different results, some more accurate than others, something partly depending on the different choices of financial instruments and partly on both the different time aspects and geographically chosen locations. This is considered a problem as former studies have reached diverse conclusions. This thesis will add information to this discussion as other financial instruments have been studied in other geographic locations. To narrow the problem further, the Historical Simulation, the Monte Carlo Simulation and the Variance-Covariance Method will be studied to determine which predicts risk more accurately during a financial crisis. This leads to the following two questions:

- With a 95 percent confidence interval, what conclusions can be made about the accuracy of the predicted losses created by the Historical Simulation, the Monte Carlo Simulation and the Variance-Covariance Method in the four periods before, during and after the financial crisis?
- For both individual instruments and portfolios, are there any differences among the three VaR models when it comes to time periods and instruments/portfolios?

1.3 PURPOSE
The main purpose of this thesis is to try to conclude which one of the three chosen Value at Risk models, is the more accurate risk predictor for financial instruments around the time of the latest financial crisis, stretching from 2006 until 2011. The chosen models are the Historical Simulation, the Monte Carlo Simulation and the Variance Covariance Method. Another aim of this study is to determine if any model is more accurate in predicting risk than another for certain financial instruments.

As risk varies in different time periods, the thesis intends to make conclusions about the credibility of the models in these different periods of times. Another question to be tested is if the models predict risk differently depending on if the instruments have been studied individually or in portfolios.

1.4 DELIMITATIONS
In order to reach the purpose of this thesis certain restrictions have been made. As mentioned in the section regarding the purpose, delimitations for the usage of VaR methods have been made. The methods to be used are: the Historical Simulation, the Monte Carlo Simulation and the Variance-Covariance Method. Calculations for these three models will be used in order to predict the value at risk. To restrict the usage of the models further, the confidence interval of 95 percent was selected.
The financial instruments studied in this thesis are the stock index OMXS30, the sectoral indexes OMX Stockholm Financials PI and OMX Stockholm Materials PI, and the foreign exchange rates USD/SEK, GBP/SEK and EUR/SEK. The indexes can be found on the Swedish stock exchange market.

Time wise, the delimitation focus on the last five years up until today, from 2006-2011. These are the years before, during and after the recent financial crisis. This time period has been split up into four smaller periods, of 40 days each. The period of the year of 2006 symbolizes a pre-crisis period, while the 2008 period denotes the early/mid part. The last two years, 2010 and 2011, both denote after-crisis periods.
2. THEORETICAL FRAMEWORK

This chapter holds theories about portfolios, Value at Risk and the models used for computing VaR measures. Advantages and disadvantages will also be described for the three VaR methods used in this thesis. Finally, previous studies regarding the subject of this thesis will be summarized.

2.1 PORTFOLIO THEORY – return and risk

Taylor and Weerapana (2007), state that a portfolio consists of a collection of assets. Mao and Särndal (1996), describe portfolios as consisting of n different securities, each with its own expected return. The value of the investment is divided among the assets, with equal or different amounts according to their respective importance. In order to do this, all assets are assigned weights. The sum of all weights always equal one.

Return is what is earned on an investment, and the expected return is the return most likely to be received for an investment. There is a strong belief that high expected return implies higher risk (Maheshwari, 2008). A portfolio combines securities to diversify and reduce risk. Risk is what can be lost on an investment, and it is often considered to be thought of as the volatility of an asset. The volatility captures fluctuations in prices on the exchange market and is often measured in terms of standard deviations. The standard deviation is a measure of dispersion; actual returns are compared to the mean of the return. (stockexchangesecrets.com) The computations for a standard deviation will be explained further in the section for statistical terms.

In portfolios, correlations between assets are always estimated. With perfect correlations between securities, the returns of the securities move together and no diversification is present. In order to reduce risk it is crucial to have securities uncorrelated to each other. Returns on securities in the same industry are usually subject to a higher correlation than securities coming from different sectors. (Markowitz (A), 1991)

There are both systematic and unsystematic risks for portfolio investments. Systematic risk cannot be eliminated by diversification, something possible for unsystematic risk. The former type of risk refers to market fluctuations such as recessions, inflations and tax-reforms. Unsystematic risk can, as mentioned, be eliminated due to the fact that it is firm specific. It can be reduced by low indebtednesses in companies. (scribd.com)

There is a rule within portfolio theory stating that investors should diversify and maximize expected return (Markowitz (A), 1991). A portfolio with maximum expected return does not need to have a minimum variance. The most elementary form of diversification can be seen in a portfolio where financial instruments hold equal weights. A portfolio containing ten different stocks, opposed to one single instrument, can reduce risk by thirty percent. (Taylor and Weerapana, 2007)

The future return of a portfolio is never certain. The return, r, can be thought of as a random variable. Amu and Millegård (2009) make the assumption that the means for each of the n assets are known, \( \bar{r}_i \), \( i = 1, ..., n \). The variance of asset \( i \) is \( \sigma_i^2 \), and the covariance between assets \( i \) and \( j \) is \( \sigma_{ij} \).
The return \((r)\) and expected return \((\bar{r})\) of the portfolio are

\[
r = \sum_{i=1}^{n} w_i r_i \tag{2.1}
\]

\[
E[r] = \bar{r} = \sum_{i=1}^{n} w_i E[r_i] = \sum_{i=1}^{n} w_i \bar{r}_i \tag{2.2}
\]

with \(w\) denoting the weight of the asset.

The variance, \(\sigma^2\), of the portfolio is

\[
\sigma^2 = E[(r - \bar{r})^2] = E \left[ \left( \sum_{i=1}^{n} w_i \bar{r}_i \right)^2 \right] \tag{2.3}
\]

\[
= E \left[ \left( \sum_{i=1}^{n} w_i (r_i - \bar{r}_i) \right) \left( \sum_{j=1}^{n} w_j (r_j - \bar{r}_j) \right) \right] \tag{2.4}
\]

\[
= E \left[ \sum_{i=1}^{n} w_i w_j (r_i - \bar{r}_i) (r_j - \bar{r}_j) \right] \tag{2.5}
\]

\[
= \sum_{i,j=1}^{n} w_i w_j \sigma_{ij} \tag{2.6}
\]
2.1.1 STATISTICAL TERMS

Some of the statistical terms have already been covered in earlier sections, but not to the full extent. Variances and covariances signify a dispersal of data in relation to a mean (Maxwell and Russo, 1999). Spiegel et al. (2002) describe the mean as a set of numbers designated by \( x_1, x_2, \ldots, x_n \) divided by \( n \), where \( n \) is the number of total observations. The measure of dispersion will also need to be calculated, as different sets of data may have the same mean. There are two measures for dispersion, the variance and the standard deviation. The variance can be denoted \( \sigma^2 \), and is nonnegative. For the set of numbers \( x_1, x_2, \ldots, x_n \) the variance formula is

\[
\sigma^2 = \frac{\sum(x_i - \mu)^2}{n}
\]  

[2.7]

The standard deviation, \( \sigma \), is achieved by taking the square root of the variance. Larger variances and standard deviations imply larger dispersal, possibly due to more varied data (Maxwell and Russo, 1999).

Another statistical term is the covariance, which takes the movements of two or more assets’ returns in consideration. The covariance can hold a positive or negative value and is written

\[
\sigma_{ij} = E[(R_i - \bar{R}_i)(R_j - \bar{R}_j)]
\]

[2.8]

The covariance will be positive if the assets’ returns move in a convergent pattern, and negative if they diverge. If the covariance for two assets is divided by their standard deviations, a correlation coefficient is generated. This signifies the strength of the covariance between the two assets. The correlation coefficient varies from 1 to -1, where 1 stands for complete correlation and -1 stands for a negative correlation (Markowitz, 1991).

\[
\rho_{x,y} = \frac{C(x,y)}{\sigma(x) \cdot \sigma(y)}
\]

[2.9]

2.2 VALUE AT RISK

Linsmeier and Pearson (1996, s.3) describe VaR as “a single, statistical measure of possible portfolio losses”. VaR measures potential losses that occur depending on movements in markets. Penza and Bansal (2001), notice the same thing as Linsmeier and Pearson (1996), that losses greater than the calculated VaR only occurs with a small probability. When measuring VaR the focus lies on future potential losses, not profits. This is why only the negative side of the normal distribution is calculated on (Best, 2001).

Duffie and Pan (1997) use another approach to explain VaR, where a time period \( t \) is decided along with a specific confidence level, denoted \( P \). The loss of the market value is expected to exceed with a probability of \( 1 - p \) in the specifically chosen time period. Jorin (2000) adds that when calculating VaR on portfolios, the portfolio is considered frozen, meaning that the content of the portfolio is static.
JPM (JP Morgan), (1996, s.7) states that: “Value at Risk is a number that represents the potential change in a portfolio’s future value”. The change differs from the chosen time horizon and degree of confidence level. Banks and financial institutions generally use a one day time horizon as the large volume of daily trading needs to be valued on a mark-to-market basis (Best, 2001). Nonfinancial firms usually apply a longer time horizon of commonly one month (McNeil, 1999).

When it comes to the choice of probability levels, there is no specific rule to be followed. The most commonly used confidence intervals range from 90 to 99 percent. JPM advocates a 95 percent confidence interval while commercial banks have chosen different probability levels. A 95 percent confidence interval means that in 1 day out of 20 a loss equal to or exceeding the VaR-measure will incur. Worth observing is that VaR estimations does not give any information about what the potential exceeded loss might be. (McNeil, 1999)

A variable that is normally distributed have values distributed symmetrically around the mean. The normal distribution is often said to have the shape of a bell. The distribution of the returns is measured with the standard deviation, which measures the dispersal from the mean. A 95 percent confidence interval uses two units of standard deviations from the mean. (Bump, 1991)

In 1998, guidelines issued by the Banks of International Settlements stated the requirement of banks holding capital aside. This was done in a preparatory meaning, for future potential extreme portfolio losses. The current regulatory framework, in that point of time, required financial institutions to calculate VaR with a one percentage confidence interval over a 10 day period. (Campbell, 2005)

Banks can use VaR to determine risk targets which means that if a firm would like to increase its risk they can increase the VaR target. Since VaR is a measure that gives information about the minimum level of a likely loss, it can be used to decide internal capital allocation. The risk measure is useful for reporting financial purposes and is commonly found in financial statement firms. (Dowd, 1998) They also often use VaR to generate information about what the potential loss could be over night (Duffie and Pan, 1997).

2.2.1 HISTORY OF VALUE AT RISK
In 1952 Markowitz published a paper on VaR. Only three months later, Roy published another paper also regarding VaR. Although the two papers were independently written they had similarities concerning optimization of portfolio risk and both used covariances to hedge and diversify portfolios. Mathematically, Markowitz and Roy presented calculations of VaR similar to one another, although they supported different parts. Markowitz focused on variances, while Roy held a historical perspective with estimations on covariances from the past in interest. Markowitz model was focused to an audience whose technical powers were lacking. This was the contributing reason to why the VaR measure became theoretical and published under the section of portfolio theory. (Holton, 2002)

The model of Markowitz had some technological boundaries. In 1970 the technology led to changes in the calculation of VaR. As a result of this, more assets could now be applied for VaR and organizations could allocate risk better. In the beginning of 1980, the markets became more unstable. Companies were financing through loans which in turn generated a need for measures of
the faced financial risks. The measure of VaR grew larger, although it was still part of the portfolio theory. (Holton, 2002)

Later in 1971, Lietaer used a simple model to describe VaR for foreign exchange instruments. He had made observations about devaluations in most currencies after the Second World War, something he tested with VaR and found they had occurred randomly. This model can be seen as the first development of the Monte Carlo Simulation. (Holton, 2002)

As mentioned above, about using loans to finance companies, Dowd (1998) talk about the leveraged markets. Derivative contracts spread rapidly and the increase affected the risk of portfolio derivatives and disclosures. As the risk increased, the demand for measuring it was extended. Older and simpler measurement tools were replaced by newer and more complex ones.

