Aarhus University
Business and Social Sciences

Value-at-Risk:
Strengths, Caveats and Considerations for Risk Managers and Regulators

Master Thesis by Bogdan Izmaylov

Supervisor: Thomas Berngruber

Department of Economics and Business

March 2014
Abstract

In this thesis, critiques and praises of Value-at-Risk measure are studied and compared to empirical evidence from the literature in order to analyze potential strengths, model risks and practical application issues of VaR. The study makes use of conceptual literature to define attractive properties and potential pitfalls in using VaR by risk managers and puts it in perspective by analyzing empirical findings. Through discussion, the main strengths and weaknesses of VaR are pointed out as well as the types of decisions which risk managers have to make in order to use the measure effectively.

This research concludes that the VaR is an extremely important, but fragile risk measure. It also emphasizes the importance of the decision making process for proper implementation and precision of estimates. VaR has proven to be an effective and intuitive risk measure with convenient properties, when calculated and used appropriately to the market conditions and risk management needs. But the empirical evidence and the GFC have shown that there is a need for better understanding of what VaR can and what it cannot measure. It is especially evident in the case of VaR use for regulation purpose, which potentially can undermine the usefulness of VaR as a measure of risk. Expected Shortfall has proven to be less precise in practical applications, but can be used in combination with VaR as a complementary measure.

This thesis proposes further research to be conducted in the areas of VaR model application guidelines and use of risk measure portfolios.
Acknowledgements

I am thankful to my thesis advisor, Thomas Berngruber, for the rewarding discussions that we had and for his guidance throughout the writing process. I am grateful to my family for their support and understanding.

I would like to thank Manuela Markova for proof-reading my thesis. All the errors remaining are my own.
## Contents

Acknowledgements.............................................................................................................. ii

List of figures........................................................................................................................ v

List of abbreviations .............................................................................................................. vi

1. Introduction ......................................................................................................................... 1
   1.1 Problem Formulation ....................................................................................................... 3
   1.2 Delimitations .................................................................................................................. 3
   1.3 Methodology .................................................................................................................. 4

2. Theory ................................................................................................................................... 6
   2.1 Value-at-risk (VaR) ......................................................................................................... 6
   2.2 Expected Shortfall (ES) and Tail Conditional Expectation (TCE) ......................... 8
   2.3 Coherency of VaR ........................................................................................................ 9
   2.4 Precision of VaR ........................................................................................................... 9
   2.5 VaR in Basel Accords .................................................................................................... 10
   2.6 Backtesting .................................................................................................................. 11
   2.7 Time horizon and the square root of time rule ......................................................... 12
   2.8 Copulas ......................................................................................................................... 12
   2.9 Extreme Value Theory (EVT) ..................................................................................... 13

3. Literature review ............................................................................................................... 14

4. Discussion ............................................................................................................................. 19
   4.1 VaR as a measure for non-normally distributed returns ........................................... 19
   4.2 The quality of high confidence level VaR forecasts – 95%, 99% VaR and higher ................................................................. 22
4.3 VaR as an aggregate measure of risk.......................................................... 25
4.5 VaR use for stress testing.......................................................................... 28
4.6 VaR as a widely adopted measure of risk for financial institutions ........ 31
4.7 VaR as an instrument for regulation in Basel Accords............................. 32

5. Conclusions and prospects for future research.......................................... 40
References ....................................................................................................... 42
List of figures

FIGURE 1. 1-DAY VAR FOR S&P500 RETURNS. ................................................................. 6
FIGURE 2. EXPECTED SHORTFALL AND VAR. ................................................................. 8
FIGURE 3. BACKTESTING ESTIMATION WINDOWS................................................................ 11
FIGURE 4. TYPES OF DISTRIBUTION TAILS. .................................................................... 13
FIGURE 5. DAILY S&P 500 RETURNS 1989-2009 CUMULATIVE PROBABILITY PLOT. ............ 20
FIGURE 7. THE DISTRIBUTION OF P&L FOR A PROJECT. .................................................. 28
FIGURE 8. SHIFT IN THE PROBABILITY DISTRIBUTION OF LOSSES CONDITIONAL ON AN ADVERSE
MACROECONOMIC SCENARIO ......................................................................................... 30
FIGURE 9. ILLUSTRATION OF THE RELATIVE ERROR (THE RATIO VAR[H]/(√HVAR[1])) FROM THE USE OF
THE SQUARE-ROOT OF TIME RULE .................................................................................. 34
FIGURE 10. P&L DISTRIBUTION BEFORE AND AFTER VAR MANIPULATION. ......................... 36
FIGURE 11. EXAMPLES OF UNLIKELY, BUT POSSIBLE DISTRIBUTIONS ................................. 36
FIGURE 12. REAL GDP IN DENMARK, BN. DKK, VS. THE LONG-TERM MECHANICAL PROJECTION. ....... 38
List of abbreviations