In 1993 measures of VaR were used by several financial firms. There were many different VaR measures during this time but most of them maintained the character designed by Markowitz in 1952 and one of his sequels in 1959. JPM introduced something called “a firm-wide VaR system” in the later part of the 1980’s where covariances were updated and calculated from historical data every three months. JPM used several ways to calculate VaR. One of them was based on a one day time horizon with a 95 percent confidence interval with the assumed normal distribution. In 1990 the profit and loss function were added into the simulation in the way that profits and losses were published at 4:15 pm every day. The VaR system developed by JPM was demonstrated by a man named Guldimann. As JPM was no vendor for software, Guldimann suggested that they publish the methodology behind the calculation of VaR as a covariance-matrix. He meant that by publishing the methodology, software vendors would start to compete on the market. (Holton, 2002)

Value at Risk went under several different names during the years of 1990’s. “Dollars-at-Risk” (DaR), “Income-at-Risk” (IaR), “Capital-at-Risk” (CaR) and “Earnings at Risk” ( EaR) were a few of the names circulating during the time. Guldimann claims that “Value-at-Risk” was developed by JPM. (Holton, 2002)
2.3 MODELS FOR CALCULATIONS OF VALUE AT RISK
There are several methods to calculate VaR with. Linsmeier and Pearson (1996) state that the
Historical Simulation, the Monte Carlo Simulation and the Variance-Covariance Method are the most
frequently used models. In addition to these three models there are other commonly used models
such as the Extreme Value Theory (EVT), the Conditional Autoregressive Value at Risk (CAViaR), the
Exponential Weighted Moving Average (EWMA) and the Orthogonal GARCH model. As with all
models there are both advantages and disadvantages making the models more or less reliable.

2.3.1 THE HISTORICAL SIMULATION
The Historical Simulation uses daily historical data of financial price changes to calculate VaR. The
financial price changes could be of both single financial instruments as well as portfolios. The
historical time perspective differs from 100 business days up till as much as five years (Best, 1998). In
an example made by Linsmeier and Pearson (1996), the chosen historical period of time is of 100
days.

The basic idea of the Historical Simulation is that hypothetical values of the changes of the portfolio
or asset is constructed a number of times depending on the selected time period. This generates a
sequence of gains and losses of the original financial instrument in question. (Linsmeier and Pearson,
1996)

Linsmeier and Pearson (1996), describes the Historical Simulation process as follows. First a financial
instrument is identified, and then its basic market factors are recognized. These are important for
calculating VaR. Interest rates are examples of basic factors. Next historical data needs to be
obtained including records of actual values for the basic factors of the financial asset for the specific
time period chosen.

Subsequently, the actual values of the basic factors are to be used to calculate percentage changes
between the days of the historical period. Then, for example, the change between the first and the
second days of the selected period is multiplied with today’s actual value of the basic factor of the
asset. This will in turn generate a hypothetical value. (Linsmeier and Pearson, 1996)

Further, the mark-to-market value of the financial instrument is to be calculated. This is done by
applying the hypothetical values gained earlier, into the value formula of the instrument. Once the
mark-to-market value has been produced, the hypothetical mark-to-market profit or loss can be
determined. The calculation of this is quite simple; the mark-to-market value is subtracted with the
actual value of today’s mark-to-market value. This is then to be repeated for all basic factors
throughout the time series. All the profits and losses gained are then arranged from highest profit to
largest loss. For a 95 percent confidence interval the fifth largest loss will be the Value at Risk. To
yield a 99 percent confidence interval the largest loss would instead be named the VaR. (Linsmeier
and Pearson, 1996)

2.3.2 THE MONTE CARLO SIMULATION
To calculate VaR using the Monte Carlo Simulation a number of observations, usually 1000 or 10 000,
are generated by a random number generator. Since the number of observations is relatively large it
demands computerization. Spreadsheets and Excel are common programs used for calculating VaR. (Linsmeier and Pearson, 1996)

The Monte Carlo Simulation starts by identifying the financial asset of interest, and its basic markets factors. Once this has been done a function expressing the mark-to-market value for the asset can be constructed. So far, the Monte Carlo Simulation has been identical to the Historical Simulation, but from this point distinct changes will separate the two, before the last few steps that are again similar. (Linsmeier and Pearson, 1996)

The distribution of the market factors is often assumed to be normally distributed in the Monte Carlo Simulation. It does not need to be normally distributed, although it is the most preferred distribution, as it is easy to work with when computing means, standard deviations and correlations of the basic factors of a financial instrument. (Linsmeier and Pearson, 1996)

Further, numbers for the basic factors' volatilities and covariances will be estimated. Random variables that are independently distributed are used for this. These variables are also normally distributed, which is necessary since they are estimates for the actual variables (the basic factors). To link the variables with the basic factors, constants are introduced. This would look like

\[
\begin{align*}
    r_1 &= a_{11}e_1 & \text{and} & & r_2 &= a_{21}e_1 + a_{22}e_2 \\
\end{align*}
\]

where \( r_1 \) and \( r_2 \) symbolize the basic factors and \( e_1 \) and \( e_2 \) characterize the random variables. The \( a \)'s denote the constants, which as explained, serve the purpose of relating the random variables to the independently distributed variables. (Linsmeier and Pearson, 1996)

If the instrument invested in is a basic instrument itself, for example a stock index, no calculation of the covariance will be possible. Instead, the daily returns are put together so that a mean of the return can be determined. From this the variance and the standard deviation can be calculated. (Linsmeier and Pearson, 1996)

The following step is to construct at least 1000 hypothetical values by using a random number generator. Once the 1000 random numbers are created they will be multiplied with the standard deviation to generate the profits and losses of the investment. These are then ranked from the largest profit to the largest loss. VaR can thus be determined by taking the fiftieth largest loss. (Linsmeier and Pearson, 1996)

For the VaR calculations of the portfolios the Monte Carlo Simulation will be used in the same manner as it will be used for the individual instruments. This type of Monte Carlo-like simulation will therefore be called the Modified Monte Carlo Simulation in this thesis.

2.3.3 THE VARIANCE- COVARIANCE METHOD
The basic idea with the Variance- Covariance Method is that VaR is calculated by multiplying the standard deviation of the value function expressed for the financial instrument with 1,65. The
number 1.65 is chosen as it is based on a 95 percent confidence interval and because the financial instrument’s basic market factors are assumed to be normally distributed. (Best, 1998)

Identical to the Historical Simulation and the Monte Carlo Simulation, the Variance-Covariance Method starts by recognizing the basic market factors in order to construct a value function. Once this has been mastered, the value function should be derived with respect to the basic market factors. When the derivation has been completed, a process called risk mapping can be performed. Risk mapping is an important part of the Variance-Covariance approach. The idea of risk mapping is that less complicated instruments, or standardized positions, replace the original instruments. Usually they are denoted $x_1$, $x_2$, etcetera. (Linsmeier and Pearson, 1996)

After the risk mapping has taken place, the standard deviations and correlations of the single instruments need to be calculated by using the standard deviations and correlations of the market factors. Following, the values of the standard deviations and correlations are put into the formula for the variance of the instrument. In the case of three standardized positions the formula can be expressed

$$ \text{Var} (\Delta V) = x_1^2 \sigma_1^2 + x_2^2 \sigma_2^2 + x_3^2 \sigma_3^2 + 2 x_1 x_2 \sigma_1 \sigma_2 \rho_{12} + 2 x_1 x_3 \sigma_1 \sigma_3 \rho_{13} + 2 x_2 x_3 \sigma_2 \sigma_3 \rho_{23} \quad [2.11] $$

When the variance of the portfolio has been given, the standard deviation can be obtained by taking the square root of the variance. This will in turn be multiplied with 1.65 for a 95 percent confidence interval, to achieve Value at Risk. (Linsmeier and Pearson, 1996)

2.3.4 HISTORICAL SIMULATION – advantages and disadvantages

The Historical Simulation method is preferable for many reasons (Linsmeier and Pearson, 1996). Firstly, it is a simple method with easy mathematical calculations (Best, 1998), without necessary estimations of statistical parameters (Bohdalová, 2007).

Secondly, the method captures the real distributions of the factors; no assumptions are made (Stambaugh, 1996). When the factors are normally distributed the value at risk of the underlying instrument is fairly good. In cases when the distribution of the factors does not show normality, but is stable over time, the Historical method has shown to give better results than other distribution-based models. Finally the Historical Simulation is not problematic to explain to others who are not familiar with risk calculations. (Penza and Bansal, 2001)

One of the most significant disadvantages with the method is that calculation is based on the basic factors historical distribution, and because the future distribution of the factors might differ radically, the results of VaR can be misleading. (Penza and Bansal, 2001)

Another weakness with the method is that each day’s return is assigned equal weights. This is not realistic as volatility is time dependent and as higher and lower returns tend to cluster together. Also interesting regarding this matter is that returns closer in time to the day when VaR is to be calculated for, has shown to play a more important role for future returns, than returns of days further back in history and should because of this be given larger weights. (Pritsker, 2005)
Further there is the flaw of which time period to choose and its length. Longer periods of data could on the one hand generate more accurate results of VaR due to its fewer risk sampling errors, but on the other hand it can be questioned for its validity (Stambaugh, 1996). It might also be hard to find consistent data for longer periods of time, something that is necessary for calculating VaR using the Historical Simulation. The method might also be hard or nearly impossible to use when it comes to calculating VaR on financial assets in emerging markets. Instruments on emerging markets might not have a representable historical period of data. (Penza and Bansal, 2001)

2.3.5 MONTE CARLO SIMULATION–advantages and disadvantages
The Monte Carlo Simulation is flexible and can generate a large number of reliable data that can be used for calculations of VaR (Penza and Bansal, 2001). It has the properties of being general and precise in slumping random variables which makes the model appealing (Srinivasan and Shah, 2000). Also, the simulation captures convexity which is often used for nonlinear instruments such as options (Best, 1998).

The method has endured criticism for its demand of computer utilization. The need for computerized calculations is time consuming, especially for larger portfolios (Linsmeier and Pearson, 1996), and the user might in some cases prefer the usage of other methods (Penza and Bansal, 2001). Several articles also state the disadvantage of having to use software applications necessary in order to generate the values which the simulation demands. Often software of this kind is costly (Srinivasan and Shah, 2000).

Linsmeier and Pearson (1996) notes that the calculated VaR can be misleading as the statistical distribution is determined by assumption and might therefore not coincide with the actual distribution of the financial assets. They also add that professional skills are essential when selecting the distribution and estimating the parameters of the Monte Carlo Simulation.

Dowd (1998) stresses, in accordance with Penza and Bansal (2001), that the Monte Carlo Simulation is to be used when simpler methods in calculating VaR are inappropriate. If methods that are less complicated are satisfactory they should be used. He also clarifies the usefulness with the method. When several problems arise, for example when there is more than one risk variable affecting the outcome, the Monte Carlo Simulation is to prefer.

2.3.6 VARIANCE-COVARIANCE METHOD–advantages and disadvantages
This is an easy and fast calculating method to reach results of VaR with (Best, 2001). What makes the Variance-Covariance Method preferable in comparison to the Historical Simulation and the Monte Carlo Simulation is that the volatilities of financial returns are predictable (JPM, 1996). The Variance-Covariance Method is also easy to implement for currencies and other financial instruments that statistics have been kept for (Best, 2001).

A drawback with the method is its difficulty of explaining it to others who lack a financial and mathematical background. Knowledge of the concepts of standard deviation and normal distribution are vital to possess if one should understand the process of the Variance-Covariance Method. (Linsmeier and Pearson, 1996) Also problematic with the method is the fact that it is not optimal for
calculating VaR for options. This is because the profits and losses of options do not hold a normal
distribution. (Best, 2001)

Another problem that may arise with this method is the lack of volatility and correlation data for the
financial instruments. Dowd (1998) emphasizes that even if the data were available it is not certain
that it could be used as the matrix might be unmanageable. A way to solve this problem is to shrink
the matrix to a more controllable and workable size.

2.4 OTHER VALUE AT RISK METHODS

Besides the three VaR methods described above, there are other models used for VaR calculations. In
the section of previous studies below, earlier studies using different VaR models will be covered.
These other VaR methods will be explained in this section.

Some of the previous studies test the Extreme Value Theory (EVT). The EVT is based on extreme
events normally including large losses, rather than small profits. The theory is often used when
estimating risk in times of crises, due to the extreme variations in financial markets. (Kellezi and Gilli,
2000) Another aspect of the theory is the fact that it is not built on the assumption of normal
distribution, which means the theory does not tend to underestimate risk, something that is occurs
with the normal distribution. (McNeil, 1999)

The Conditional Autoregressive Value at Risk model, also often referred to as the CAViaR model,
focus on the quartile rather than the distribution of the return of the financial instrument. Describing
the structure of the actual calculation of the theory can be made by taking the weighted average
between the VaR and all the other losses larger than the estimated VaR. (Engle and Manganelli,
2002)

The Exponentially Weighted Moving Average (EWMA) theory is about weighting together all
historical prices of an asset, where the more recent prices are given greater weights to constitute
their importance. The reason to this is that an assumption is made stating prices closer to today be
more relevant for the outcome of tomorrow’s price. (Poon, 2008)

For the Orthogonal GARCH (O-GARCH) model, data obtained from linear transformations are used for
estimating VaR. The O-GARCH is based on unconditionally uncorrelated variables taken from original
data. The linear transformation is put into an orthogonal matrix from which VaR can be sought out.
(Joneau et al, 2007).

2.5 PREVIOUS STUDIES

Bao et al (2001) compare risk for different VaR models in five Asian emerging markets in the years of
1997-1998’s financial crisis. Composite Price Indexes are studied on the Indonesia Jakarta Stock
Exchange, Korea Stock Exchange and Malaysia Kuala Lumpur Stock Exchange. Also, the Taiwan
Weight Index and the Thailand S.E.T. Price Index are considered for the comparison. For all above
mentioned financial instruments a 95 percent and a 99 percent confidence interval were chosen.
There are several methods used in this study, where some methods prove more significant results than others. In this study the Historical Simulation, the Extreme Value Theory (EVT) and Conditional Autoregressive Value at Risk (CAViaR) model are brought more attention to as they are models which have shown to be more or less predictable.

The comparisons of the VaR results were made in three different time intervals during the time of the crisis. The first period regarded the time before the crisis incurred, while the second period considered the time when the crisis bloomed at its most, and conclusively the third period evaluated a time after the crisis was considered to be over. The three periods were named accordingly; the before crisis period, the crisis period and the after crisis period.

For the first crisis both the symmetric and asymmetric CAViaR models showed fine predictions of VaR. The EVT models showed proof of poor performance. Other poor models for this first period of time are for example the Historical Simulation, although it performed more accurate values than the EVT models. The performance of most of the models in the mid-crisis period showed underestimations.

The results of the models for the third period are in line with the results calculated for the first period. The Historical Simulation has once again indicated on good performance in times of non-crisis periods. Lastly the Bao study made the conclusion that VaR methods differ in prediction when comparing periods during financial crises and periods of other times.

Since the early 1990’s the Asian equity markets have been exposed to radical changes in volatility, generating extreme negative losses. Pownall and Koedijk (1999) studied the IFC Asia 50 Index on the Asian equity markets during the time from 1993 to 1997. In their study they reached the conclusion that VaR calculations for Asian equity markets may not be normally distributed, but instead have a distribution of a more fat tailed character. The normal distribution therefore tends to be a bad assumption when predicting VaR during financial crises.

Another study focusing on VaR during a financial crisis is made by Kourouma et al (2010). The examined crisis is the 2007/2008 crisis. They used the Historical Simulation, assuming normality, and the EVT for calculating the possible losses of CAC 40 and Standard & Poor’s (S&P) 500 stock indexes. The data used for this study stretches from January 4th 1988 until December 10th 2009 and the calculations are made for a one, five and ten day time horizons.

For both of the indexes, Kourouma et al (2010) notice a negative skewness\(^1\) for each of the given time horizons implying a lower return than the average. The kurtosis\(^2\) is higher than three in all time horizons, indicating a leptokurtic distribution. This means that the returns of the indexes have a thin waist and fat tails. Those VaR models with assumptions of normality must therefore be rejected and replaced with the EVT as this method counts in a distribution of fat tails. At last it can be said that

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\(^1\) Skewness measures the asymmetry of a distribution. For a normal distribution the skewness is zero. If the skewness holds a negative value it means that the distribution of the data is skewed to the left, while for positive values the data is skewed to the right. (M. W. Bump, 1991)

\(^2\) The kurtosis is a measure for how flat or peaked the distribution of the data is around the mean. A high value of kurtosis indicates that the area around the mean is sharply peaked, while a low value of kurtosis indicates a flat top. (M. W. Bump, 1991)
this study has reached the result that the EVT model is the better and more reliable model compared to the Historical Simulation in times of financial crises.

Chiriac and Pohlmeier (2009), created portfolios for which VaR were estimated. The portfolios were created for 2007 and 2008, and the time horizon of one day was chosen. The aim of this paper was to calculate VaR for portfolios before, as well as during, the financial crisis by using several different methods. The main calculations are based on data with 250 and 1250 daily observations (m). The authors also introduce two other perspective of time, where m equal 50 and 100. The reason they chose to make calculations of VaR for portfolios was that it had never been done before. The portfolio consisted of four indexes corresponding to equities, commodities, foreign exchange and fixed income. The indexes were equally weighted in the portfolio.

Conclusively, Chiriac and Pohlmeier (2009), state that all methods are almost equally trustworthy. In the pre-crisis period the methods all performed similar, rather good predictions. In the second period, the methods seemed to lack the ability of generating good results.

Turkey and Croatia formed the basis for another study made by Zikovic and Aktan (2009), where VaR methods were used to determine the risks involved with investments in emerging markets. The indexes used for this was the Turkish stock index XU100 and the Croatian stock index CROBEX. Among eight different models, there were two that performed distinctly better results. These two models were the Hybrid Historical Simulation (HHS) and the EVT model. The HHS and the EVT showed better results in predicting the risks of investments in the indexes during the crisis.

Paskelian and Hassan studied the daily stock market indexes for seven Middle Eastern and North African countries during 1996 through 2002. They used the three traditional VaR models in combination with the EVT model. The traditional models are the Historical Simulation, the Monte Carlo Simulation and the Variance-Covariance Method. Surprisingly, the traditional models performed better VaR estimations than the EVT model in their study.

Bredin and Hyde (2002) examine several foreign exchange traded portfolios. The daily exchange rates in the portfolios were studied from 4th January 1990 to 17th December 1998. There were four different holding periods for which VaR were calculated upon; 50 days, 125 days, 250 days and 500. The portfolios were provided by the Bank of Ireland. The Irish Punt is put against the UK Sterling, US dollar, Dutch guilder, French franc, German deutschmark and Italian lira. The Variance-Covariance Method, the Exponential Weighted Moving Average (EWMA) approach, the Orthogonal GARCH and the Historical Simulation were the chosen VaR models for this study. They concluded that the EWMA and the Orthogonal GARCH outperformed the other models. Even though the last one mentioned provided the most accurate measures, Bredin and Hyde valued the EWMA as the most appropriate model.

2.6 THE UNDERLYING ASSETS

An underlying asset is a financial instrument based on a derivative’s price; it could be a currency, a commodity, a stock or a bond. Futures contracts and options are also a couple of examples of underlying assets. (Chance and Brooks, 2010) In this thesis the underlying financial instruments calculated upon are; the stock index OMXS 30, the sectoral indexes OMX Stockholm Financials PI and OMX Stockholm Materials PI, and the cross rates USD/SEK, GBP/SEK and EUR/SEK.
2.6.1 INDEX

An index is a value that weights together the changes of several different financial instruments. The index is measured in relation to a specific date, a sort of start date. The value of the index for this date will be 100, and as the financial instruments which the index is built upon changes, the index will adjust accordingly. The development of the instruments will be altered in a percentage increase or decrease of the index. (aktiespararna.se)

Most indexes are market-weighted, meaning that each instrument’s involvement in the index is represented with a weight equal to its size and impact on the exchange. Indexes that are equally weighted also occur in the market, implying that each instrument is denoted with the same importance. (aktiespararna.se) For the three indexes studied in this thesis there are attachments of what companies the indexes are based on.

2.6.1.1 STOCK INDEX- OMXS 30

OMX Stockholm 30 (OMXS 30) is an index based on the 30 most actively traded stocks on the Stockholm Stock Exchange. These 30 stocks are all emitted by large companies holding high liquidity. Twice a year, the first two business days of January and July, the index is revised in order to maintain that the index holds the 30 most traded stocks; this is done by checking shares tradability over the last 7 months. These are then the 30 shares that qualify to be included in the index. Since the stocks are not traded at the same intensity, weights are denoted to indicate their different importance that they play. This results in that some stocks affect the outcome of the index more than other stocks. (nasdaqomx.com)

2.6.1.2 THE SECTORAL INDEXES

Sectoral indexes measure the development of stocks in different sectors of the economy (nasdaqomx.com). Sectoral indexes exist in both PI and GI form. The PI stands for price index while the GI is a gross index. A price index is based only on the development of the stocks, whereas a gross index takes dividends into account as well. The latter index mentioned is therefore often called a reinvested index. (aktiespararna.se) For this thesis VaR will be calculated for the OMX Stockholm Financials PI and the OMX Stockholm Materials PI, which are both price indexes.

The past five years development for the OMXS 30, the OMX Stockholm Financials PI and the OMX Stockholm Materials PI are displayed in the diagram below.

Figure 1, Closing prices- indexes

![Closing prices- indexes](image-url)
2.6.2 CURRENCIES

Daily, currency rates are calculated by the Swedish Central Bank with the formula \((\text{buy} + \text{sell})/2\). These rates are then computed by NASDAQ OMX to obtain a mean, which is called the mid-price. Exchange rates are commonly calculated using cross rates. Cross rates are when two exchange rates are used in order to generate a third one. Any currency can be bound as the base currency (riksbank.se). When using cross currencies for investments the first currency is called the base currency, and the second is called the quote currency (tradingcurrency.com).

Historically currencies were usually only traded among banks and different institutional traders. Later it has become more common among smaller traders to deal with currencies thanks to improved technological advancement. When investing in currencies, there are four major currency pairs, EUR against US Dollar, US Dollar against JPY, British Pound against the US Dollar and US Dollar against Swiss franc. (tradingcurrency.com)

Today, the largest financial market is the foreign currency exchange market, also called the FX market. (tradingcurrency.com) The FX market is more liquid than other financial markets and as currency trading is not focused to a specific exchange, it can be traded at any time of the day (foreigntradingstrategy.org). As the FX market is more liquid than other markets, it brings lower transaction costs due to the lacking need of stockbrokers (tradingcurrencies.com).

The closing prices of the cross rates USD/SEK, GBP/SEK and EUR/SEK over the last five years are presented in figure 2.