BCBS – Basel Committee for Banking Supervision

ES – Expected Shortfall

ETL – Expected Tail Loss

GFC – Global Financial Crisis

HS – Historical Simulation

iid – Identically and Independently Distributed

MC – Monte Carlo

MPT – Modern Portfolio Theory

niid – Normal Identically And Independently Distributed

RMP – Risk Management Professional

TCE – Conditional Tail Expectation

VaR – Value-at-Risk
1. Introduction

My ventures are not in one bottom trusted,
Nor to one place; nor is my whole estate
Upon the fortune of this present year:
Therefore, my merchandise makes me not sad.
W. Shakespeare

Risk is ubiquitous in all areas of human life, but it is convenient to consider a specific definition depending on the area of interest. In the context of financial literature, the term risk refers to the change related to the variability of the future value (Artzner, Delbaen, Eber, & Heath, 1999). Oxford English Dictionary defines the word risk as:

“(Exposure to) the possibility of loss, injury, or other adverse or unwelcome circumstance; a chance or situation involving such a possibility. “

In order to assess variability of the future value, a risk measure (a way of calculating risk) is used to produce a risk measurement or risk metric (a number which quantifies the risk). The most common measure is the volatility of the price or return. The volatility of returns is easier to predict and thus the price volatility is calculated based on the return volatility. Usually, high returns are associated with higher variability in return and thus higher volatility. The famous work of H. Markowitz on portfolio selection has popularized the use of volatility as a measure of risk and introduced the Modern Portfolio Theory (MPT) together with the concept of “efficient frontier”. At its core, the MPT or mean-variance theory presents the benefits of diversification for achieving a minimum variability of outcomes for a given rate of return. One key assumption is that the asset returns are normally distributed, which is almost never true for financial data. The risk is underestimated when the assumption does not hold, thus the focus in the academic research has been on the improvement of volatility forecasts, which in turn would lead to more precise risk estimates and more
efficient investments. The volatility measures both the upside and the downside risk. Roy (1952) argued that a more realistic situation is when the individuals are not pursuing maximum gains, but reduction of the probability of losses, thus suggesting that a risk measure should reflect the downside variability in returns.

The risk management field has experienced huge growth and revolutionary changes in the past two decades. Many new methods for measuring and managing risks have been developed, with some of them even becoming industry standards and bases for regulation. One of such measures is the Value at Risk (VaR). After being made available to the public by JPMorgan Risk Metrics group in 1993, it was quickly adopted by the industry professionals and Basel II accord has chosen it as a recommended measure for market risk. The first comprehensive work on VaR was provided in the book of P. Jorion “Value at Risk: The New Benchmark for Managing Financial Risk” in 1996. Some of the attractive properties for which VaR owes its popularity are that it is an intuitive measure, it can be used to aggregate different risks (in contrast to volatility, where it makes little sense comparing volatilities of different types of risk), and it is very easy to implement.

VaR as a measure and metric of risk is the central topic of this thesis, which aims to study the current research and evidence, in order to assess the quality of VaR as risk measure for the purposes of regulation and risk management. The motivation for this study comes from the fact, that even though VaR has been criticized since the time it has been introduced for the lack of precision, unrealistic assumptions and inability to predict extreme events, it has become very popular among the Risk Management Professionals (RMPs) both in financial and non-financial companies. The latest financial crisis has shown that we still are not as good at assessing risk as we would like to be, and that there are significant reasons for revision of risk measures we use and the ways we use.
them. This is why the pros and cons of VaR need to be reviewed in order to check the adequacy of the 20-year old risk measure in the modern world.

1.1 Problem Formulation

Taking into account the latest developments in risk management and their failure during the Global Financial Crisis (GFC), this thesis aims to review the quality of Value-at-Risk measure and its alternatives, like Expected Shortfall (ES). Many methods for computing VaR exist, and this thesis will attempt to assess the ability of this risk measure to serve its purpose by relying on the characteristics of the most common VaR calculation methods.