**Figure 2, Closing prices- cross rates**

![Closing prices- cross rates](image-url)
3. METHOD

The method is divided into two parts, the first one describing scientific methods, and the second one explaining the approach of this specific thesis. The latter part thoroughly describes the calculations of the three VaR methods for individual instruments as well as portfolios.

3.1 SCIENTIFIC METHODS

The concept of scientific methods is to describe methods and approaches normally used in the science. Following, the quantitative method will be explained as this thesis is performed in such a way. Along with this, the meanings of validity and reliability will be discussed in general, to later be applied to the subject of this thesis.

3.1.1 A QUANTITATIVE APPROACH

According to Newman and Benz (1998) some have claimed quantitative researches to categorize as empirical studies, while others have claimed it belongs under statistical studies. Curwin and Slater (2008), state it as the numerical testing of a hypothesis. A quantitative approach estimates the relationships between different variables, such as their correlations and means.

In this thesis, calculations are based on closing prices for financial instruments. Calculations to determine relationships between the variables are made to generate correlations, variances, covariances and standard deviations. The VaR estimations are in turn based on these calculations. In order to make conclusions, the theory of VaR is put into context and referred to. This does not make this thesis purely quantitative, but it is its main approach. This is in consensus with Åsberg (2001), who claims there are no single-handed quantitative or qualitative method.

3.1.2 DEDUCTIVE APPROACH

Deductive research tests existing theories and/or hypothesis for empirical observations (Crowther and Lancaster, 2008). The purpose in this case is to test models, not to construct them, as it assumes already existing models. These models; the Historical Simulation, the Monte Carlo Simulation and the Variance-Covariance Method are well established VaR models developed and tested during the second part of the last century. In this thesis these models are tested in new conditions, both considering the choice of financial instruments and the time period studied.

3.1.3 VALIDITY

Kwok and Sharp (1998) explain the presence of validity if the procedures used measure what was intended to be measured. Svenning (2003) describes internal and external validity. Internal validity describes how well the results of the thesis are consistent with the reality, while external validity expresses how applicable the results are in other situations.

The internal validity of this thesis is considered high because VaR was measured with the Historical Simulation, the Monte Carlo Simulation and the Variance-Covariance Method. The steps of these methods were carefully followed according to instructions made by Linsmeier and Pearson (1996). The degree of external validity may not be seen as high since the restrictions of instruments used in
this thesis are rather few. Also, the time periods studied lie in a time span from 2006 to 2011 and is of 40 days each.

3.1.4 RELIABILITY
Kwok and Sharp (1998) describe reliability as yielding consistent results, vital for the validity. It is often defined as to which degree it is free from error. Consistent results have the meaning of achieving similar or the exact same results if the empirical studies were repeated.

All information being used in this thesis is publicly available. The data would thus be the same; with the only difference being the Monte Carlo estimations, because of its usage of random variables. The random numbers will result in different VaR results, but will in the end be approximately the same. The approach can therefore be seen as reliable.

3.1.5 SOURCE CRITICISM
Source criticism is an evaluation of references and how these have an effect on reliability (Kylén, 2004). For this thesis sources has been used both for the theoretical framework and the empirical results. For the former, several research papers have been the main source, although literature and web sources have been contributing sources as well. Even though some of these sources were published during the mid and late part of the 1990’s they are considered relevant as the foundations of the methods remain the same today. In those cases when editions have not been updated, but still used as a source, triangulation has been employed. The scientific articles have been collected from several data bases, such as Scirus, SSRN, Google Scholar and LibHub.

For the empirical part of the thesis, only one type of source has been employed; web sources. The closing prices for the financial instruments were obtained from Nasdaq OMX and the central bank of Sweden, Riksbanken. Both of these sources are considered to hold reliable data since the former is the world’s largest exchange company and the latter is a government authority.

3.2 METHOD USED IN THIS THESIS
As stated earlier, this thesis has a deductive approach. It holds multiple calculations of VaR, generated by the Historical Simulation, the Monte Carlo Simulation and the Variance-Covariance Method. The approach for these calculations will further be described below.

3.2.1 CHOSEN FINANCIAL INSTRUMENTS
As already mentioned, the financial instruments calculated on in this thesis are the OMXS 30, the OMX Financials PI, the OMX Materials PI as well as three foreign exchange rates of USD/SEK, GBP/SEK and EUR/SEK.

All above mentioned financial instruments have been selected for one or several reasons. The OMXS 30 was chosen as it contains the thirty most actively traded stocks on the Stockholm Stock Exchange. It is a benchmark and is often referred to when discussing the ups and downs of the stock market.
The OMX Financials PI was selected as this thesis is in the area of finance which makes it interesting to study how well or poorly the financial sector estimated risk in the time span of the latest financial crisis. The OMX Materials PI was considered to be of interest for analyzing how another sectoral market behaved and predicted risk during these times. The choice of bringing two sectoral indexes had the purpose of comparing if the predictions of the models were better or worse for one of the sectors compared to the other. If so, was there a difference only in the occasion of financially troubled times or also in times of normal economy growth and stability?

The OMX Financials and the OMX Materials indexes were available in PI, price index, and GI, gross index, form. The reason to why the PI form was selected was simply because historical data for the GI index form was not available.

Exchange rates change daily and are quickly affected in times of financial instability. Exchange rates were therefore a given instrument to calculate VaR for. The choice of the exchange rates, the USD/SEK, GBP/SEK and the EUR/SEK has also a well designed purpose. The dollar is a currency of most importance as it was the most traded currency in early 2009 (forextrading.se). Nearly 85 percent of all transactions in spot prices were in US dollars. The second largest currency to be traded was the euro, which was used in 38 percent of all transactions. They both played vital parts in the foreign exchange markets and also had an effect on Sweden and its currency. The Japanese Yen (JPY) was the third largest foreign exchange rate, although its impact will not be considered in this thesis. The GBP in contrast does, and it came on fourth place on the list of mostly traded foreign exchange rates in the beginning of 2009. The GBP was considered to be geographically closer to Sweden and play a more essential part for the Swedish economy and therefore the SEK. The reason to why the year of 2009 was chosen as a reference for most traded currencies was that calculations in this thesis were made both before and after this year.

3.2.2 THE SOURCE OF DATA
The data used in this thesis are series of historical closing prices for the financial instruments. Daily data for the OMXS 30, the sectoral indexes OMX Financials Stockholm PI and OMX Stockholm Materials PI have been collected from Nasdaqomx, which contain information about the Nordic Exchanges. The data for the three foreign exchange rates: USD/SEK, GBP/SEK and USD/SEK were gathered by the Swedish Riksbank, which is the Central Bank of Sweden.

3.2.3 VALUE AT RISK CALCULATIONS
The VaR calculations have been simulated in the Swedish version of Microsoft Excel. Among multiple financial programs representative for these types of calculations, Excel was chosen as it is applicable for calculations of VaR. In the program there are both financial and statistical formulas for means, standard deviations and percentile functions, all needed for the calculations included in this thesis.

In order to make a comparison between the methods several delimitations was made. As the financial crisis had its peak in 2008 it was of interest to study how the methods estimated VaR during and around this time. The estimations were divided into four periods. The historical time series for the period of 2006, symbolizing a pre-crisis period, stretches from 2005-12-30 to 2006-07-24 for 101 days of observations plus 40 days for actual VaR calculations. The 2008 and 2010 periods denote the
early/mid part of and the later part of the crisis. The historical time series for these two are 2007-12-28 to 2008-07-21 and 2009-08-10 to 2010-02-26 respectively. The last period of time stretches from 2010-08-11 to 2011-02-25, denoting the after-crisis period. The observations used for the computations of the instruments were consistent with regards to the lack of less than a handful of observations. For example, there was data missing for one day in one of the instruments, something that was regulated by pushing the time span one day back.

The four periods have been created over the time from 2006 to 2011 with the purpose of studying differences in risk estimations. The first time period was picked as it is considered a time right before the crisis started. The motive for the time perspective of the second period was that the crisis had its peak. The third period was chosen in order to look at the estimations of VaR in a time when financial markets started to stabilize. The fourth and last period was selected as it is close in time to the present and the markets are now considered to function as “normal”.

The chosen confidence interval was 95 percent, meaning that VaR was to incur on one day out of twenty. To test this theory, calculations were made for a time span of 40 days. By looking at results for 40 days, it was possible to determine whether or not VaR actually occurred at 95 percent of the time. Another delimitation was made concerning the size of the investment for the single financial instruments and the portfolios. The investment was put at 1 000 000 SEK because it was considered a realistic size of capital to invest.

Further, the three VaR methods; the Historical Simulation, the Monte Carlo Simulation and the Variance-Covariance Method will be explained separately for the individual assets. Then, the usage of the methods when dealing with portfolios will be declared.

The Historical Simulation is calculated using historical data, in this case 101 days observations was selected, in order to generate 100 daily returns. If a larger amount is chosen it may have an inefficient effect on the calculations of VaR as the older data might not be as representative as newer data. The choice of 100 daily observations was mainly used as it was considered a representative time interval, supported by Linsmeier and Pearson (1996) who advocates this. The other reason to why this perspective of time was used is as the calculations in this thesis are not to be influenced on each other. It was important to hold the periods and their results separated from each other, in order to be able to analyze the differences between the methods in different times of the financial crisis. An assumption that the historical data has a normal distribution was made.

For all instruments the Historical Simulation has been calculated as follows. The closing prices for an instrument were pasted into an Excel file for 101 days prior to the day that VaR was to be calculated for. The percentage changes were then obtained by using the formula \((p_t - p_{t-1})/p_{t-1}\). In order to continue calculating the hypothetical value the percentage change of the daily closing prices were multiplied with the most recent day’s closing price. Next, to determine VaR at 95 percent, profits and losses were calculated by taking the hypothetical value minus the closing price of the most recent day. The profits and losses generated were then ranked in the order of highest loss to biggest profit. These numbers were then multiplied with 1 000 000 SEK divided by the most recent day’s closing price, \((PoL*(1000000/closing\ price\ of\ the\ day\ before))\). This was repeated forty times until 40 different values were obtained. Thus, the data used for each day were slightly different compared to
the next day, since the 101 observations continuously moved one day ahead for each daily calculation.

As an example to constitute this, imagine that VaR on an investment in the stock index OMX Stockholm Materials PI will be calculated for June 12 2006. The closing prices for the 101 prior days stretch from 2006-01-13 to 2006-06-09. The closing price for 2006-06-09, also called the most recent day’s closing price, is 304,24.

Table 1, A sample of the Historical Simulation calculations

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<th>Date</th>
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<th>Daily return</th>
<th>% increases or decreases</th>
<th>Hypothetical value</th>
<th>P&amp;L</th>
<th>Ranking of P&amp;L</th>
<th>Investment</th>
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<td>0,0218516</td>
<td>0,978188517</td>
<td>310,8881229</td>
<td>6,64812294</td>
<td>-14,2023306</td>
<td>-46 681,34 kr</td>
</tr>
<tr>
<td>2006-01-20</td>
<td>279,46</td>
<td>0,025052269</td>
<td>1,025052269</td>
<td>311,8619022</td>
<td>7,62190221</td>
<td>-11,6218932</td>
<td>-38 199,75 kr</td>
</tr>
<tr>
<td>2006-06-09</td>
<td>304,24</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The first step after the closing prices have been pasted into the document, is to calculate the difference between the prices by taking: (268,78-267,01)/267,01 which equals 0,006628965. Adding 1, generates 1,006628965. The hypothetical value is then 306,2567964 calculated by: 1,006628965*304,24. The profit and loss is done by subtracting 304,24 of the hypothetical value, generating 2,01679637. The ranked profits and losses are then computed: -23,0076367* (1000000/304,24). The shaded value in table 1 is the VaR for the Historical Simulation due to the 95 percent confidence level chosen.

The Monte Carlo Simulation starts off in a similar way to the Historical Simulation by calculating the daily returns from the daily closing prices of 101 dates. The next step is different; the average return, the mean, \( \bar{r} \) is calculated from the last 100 daily returns \( r \). The return was constructed for all 100 days by taking today’s value minus yesterday’s value, divided by yesterday’s value

\[
r = \frac{(r_t - r_{t-1})}{r_{t-1}}
\]

The mean was constructed by adding all daily returns and dividing them by 100, the formula used for this:

\[
\bar{r} = \frac{\sum(r)}{100}
\]

Next the variance of the closing prices was generated with the formula:

\[
\sigma^2(r) = \frac{\sum(r - \bar{r})^2}{100}
\]
Knowing the variance, the standard deviation was calculated by raising it to the power of 0.5;

$$\sigma(r) = \left(\frac{\sum (r - \bar{r})^2}{100}\right)^{0.5}$$

The variance and standard deviation is not only estimated once, but continuously for all forty days so that each VaR measure has as recent data as possible. The time span of 101 days is on 40 times continuously pushed forward one day at a time. The approach of these calculations is shown below in table 2.

### Table 2, A Sample of the Variance-Covariance and Monte Carlo calculations

<table>
<thead>
<tr>
<th>Date</th>
<th>Closing price</th>
<th>Daily return</th>
<th>Average return</th>
<th>$r\bar{r}$</th>
<th>$(r\bar{r})^2$</th>
<th>Variance: $(r\bar{r})^2/100$</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006-01-13</td>
<td>267.01</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2006-01-16</td>
<td>268.78</td>
<td>0.006628965</td>
<td>0.001518532</td>
<td>0.005110434</td>
<td>2.61165E-05</td>
<td>0.000421931</td>
<td>0.020540955</td>
</tr>
<tr>
<td>2006-01-17</td>
<td>268.08</td>
<td>-0.00260436</td>
<td></td>
<td>-0.004122892</td>
<td>1.69982E-05</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2006-01-18</td>
<td>266.8</td>
<td>-0.004774694</td>
<td></td>
<td>-0.006253226</td>
<td>3.96047E-05</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2006-01-19</td>
<td>272.63</td>
<td>0.021851574</td>
<td></td>
<td>0.020333043</td>
<td>0.000413433</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2006-06-09</td>
<td>304.24</td>
<td>0.032406936</td>
<td></td>
<td>0.030888404</td>
<td>0.000954094</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Once this has been mastered the second part of the Monte Carlo Simulation consists of generating one thousand random variables ($e_i$). The random number generator in the Swedish version of Excel is used by writing SLUMP in the equation field twelve times, subtracting it by 6,

$$=\text{SLUMP() + SLUMP() + SLUMP() + SLUMP() + SLUMP() + SLUMP() + SLUMP() + SLUMP() + SLUMP() + SLUMP() + SLUMP() - 6}$$

This was repeated 1000 times for each VaR calculation. As the e’s are random variables, the random values are subject to change each time anything in the file is touched. To eliminate this occurrence, the cells were locked. The locked random values contained were then multiplied with the standard deviation, denoted $a$, to generate what was lost, denoted $x$.

$$x = e \times a$$

The loss ($x$) was in turn ranked from highest loss to largest profit and then multiplied with 1 000 000 SEK signifying the investment in the instrument.

The Variance-Covariance Method is constructed in a way similar to the Monte Carlo Simulation. Table 2 therefore holds formulas and values representable for both methods. Instead of running random computations as in the Monte Carlo Simulation, the standard deviation is multiplied by 1.65

$$1.65 \times a$$

The number 1.65 represent the confidence interval of 95 percent. The potential gain or loss was further multiplied with an investment of 1 000 000 SEK.
For each day that VaR was calculated for the single instruments, it was also calculated for portfolios. The portfolios consist of all single instruments, although they have been assigned different weights in three types of portfolios. In the first portfolio, all assets have been assigned equal weights, while the weights in the second and the third portfolios have a 30/70 percent ratio between the indexes and the currencies. The 30/70 percent ratio was picked to create an unbalance in the portfolios, in order to be able to make conclusions about potential differences in predictions of VaR among the three VaR methods.

The portfolio calculations differ somewhat between the Historical Simulation, the Monte Carlo Simulation and the Variance-Covariance Method. For the Historical Simulation the weights were first calculated into the value they should possess once the investment of 1 000 000 SEK was made. For instance, if there are six equally large portfolio weights, the investment of 1 000 000 SEK is divided by six. These weights were multiplied with the returns of the financial instruments in order to generate hypothetical values. The hypothetical values were then summarized so that the hypothetical value of the portfolio could be created. The formula for the hypothetical value of the portfolio is

\[
V = OMXS\ 30 \times \left(1 + \frac{\Delta I}{I}\right) + FPI \times \left(1 + \frac{\Delta F}{F}\right) + MPI \times \left(1 + \frac{\Delta M}{M}\right) + USD \times S_U \times \left(1 + \frac{\Delta S_U}{S_U}\right) + GBP \times S_G \times \left(1 + \frac{\Delta S_G}{S_G}\right) + EUR \times S_E \times \left(1 + \frac{\Delta S_E}{S_E}\right)
\]

where \(V\) is the hypothetical value of the portfolio. \(OMXS\ 30, FPI\) (OMX Stockholm Financials PI), \(MPI\) (OMX Stockholm Materials PI), \(USD, GBP\) and \(EUR\) stand for the values of the instruments’ returns on the day before VaR is to be calculated. If VaR is to be calculated for May 29, these returns should represent values from May 26, since this is the day previous to May 29.

Further, the hypothetical value was subtracted by 1 000 000 SEK for each of the 100 days. These were in turn ranked from the largest to the smallest of returns, with the fifth largest loss representing the VaR. This was repeated 40 times for the period of 40 days.

When calculating VaR for the portfolio using the Variance-Covariance Method; the returns, expected returns, variances and standard deviations were calculated for each instrument included in the portfolio. These four terms were all calculated with the same types of formulas described for single instruments above. For this method covariances between all instruments were also calculated in order to generate the portfolio variance and standard deviation. The 2.8 formula presented earlier is used for this, here presented with two instruments, \(i\) and \(j\).

\[
\sigma_{ij} = (r_i - \bar{r}_i)(r_j - \bar{r}_j)
\]

Once the covariances were obtained, the variance of the portfolio could be calculated. The formula for the variance of the portfolio is,

\[
\sigma^2(\rho_p) = w_1^2 \sigma_1^2 + w_2^2 \sigma_2^2 + w_3^2 \sigma_3^2 + \cdots + w_6^2 \sigma_6^2 + 2w_1w_2 \sigma_{12} + 2w_1w_3 \sigma_{13} + 2w_1w_4 \sigma_{14} + \cdots + 2w_5w_6 \sigma_{56}
\]
Since there are six instruments used in this thesis the terms in the formula are denoted with numbers from one to six. To get the standard deviation of the portfolio the variance was raised to the power of 0.5. The standard deviation was then multiplied with 1.65, as a 95 percent confidence interval is used, before the investment of 1 000 000 SEK was multiplied to generate VaR.

For portfolios, the calculations of VaR are the same as for the individual instruments once the standard deviation is determined for the portfolio. To determine this, data of returns and expected returns were drawn from each individual instrument’s calculation. These were then used to generate the variances and standard deviations. Next, the covariances were computed using the formula stated in the statistical terms section earlier. By using the assigned weights, the variances and covariances were together used to form the portfolio variance. The variance formula for this can be found in the section for portfolio theory, as formulas 2.7 and 2.8. The variance, the standard deviation and the covariance were separately estimated for all 40 VaR dates.

The Variance-Covariance Method was computed by taking the standard deviation of the portfolio variance. The VaR of the Variance-Covariance method was then generated by multiplying the portfolio standard deviation by 1.65. At the end of this the estimation of VaR was made by the multiplication of 1 000 000 SEK investment.

For another estimation of VaR, the portfolio was considered as an individual instrument. The standard deviation of the portfolio was thus used in order to run normal Monte Carlo calculations similar to the ones used for single instruments. This is what is called the Modified Monte Carlo Simulation. The reason to why this type of calculation was made was that the real Monte Carlo Simulation was more complex compared to the chosen type of calculation.

The VaR estimates, both for single instruments and portfolios, were then ordered in tables. For single instruments the results were put into diagrams showing both the actual development of the instrument along with the estimates of the three models. The results representing actual outcomes were calculated by the changes between the closing prices of each instrument. These changes were then multiplied by 1 000 000 SEK in order to be able to compare them to the estimations.

To present the VaR between the different time periods, linear diagrams were preferred as certain variables were studied over time. The diagrams are presented in the following chapter of Empirical Results and Analysis.
4. EMPIRICAL RESULTS AND ANALYSIS

This section for empirical results and analysis is separated in two parts; individual instruments and portfolios. Both the single instruments and the portfolios will be presented in diagrams. Next the results will be analyzed according to the predictions made by the Historical Simulation, the Monte Carlo Simulation and the Variance-Covariance Method.

4.1 INDIVIDUAL FINANCIAL INSTRUMENTS

The six financial instruments; the OMXS 30, the OMX Stockholm Financials PI, the OMX Stockholm Materials PI, the currencies USD/SEK, GBP/SEK and EUR/SEK has been compiled into several diagrams. The diagrams show the development during one time period for each instrument. Each diagram holds the development of the real outcome along with the VaR estimations in a 95 percent confidence interval for the Historical Simulation, the Monte Carlo Simulation and the Variance-Covariance Method. The real outcome represents the return once the investment of 1 000 000 SEK has been made. Important to remember when studying the diagrams is that the predictions of VaR only state the minimum loss on one day out of 20.

4.1.1 OMXS 30

Following are the four diagrams for the OMXS 30.

Figure 3 OMXS 30 (2006)

Studying the diagram for VaR measurements in 2006 one could see that all three methods estimate VaR similarly. The Historical Simulation estimate VaR to be larger than the Monte Carlo Simulation and the Variance-Covariance Method. It also shows that the daily results are the same and only drops twice to larger estimates of VaR. The two changes occur during the first ten days of the period. The two other methods also show on lower estimates for this first quarter of the period. The red line, the Monte Carlo results, signified as the more fluctuating line, meaning VaR differs drastically from day to day. The VaR results constituted by the Variance-Covariance Method appear almost as a mean of the Monte Carlo results. This is the method showing the most gradual changes, although with a decreasing development.

As mentioned, that the VaR only coincides with the real results of the stock index in the beginning of the period, it should be said that the index only show on big dips in this part of the period. The latter
part, about the last 30 days, the negative fluctuations of the returns are much smaller than the predicted VaR.

Figure 4 OMXS 30 (2008)

![OMXS (2008) chart]

In comparison to the period in 2006, this time span all three methods demonstrate an increase of smaller estimates of VaR on the whole. The actual results of the OMXS 30 presented in the diagram, mostly appear on the negative side of returns, with fluctuations increasing with time.

The three methods again follow the same pattern when predictions of VaR were made for the 40 day period. The real result coincided with the expected VaR estimations about three times. On one specific date, 25 June, the actual loss was about 10 000 SEK greater than the risk predictions made by the methods. On the other two occasions when VaR coincided with the actual results, the size of the loss of the instrument matched the predictions quite well. In the former part of the period, the Historical Simulation estimates the risk to be identical for several days at a time. It steadily leaps to lower predictions of risk until 20 days into the period where it starts assuming different VaR for each day. The Monte Carlo Simulation and the Variance-Covariance Method estimate VaR equally throughout the whole period. Also noticeable is that the Historical Simulation estimates VaR to be smaller than the other two methods, something opposite to the predictions seen in the 2006 diagram.

Figure 5 OMXS 30 (2010)

![OMXS 30 (2010) chart]
The line indicating the actual result, show rather even fluctuations apart from changes around 1 February, when a large return is followed by a large loss. The Historical Simulation again estimates VaR lower in general compared to the other methods. The changes during this period occur more often than previous years. The results from the Monte Carlo Simulation and the Variance-Covariance Method follow the same path as the Historical Simulation, but estimates VaR higher on most days.

During the period, the real losses of the investment in the index reach the level of predicted VaR almost twice. To be exact it is only the Historical Simulation that predicts VaR to occur the first time the return takes on a big drop, but the Monte Carlo Simulation and the Variance-Covariance Method are still close enough to almost be considered to have occurred. The difference between the actual loss and the predictions made by these two models were less than 100 SEK. On the second time all three methods did not estimate the loss to be as great as it were, which is in accordance to what the VaR measurement is all about.

Figure 6 OMXS 30 (2011)

The outcome of the real result in the 2011 diagram show less variation compared to the previous periods, which slightly diminish during the second part of the time span. The three methods predict VaR similar to each other through the whole time, with one exception. For approximately one third of the period, from 10 January to 2 February, the Historical Simulation show estimates of much lower numbers of VaR compared to the other models and to its own predictions for the other part of the period. During this specific time VaR calculations estimated the minimum loss to be 10 000 SEK less than the actual loss of the investment. The loss of the investment in the index is equal to, or greater than, the estimations of VaR three or four times, something that is not in accordance with what is expected when using a 95 percent confidence interval.

Table 3, Incurrence of VaR, OMXS 30

<table>
<thead>
<tr>
<th>Periods</th>
<th>Historical Simulation</th>
<th>Monte Carlo</th>
<th>Variance-Covariance</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006</td>
<td>2</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>2008</td>
<td>3</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>2010</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2011</td>
<td>4</td>
<td>3</td>
<td>3</td>
</tr>
</tbody>
</table>

In all four diagrams the estimations of VaR for the Monte Carlo Simulation and the Variance-Covariance Method follow the same pattern. The Historical Simulation on the other hand, shows a diverse pattern. This might be because the Historical Simulation is based on actual data from the past
101 days, while the Monte Carlo Simulation and the Variance-Covariance Method uses the standard deviation calculated from the last 100 days.

When looking at how the different periods stand out from each other it can be determined that the 2006 and 2008 diagrams hold larger fluctuations, with bigger gains and losses compared to the two latter periods examined. The reason to this may be an effect of more unstable financial markets in the pre-crisis and mid-crisis periods than in later periods. Even though the fluctuations are larger, the VaR models have not captured more losses than in other periods.

4.1.2 OMX STOCKHOLM FINANCIALS PI
The VaR predictions of the OMX Stockholm Financials PI index are presented in the diagrams of this section along with the real development of the index.

Figure 7 OMX Stockholm Financials PI (2006)

Similar to the 2006 OMXS 30 diagram, losses exceed VaR estimates for all three methods in the beginning of the period. Also, the volatility of the real result of gains and losses of the investment has in the first third of the period excessively larger losses than gains. Again the Historical Simulation, the Monte Carlo Simulation and the Variance-Covariance Method remain on the same level for all daily estimations, although they slightly decrease in the second half of the period.

Losses reached VaR levels only in the first third of the period, while losses for the rest of the period stayed much smaller. Again, as in the previous figures for individual assets, the predictions lie on the same scale for most part of the period.
For the period in 2008 all methods predict VaR equally, although the Historical Simulation again, differs from the other two. This time its predictions lie about 4000 SEK below the others. The method’s predictions of VaR are also quite steady over the whole period, even if they all contain small differences throughout time. Estimates of the Historical Simulation are unusually inconsistent.

The first half of the period the volatility of the real results are rather small, with two exceptions where the losses reach levels of 30 000 SEK. The second half of the period shows higher volatility, with gains and losses differing of 90 000 SEK. Due to these fluctuations VaR occurred as much as six times for one of the methods. In accordance to Linsmeier and Pearson (1996), VaR should only occur twice for a 40 day long period when calculating on a 95 percent confidence interval. In this case the theory did not hold. It might be because the peak of the financial crisis is assumed to have occurred in 2008. Since the financial index is composed by Swedish banks, investment companies and real estate companies, shown in the Appendix, which was a sensitive sector to the crisis, these types of companies were exceptionally exposed to risks.
Figure 9 displaying the VaR predictions and actual outcome of the OMX Stockholm Financials PI in the beginning of 2010 show that the loss of the index occurred only once. This might be because the crisis started, or had already, stabilized. The models overestimated VaR in this period. The Historical Simulation might have estimated risk higher since it is based on historical data representing closing prices closer to the peak of the crisis. The observations used for these predictions stretches back to September 2009, a time when presence of the crisis still remained.

Further, VaR estimations are diminishing over time for all models, which could be considered an effect of the ongoing stabilization of the financial market.

Figure 10 OMX Stockholm Financials PI (2011)

In 2011, the outcome of the investment in the index moved from gains of almost 20 000 SEK to losses of about 17 000 SEK. This is less than in some other periods, for example in 2006, but the changes occur more often and evenly. The VaR predictions occur more than twice in this period and on the same time for all three models. The Historical Simulation has predicted VaR higher on one occasion and the large negative return has thus only coincided with this model’s predictions.

Table 4, Incurrence of VaR, OMX Stockholm Financials PI

<table>
<thead>
<tr>
<th>Periods</th>
<th>Historical Simulation</th>
<th>Monte Carlo</th>
<th>Variance-Covariance</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006</td>
<td>3</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>2008</td>
<td>6</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>2010</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2011</td>
<td>4</td>
<td>3</td>
<td>3</td>
</tr>
</tbody>
</table>

For all periods except 2010, losses have exceeded the estimates of VaR. In 2010 on the other hand, VaR has been overestimated. When the diagrams are compared, the actual results of the instrument’s investment with higher volatilities than -20 000 to 20 000 SEK is found in the diagram for 2006. The period when losses have exceeded VaR predictions the most, is in 2008. This was a period in the middle of the crisis, and could therefore be the reason to why losses reached VaR levels. This is probably because all three models are based on calculations from historical data, the Historical Simulations is connected to the past as it uses old data to create hypothetical values, while the Monte Carlo Simulation and the Variance-Covariance Method have standard deviations based on historical data. The history of 100 days, go back to a period when the crisis had just started and when
the volatility of the OMX Stockholm Financials PI probably was more stable. The 100 day period started on 2007-12-28. The VaR methods did not fully capture the changes of the market, as they used historical prices for the calculations. The result of this could lead to underestimations in risk. As these underestimations of risk were made while the actual result was affected more by new expectations due to the crisis, it led to more than two occurrences of VaR in 2008.

4.1.3 OMX STOCKHOLM MATERIALS PI
The risk predictions of the other sectoral index, the OMX Stockholm Materials PI, are displayed in the following diagrams.

Figure 11 OMX Stockholm Materials PI (2006)

Similar to the OMXS 30 and the OMX Stockholm Financials PI, the OMX Stockholm Materials PI show the same type of results for the three VaR methods. The development of the index itself is also similar to the development of the other two indexes. The path of the results of the Historical Simulation goes along with the Monte Carlo Simulation and the Variance-Covariance Method, until 2006-06-12, where it starts to estimate VaR higher. In this first part of the time span the return of the index merges towards the VaR estimates. In this period the return of the index fluctuates from -60 000 SEK to 60 000 SEK, which is more than any other instruments volatility.

Figure 12 OMX Stockholm Materials PI (2008)
The Historical Simulation starts off by estimating VaR to the same level for the first quarter of the period. The Monte Carlo Simulation and the Variance-Covariance Method estimate VaR more diverse. In the second quarter the estimates for all models start to get lower and very similar. Losses go down to VaR measures about three times. On two other occasions the losses are approximately 300 SEK away from the estimations of VaR. In comparison to the Financial Index losses reach predicted VaR only half as many times, yet still too many times according to what the literature states.

Figure 13 OMX Stockholm Materials PI (2010)

Here, the theory of losses coinciding with the VaR twice for calculations with a 95 percent confidence interval holds. The three risk models predict VaR to the same levels throughout the entire period. This may be an effect of the historical observations from which the calculations are based upon, had similar returns.

In comparison to the other sectoral index in 2010, the diagram for the OMX Stockholm Materials PI, show two losses dropping below VaR predictions. There is one more incurrence of VaR, making the models better estimates for the Materials PI.

Figure 14 OMX Stockholm Materials PI (2011)
Occasionally, the Historical Simulation measure risk lower than the Monte Carlo Simulation and the Variance-Covariance Method. Other than that, all models show on quite steady developments of the VaR measures. The volatility of the actual outcome is higher in the first part of the period and decreases in the second half.

In the period of the beginning of 2011, losses reach estimations of VaR less often compared to the other periods. In 2011 the crisis has been considered to be over and concluded from this is that the models are not accurately estimating VaR.

<table>
<thead>
<tr>
<th>Periods</th>
<th>Historical Simulation</th>
<th>Monte Carlo</th>
<th>Variance - Covariance</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>2008</td>
<td>3</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>2010</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>2011</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

When studying the OMX Stockholm Materials PI it can be observed that all VaR measures by the three models incur the same amount of times. The only exception can be seen in 2008 for the Monte Carlo Simulation, where the loss stretches down to the VaR predictions twice. Where the two other models do reach the estimated VaR’s, the Monte Carlo Simulation only barely misses it, the difference is 44 SEK.

The three models predict VaR very close to each other for all four periods, with the exception of the period in 2006, where the Historical Method estimates VaR to be a little bit higher than the rest.

For the OMX Stockholm Materials PI VaR incurrences diminish gradually from the first pre-crisis period to the last period studied. The fluctuations for the return are larger for the 2006 and 2008 periods. These are both times before and during the crisis which contributed to higher uncertainty regarding the risk. In the two first periods, incurrences of VaR do not agree with theory since losses exceeds estimations too often, while the last period show too few incurrences for the theory to hold. The only period matching the theory is the 40-day long period in the beginning of 2010.
4.1.4 CURRENCY, USD/SEK

Now, studying cross rates, the returns of an investment of 1 000 000 SEK in the USD and the estimations of VaR by the three risk models are presented below.

Figure 15 Cross rate, USD/SEK (2006)

For the indexes the models kept on estimating VaR very alike, with occasional exceptions for the Historical Simulation. This seems to be repeated for the 2006 VaR predictions of USD/SEK. For the Monte Carlo Simulation and the Variance-Covariance Method there are two occurrences of when losses coincide with VaR. The theory of how many times losses should equal or exceed VaR has in this case almost happened. The dispersion of the returns, signified by the purple line, is not as significant as it was for the indexes.

Figure 16 Cross rate USD/SEK (2008)

The returns of the investment in the USD currency in 2008 display high volatility at first, followed by smaller fluctuations. There is a particular downfall in the return on 4 June, the only time the loss exceeds VaR predictions.

Further, in the latter part of the diagram a period of smaller volatility in the cross rate occurs and no losses reach predictions of VaR anymore. This might be because the calculations are based on
historical closing prices, as mentioned before. The USD decreased during the crisis, an effect that might be seen here. Since the VaR predictions were made on data from the past it could not catch these changes in its estimations.

Figure 17 Cross rate USD/SEK (2010)

![Graph showing USD/SEK from 2010-01-08 to 2010-02-23, with observations at intervals of two days.]

Until now, the estimations of the Monte Carlo and the Variance-Covariance Methods have taken the same path. So far throughout the thesis, the estimations of the Variance-Covariance Method could be seen as a mean of the estimations made by the Monte Carlo Simulation as it usually has a more even development. Here, the methods follow the same development throughout the whole period. The Historical Simulation also takes a unique turn as it constantly lies above the other two methods, with lower risk predictions. It also estimates VaR almost the same for every level. This led to that it was only the Historical Simulation predictions of VaR that coincided with the actual losses.

Figure 18 Cross rate USD/SEK (2011)

![Graph showing USD/SEK from 2011-01-07 to 2011-02-22, with observations at intervals of two days.]

Of an investment of 1 000 000 SEK in the USD in the beginning of 2011, the return fell to losses of about 17 000 SEK twice for the Monte Carlo and Variance-Covariance Methods. It was on these two occasions that VaR predictions were reached. The Historical Simulation predicts VaR slightly higher through the whole period, although the models predict VaR fairly the same. The reason to why the
The results of the models are very equal is probably because the historical observations used for the simulation has been pulling to a similar mean. Either the returns have barely been fluctuating or they have fluctuated a lot but cancelled each other out.

Table 6, Incurrence of VaR, Currency USD/SEK

<table>
<thead>
<tr>
<th>Periods</th>
<th>Historical Simulation</th>
<th>Monte Carlo</th>
<th>Variance-Covariance</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006</td>
<td>1</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>2008</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2010</td>
<td>2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2011</td>
<td>1</td>
<td>2</td>
<td>2</td>
</tr>
</tbody>
</table>

Until now, the times that losses have reached VaR predicted levels, has never been this low. The reason to this might be that the other instruments are indexes, put together of many different companies. The purity of the USD currency makes it more exposed to risk, as it is only the development of one instrument.

Support to the theory, that the loss equals or exceeds VaR predictions twice on a 40-day long period with a 95 percent confidence interval, can only be claimed to hold twice for the Monte Carlo and Variance-Covariance Methods, and once for the Historical Simulation. What may be of interest is the fact that when the Historical Simulation method did have its two occurrences with the actual loss, none of the other two models had estimated risk low enough to coincide with the actual losses. This took place on the first 40 days of 2010, a period of which the Historical Simulation constantly measured VaR lower than Monte Carlo and Variance-Covariance. Noticeable is that these two models did not estimate VaR higher than the Historical Method in any of the other periods studied. To summarize these observations one might think that it is the pure techniques used in the different models that caused these differences in predictions.

Further, the loss of the investment in the instrument has dropped to VaR estimations by the Monte Carlo and Variance-Covariance Methods the exact same amount of times, and on the same dates.

In the period of 2008, there is a large loss far bigger than the other. This loss exceeds VaR measures by more than 10 000 SEK. This is the only time that the loss incurred with the VaR. Although a few days later there was another loss close to dropping down to levels of VaR estimations.
4.1.5 CURRENCY, GBP/SEK
The risk estimations for the GBP are shown in this section.

Figure 19 Cross rate, GBP/SEK (2006)

Looking at Figure 19 above, one can see that the developments of the risk estimations are similar, especially in the first half of the period. The loss exceeds the estimations of VaR once, but is very close to exceeding it twice. Here, as well as in former estimations made for the USD in the same period, the estimations lie on the same level throughout the entire 40-day period.

Figure 20 Cross rate, GBP/SEK (2008)

The returns of the GBP show particularly large fluctuations between gains and losses. One of the two drops reaches VaR estimations, with the other drop not far behind, only a 500 SEK in difference. Once again the Historical Simulation estimates VaR higher than the other models, something seen in the VaR predictions for the indexes. The estimations keep a steady pace upwards, predicting risk lower as the days in the period pass.
Compared to the former period in figure 19, the estimations for the 40-day period in 2008 are noticeably higher. The difference, about 5 000 SEK, might be an effect of the decrease of the currency in the beginning of the period.

Figure 21 Cross rate, GBP/SEK (2010)

On the second day of the 40-day period in 2010 there was a big loss stretching past VaR predictions. On the following days the losses are minimalistic in comparison to the second day loss, until the mid section of the period where the loss equals and exceeds the risk estimations three times during a 9-day period. On all occasions the Historical Simulation has estimated VaR lower than the Monte Carlo Simulation and the Variance-Covariance Method. The latter mentioned models estimated the risk of the instrument similarly for all dates. On January 5, the prediction of VaR dropped with approximately 5000 SEK, something depending on the historical closing prices of GBP used for the calculations.

Figure 22 Cross rate, GBP/SEK (2011)
The risk predicting models show dissimilarities in their estimations of VaR in the beginning and end of the diagram. The Historical Simulation is the one differing from the other two models’ predictions which lie on the same level of potential loss all the way through the period.

According to theory, the Historical Simulation and the Variance- Covariance Method predicted losses to occur twice in the time span of the 40 days in 2011. For the Monte Carlo Simulation, the predictions were overestimated on these occasions, although it must be added that the predictions did not lie far behind.

Table 7, Incurrence of VaR, Currency GBP/SEK

<table>
<thead>
<tr>
<th>Periods</th>
<th>Historical Simulation</th>
<th>Monte Carlo</th>
<th>Variance- Covariance</th>
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</thead>
<tbody>
<tr>
<td>2006</td>
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<td>1</td>
<td>1</td>
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<tr>
<td>2008</td>
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<td>1</td>
<td>1</td>
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<tr>
<td>2010</td>
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<td>4</td>
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</tr>
<tr>
<td>2011</td>
<td>2</td>
<td>0</td>
<td>2</td>
</tr>
</tbody>
</table>

The times losses reach levels of estimated VaR keep being low, as was the case for the outcomes of the USD. The year of 2010 on the other hand show more incurrences. The risk estimating models have for this period underestimated risk in accordance to the theory. This might be because the fall of 2009, where the observations are taken from, had lower losses of the return than in the beginning of 2010.

Previously, the estimations of VaR from the Monte Carlo Simulation and the Variance- Covariance Method have incurred with losses on the same times. For the GBP this has not been the case. There is a difference in the estimations in the two last time periods. These periods were considered the after-crisis periods and should not have been affected by closing prices in the same way as in the other periods. The estimations only show on minimal diverges of 200-500 SEK per an investment of 1 000 000 SEK.

4.1.6 CURRENCY, EUR/SEK
The results of the risk calculations for the last single instrument, the EUR/SEK cross rate, will be presented in diagrams below.

Figure 23 Cross rate, EUR/SEK (2006)
The movement of the returns has not yet been influenced by the approaching financial crisis. The volatility of the returns of the financial instrument is evenly pictured in figure 23, with a couple of losses deviating from the pattern. These two drops of returns reaches below the estimated VaR levels of all three models. The predictions of the models all look somewhat alike. The Monte Carlo method fluctuates a bit more from day to day, while the Historical and Variance-Covariance methods move smoothly.

Figure 24 Cross rate, EUR/SEK (2008)

![Figure 24 Cross rate, EUR/SEK (2008)](image)

The VaR predictions are steadily decreasing in value from day one to day 40. Because of this the last loss observed in the diagram coincides with the VaR estimations for all models. Had the developing curves of VaR not increased, this loss might have been registered as a VaR loss. As in the diagram for 2006, this time period also supports the VaR theory.

Figure 25 Cross rate, EUR/SEK (2010)

![Figure 25 Cross rate, EUR/SEK (2010)](image)
Losses exceed VaR four times in the 40-day period in the beginning of 2010. This occurred a couple more times than it did in the two previous time periods. The Historical method’s predictions reached higher levels after the last loss exceeded VaR, something not affecting the outcome of the return and VaR occurrences.

Figure 26 Cross rate, EUR/SEK (2011)

There are distinct fluctuations in the return of the EUR in the beginning of 2011. In the first large drop of the EUR the predicted VaR of the Historical Simulation is reached. It is interesting that the predictions made by the Historical Simulation were exceptionally lower the days before and during this time. Had this not been the case, the occurrence of the loss reaching VaR levels had never taken place. On the other two occasions the losses did not exceed VaR by more than 2000 SEK at the most. There was a fourth time when losses dropped close to estimated VaR’s, although the loss did not reach far enough to qualify to have an incidence together with estimated risk values. After the losses reached these levels, the estimations started to fall before they again climbed upwards to levels similar to those in the beginning. Besides from the period where the Historical Simulation estimated VaR lower, the three models predicted VaR almost entirely the same.

Table 8, Incurrence of VaR, Currency EUR/SEK

<table>
<thead>
<tr>
<th>Periods</th>
<th>Historical Simulation</th>
<th>Monte Carlo</th>
<th>Variance-Covariance</th>
</tr>
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<td>2006</td>
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</tr>
<tr>
<td>2011</td>
<td>3</td>
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</tbody>
</table>

The theory of VaR has for the first time shown to be quite accurate. In 2006, 2008 and 2011, the predictions occurred in actual losses twice during a 40-day period except for the Historical Simulation method in 2011. It is not surprising that the Historical Simulation predicted lower values as this has been the case throughout the whole study of the single financial instruments.

In the 40-day period in the beginning of 2010 there were four times when losses dropped to VaR estimations. Why this happened may have been a cause of the models not being able to capture the changes in the market quickly enough. If information about the changes cannot be found in the
closing prices of the last 100 days, they cannot cope with fast changes in the market. Considering that the 100 historical observations were taken from the fall of 2009 and the actual returns were observations from 2010, changes occurring right around the beginning of 2010 will not be included in the calculations of the VaR estimations. It seems like the data taken from the fall contained smaller fluctuations. If this was the case, estimations will consequently underestimate VaR for the coming period where larger losses suddenly started to occur.

4.2 FINANCIAL INSTRUMENTS IN PORTFOLIOS

In this section the focus will lie on comparing the models to one another instead of testing it to the actual return of the portfolio. Therefore the diagrams will solely display the predictions of VaR for the different periods.

The portfolios, constructed by the six instruments earlier studied individually are computed in three portfolios. The portfolios hold different weights, and for each 40-day period there will be three diagrams. Totally, there are twelve diagrams covered in this section. In most of the diagrams the predictions of the modified version of the Monte Carlo Simulation are thoroughly consistent with the predictions of the Variance-Covariance Method, why the red line might not be clearly visible.

4.2.1 PORTFOLIOS 2006

Below are the three different weighted portfolios for the first 40-day period. Each figure shows predictions of VaR by the Historical Simulation, the modified Monte Carlo Simulation and the Variance-Covariance Method. The models estimations are denoted by the blue, red and green line respectively.

Figure 27 Portfolio; equal weights (2006)
The developments of the VaR predictions in the pre-crisis period are very similar for the portfolios. The Historical Simulation estimates risk on a more volatile scale than the modified Monte Carlo Simulation and Variance-Covariance Method. This can be seen by the blue line which has more distinct changes. In the beginning of the period it fluctuates more, to gradually diminish, until finally making complete horizontal estimations.

To analyze the Historical Simulations estimations further, it should be observed that the heavier the weights assigned to the indexes, the larger the differences in VaR estimations become. When the indexes hold 30 percent of the entire portfolio, predictions are made from losses of 7 000 SEK to a little more than 10 000 SEK. Once they make out 50 percent of the portfolio, the predictions vary

![Different weighted portfolio: Index 30% and Currency 70% (2006)](image)

![Different weighted portfolio: Index 70% and Currency 30% (2006)](image)
from 9 000 SEK to 17 500 SEK. Finally, letting the content in the portfolio consist of 70 percent of indexes, the difference in losses reach about 12 000 SEK, going from about 13 000 SEK to 25 000 SEK.

The modified version of the Monte Carlo calculations and the Variance-Covariance Method estimate risk extremely similar. For these two methods the fluctuations lie around the same amount for each of the different portfolios. This may probably be an effect of the estimations of the covariances, which makes the daily changes in VaR rather small.

Lastly, all three methods start with lower predictions of VaR, and end with larger predictions. Also, all methods show on more stable estimations towards the end of the 40 day period for all three portfolios.

4.2.2 PORTFOLIOS 2008
For the 2008 period, the methods’ predictions of VaR are presented in the three next figures. The estimations made by the three methods are shown by the lines, similar to what was described for the 2006 portfolios.

Figure 30 Portfolio; equal weights (2008)
For the portfolios created in the second period, the models show patterns of an increase in the volatility of the Historical Simulation’s predictions. This may be due to that the daily changes in closing prices for the instruments are more volatile during this time of the crisis. The results of the Historical Simulation are as in the previous section of portfolio diagrams, they have less variation when estimating risk at the end of the period. Estimations of the risk of the investment grow with the increase of indexes.

When the indexes hold 30 percent of the portfolio, the predictions by the Historical Simulation are larger than the predictions made by the modified Monte Carlo Simulation and the Variance-Covariance Method throughout the whole period. This can easily be seen by the blue, red and green lines in figure 31.
The developments of the predictions are declining in risk as VaR is estimated for the 40 days of the period. Even though this is the case for all three methods, there are more fluctuations in the Historical Simulation estimations than in the other two methods’ estimations.

4.2.3 PORTFOLIOS 2010
The estimations of VaR for the period of the beginning of 2010 are displayed in the following figures. There are, as in the sections of the 2006 and 2008 periods of portfolios, differently weighted portfolios. The first one holds equal weights, while the second and the third portfolios hold 30 and 70 percent of indexes and currencies, and vice versa.

Figure 33 Portfolio; equal weights (2010)

![Graph showing Portfolio; equal weights (2010)](image)

Figure 34 Different weighted portfolio: Indexes 30% and Currencies 70% (2010)

![Graph showing Different weighted portfolio: Index 30% and Currency 70% (2010)](image)
As, in the other figures for the 2006 and 2008 periods, the predictions of VaR for all methods in these last three figures show similar patterns in the development. Also, as mentioned in the two other time periods for the portfolio calculations, VaR is more volatile and larger when indexes stand for 70 percent of the holdings of the portfolio. This is mostly visible for the red and green lines, but also for the blue line.

Most of the times the red and green lines, symbolizing the modified Monte Carlo Simulation and the Variance-Covariance Method, estimate risk lower than the blue line, the Historical Simulation’s estimations. In figures 33 and 34 the developments of VaR get slightly lower by the last days of the period while in figure 35 this is only the case for the red and green lines.

Compared to the 2008 period, the estimations of the Historical Simulation show on slightly smaller differences, which might be because of stabilizations in the market.

4.2.4 PORTFOLIOS 2011
Lastly, the VaR estimations in the last period are represented in this section. The methods are represented in the figures in the same way as they have for the previous periods for the portfolios.

Figure 36 Portfolio; equal weights (2011)
As mentioned earlier about more stabilized times in markets in 2010, the same can be seen for this period. All methods end with slightly lower risk estimations towards the end. The estimations of the modified Monte Carlo Simulation and the Variance-Covariance Method are less varied compared to the Historical Simulation.

Throughout all three portfolios the estimations of the Historical Simulations lie below the other two models, something indicating on higher VaR predictions. Higher risk estimations are again seen as indexes increase in the portfolio.

Similar to the other figures displaying the developments of the VaR estimations, the Historical Simulation tend to estimate VaR on an evenly basis, with exceptions of sporadic changes. This is as before different to the other two methods. The modified Monte Carlo Simulation and the Variance-Covariance Method use estimated covariances for their risk calculations, while the Historical Simulation is based on historical closing prices.
5. CONCLUSIONS

From results in the analysis, conclusions will be made and summarized in this part. The purpose and questions shaping this thesis will thus be answered accordingly. First, conclusions about individual instruments will be presented, followed by portfolios.

The purpose of this thesis was to make conclusions about the accuracy of the Historical Simulation, the Monte Carlo method and the Variance-Covariance method before, during and after the financial crisis of 2007/2008. The computations were made with a 95 percent confidence interval, meaning the actual return would drop and reach VaR estimations twice in the 40 day period. Throughout the empirical section, the Monte Carlo Simulation and the Variance-Covariance estimated risk similarly, while the Historical Simulation in comparison showed deviating results.

All models under- and overestimates risk in all periods, but there is no periodic pattern. In general there is no visible pattern that any method should be more or less accurate than any other. It is on the other hand evident that the models predict VaR similar in certain time periods. For those time periods when this is not the case, two of the models have still predicted VaR evenly while the difference to the third model’s predictions have either been under- or overestimated by a couple of hundred SEK. No distinct differences about the accuracy can be detectable before, after or during the crisis.

For the conclusions regarding the VaR models’ predictions of individual instruments in the second question, they have shown to predict VaR and losses for the EUR twice in the periods of 2006 and 2008. This included all three methods and was also seen to almost be the case for the 2011 period. Because of this, the models can be said to predict potential losses more accurately for the EUR. For the other financial instruments there are no clear conclusions to be made about the models’ predictions in any time periods. This is because there is no visible connection between the estimations for the different instruments.

Regarding the portfolios and the predictions of the models in the different time periods, the conclusions are that the Variance-Covariance Method and the modified Monte Carlo Simulation predicts VaR less fluctuating and almost exactly the same, compared to the Historical Simulation which show on a few sporadic volatilities. The first two models mentioned have also shown on lower risk estimations throughout the periods compared to the latter model. Also, the more indexes the portfolios hold, the higher are the predictions of VaR.
6. DISCUSSION

In this final part, the results and conclusions are discussed and commented. The results are also compared to previous studies.

6.1 COMMENTS

The result of the conclusion was that no method could be said to be more or less accurate than any other in the four periods studied. The only distinguishing remark was that all methods seemed to predict losses to VaR levels more accurately for the EUR in the two first and the last periods. Other than that, the methods have under- or overestimated VaR. These predictions cannot be detected for any specific period, making it a bit difficult to make conclusions about if the pre-crisis period differed from the mid or later part of the crisis, or the other way around.

Before starting the calculations of VaR in this thesis there were expectations of that the predictions would show different results regarding the different time periods. To give an example of this, expectations for estimations of the 40-day long periods in 2006 and 2008, were that risk would be strongly underestimated. The results though, showed on no clear pattern of this as mentioned above.

The Historical Simulation used daily historical data for its risk predictions, consequently leading to underestimations in risk. Several of the previous studies described earlier, concludes the same consequence. Bao et al (2001) claims that most of the models used in his study, among them the Historical Simulation, showed underestimations in the mid-part of the crisis. Kourouma et al. (2010) mention the Extreme Value Theory (EVT) is a more reliable model to use in unstable financial times. Both of these previous studies agree, along with this study, that the Historical Simulation does not capture future fluctuations as it is based solely on the past. For example, if the market would become unstable and if closing prices would change distinctively for the actual return of an instrument, these changes are not incorporated in the estimation.

The development of the indexes and currencies presented in the empirical section for VaR on single instruments show that all financial instruments follow the same estimation pattern through time. For the indexes there are larger falls and rises, while the VaR estimations for the currencies are presented with smoother and smaller changes.

As mentioned in the section of the conclusions, the year of 2006 for example, showed underestimations for all three indexes. If comparing the development of the indexes, closing prices were continuously rising. When this happens, the daily historical data, making out the basis for the risk estimation, is not as high as it is for the closing prices 100 days ahead. This led to bigger dips of the return, which consequently mean that the return drops to VaR estimations more than twice. The Historical Simulation is therefore a VaR model not considered too represent and capture the changes very well.

Former studies, presented earlier, do not mention the outcome of the Variance-Covariance and the Monte Carlo as the Historical Simulation. Although these models do not solely depend on historical data, they still use it in order to form standard deviations. It has been clear that these two models follow each others’ paths, which is why one of the two models sometimes cannot be visualized in the diagrams as they predict estimations of VaR very close. Paskelian and Hassan made the same selection of VaR models as this thesis, where the Historical Simulation, the Monte Carlo Simulation
and the Variance-Covariance Method performed better than the EVT model. This shows that the EVT model is not the only method to predict the most accurate risk estimations.

The accuracy of the models differs both for assets and through time. It may depend on that the estimation periods are too short and it may depend on the choice of VaR models. They tend to either under- or overestimate the incurrence of actual losses and VaR. Berman (2009) stated that VaR models do not make good estimations in times of crises, as the VaR models depend on short-term volatilities, opposite to the crisis which depend on long-term volatilities.

Lastly, the results should only be interpreted with reservation; this is because all models were assumed to be normally distributed. The conclusions of the results in this thesis are based on the assumption that the data used for the methods are normally distributed which might not be the case for the real distribution of the instruments. Results may therefore not be entirely accurate.

6.2 FURTHER STUDIES

This thesis has applied the Historical Simulation, the Monte Carlo Method and the Variance-Covariance Method for six financial instruments with a 95 percent confidence level. The conclusions are based on these specific choices of approaches, instruments and confidence level, and would differ if anything was changed.

The Historical Simulation has data from 101 days and the Monte Carlo method uses 1000 random variables. It would be interesting to see possible differences in risk estimations if these two parameters were changed, for example to 200 and 2000 respectively. A 95 percent confidence interval is also applied in this thesis, which could be changed to a 90 or 99 percent level for instance.

There crisis was divided into four parts, all representing different time intervals. Further research could include studies of other periods of the same crisis and/or compare it to earlier crises in order to find similarities and differences in risk predictions between them. In the section for previous studies, it was noticeable that the EVT model more accurately predicted risk in crises. This model was not used in this study. It would therefore be interesting to compare results by the Historical Simulation, the Monte Carlo method and the Variance-Covariance Method with results from the EVT model before, during and after the crisis.
7. REFERENCES
The Excel-files holding the computations for VaR are not presented in this thesis, but will be handed to the reader by request on the following email addresses: jonna.flodman@gmail.com, malin.e.josefin@gmail.com

ARTICLES
Amu, F., Millegård, M. (2009). Markowitz Portfolio Theory, (in press), (2-6), s.2


Bohdalová, M. (2007). A comparison of Value- at- Risk methods for measurement of the financial risk. Comenius University, Bratislava, s. 4


Duffie, D., Pan, J. (Preliminary draft, 1997). An overview of Value at Risk, (in press), (1-39), s. 3, 4


**LITTERATURE**


**ELECTRONICAL SOURCES**

Aktiespararna (2011-03-01)
(http://www.aktiespararna.se/ungaaktiesparare/Utbildning/Aktier/Index/)

Forextrading (2011-04-03)
(http://www.forextrading.se/mest-handlade-valutor-jan-maj-2009)

Nasdaqomx (2011-03-01)

Riksgälden (2011-02-15)
(https://www.riksgalden.se/templates/Secure/Page____514.aspx)

Riksbanken (2011-02-15)

Scribd (2011-03-17)

Stockexchangsecrets (2011-04-03)
(http://www.stockexchangsecrets.com/volatility.html)
8. APPENDIX

*Below, appendix is presented as it is referred to in the thesis.*

In this section the indexes are presented with the stocks that they possess.

### 8.1 Instruments in OMX Stockholm 30

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### 8.2 Instruments in OMX Stockholm Financials PI

On 2011-01-31 the OMXS 30 contained the following financial instruments:

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8.3 Instruments in OMX Stockholm Materials PI

1  Billerud
2  Boliden
3  Bergs Timber B
4  Höganäs B
5  Holmen A
6  Holmen B
7  Lundin Mining Corporation SDB
8  Nordic Mines
9  Profilgruppen B
10 Rottneros
11 Rövik Timber B
12 SCA A
13 SCA B
14 SSAB A
15 SSAB B
16 Stora Enso A
17 Stora Enso R