The problem of VaR ability to forecast risk can be divided into several research questions, which are connected to the criticism of VaR in “The World According to Nassim Taleb” (1997), “Roundtable: "The Limits of VAR" (1998), “Private Profits and Socialized Risk” (2008), etc. These research areas are formulated as follows:

1) VaR as a measure for non-normally distributed returns.
2) The quality of high confidence level forecasts – 95%, 99% VaR and higher.
3) VaR as an aggregate measure of risk.
4) VaR use for stress testing
5) VaR as a widely adopted measure of risk for financial institutions
6) VaR as an instrument for regulation in Basel Accords.

1.2 Delimitations

In the scope of this thesis, only VaR and ES measures are considered, being some of the most ubiquitous downside risk measures. Even though many different methods for estimation of these measures exist, only the most popular and praised in the financial literature will be considered. More detailed information about the calculation of risk measures will be discussed in the Theory Chapter.
The purpose of this thesis is not to build up on the current methods of calculating VaR, but to assess the benefits and caveats of using it as a risk measure. The precision of different methods is outside the scope of this study, all the assumptions and discussions will be made assuming the best possible precision of the risk measures, based on the current literature. In other words, the model risk of risk measures will be researched.

It is not the ambition of this research to come up with a perfect measure of risk, or at least the one better than the ones currently used. The task is to find out where the VaR excels, where it falls short, and to identify the implications of these qualities for risk management practitioners and regulators.

1.3 Methodology

The methodology of the thesis is based on selection, review and discussion of VaR-related conceptual and empirical literature. The main focus are the articles and risk management books published between 1996 and 2013. The methods and theories are discussed and compared in the context of their applicability in financial and non-financial institutions. These theories are compared to the empirical studies of VaR and related risk measures, as well as to regulations implemented by the Basel Committee on Banking Supervision (BCBS). The primary source of articles is Scopus, the largest citation and abstract database of peer-reviewed literature. As a primary methodology and methods guide, “Research Methodology: Methods and Techniques” by Kothari (2011) is used.

The quality of VaR measures is assessed by the following criteria, which hare based on the research questions:

1) Precision.
2) Transparency.
3) Robustness to manipulation.
4) Coherency, as defined by (Artzner et al., 1999).
5) Ease of implementation.

The chosen criteria aim to review the statistical properties and the role of the measure in aiding the decision making process. The criterion ease of implementation aims to study the resource and information requirements of a risk measure as well as its applicability in the environment of limited computational resources and sample data.

Through systematic literature research and discussion of challenges in the field of risk management, the thesis aims Value-at-Risk and several alternatives as risk measures and metrics. The ultimate goal, in the light of the GFC, is to find out whether these tools are still adequate in the risk management field.
2. Theory

The purpose of this section is to lay out some theoretical concepts used for VaR & ES calculations and provide a review of statistical properties of these risk measures. The aim of this section is to be the reference for some of the main concepts from Literature Review and Discussion sections. Mainly the statistical methods for VaR calculation are reviewed with the exception of Basel Committee’s recommendations on the use and backtesting of VaR models. This section aims to familiarize the reader with the concepts which are related to VaR popularity and critique. Dowd (1998), Jorion (2007; 2009), Danielsson (2011) provide more in-depth description and analysis of VaR methods.

2.1 Value-at-risk (VaR)

VaR is calculated as a quantile of the distribution of gains and losses for a target forecast period. This quantile shows the worst possible loss over the chosen time period and confidence level. For example, calculating the 95% 1-day VaR means finding the 5% quantile of the lower tail of the 1-day returns distribution.

![Figure 1. 1-day VaR for S&P500 returns. Source: own calculations.](image-url)
Every VaR calculation starts with setting a confidence level, choosing the holding period and estimating the probability distribution. The latter leads to essentially two ways for calculating VaR: non-parametric and parametric.

The non-parametric, also called Historical Simulation (HS), VaR is very easy to implement if the price or return data is readily available. There is no need for any assumptions regarding the shape of the distribution of returns, only that they are identically and independently distributed (iid). The observed returns are arranged by size, and depending on the confidence level \( \alpha \) and number of observations \( n \), the observation following the first \( \alpha \% \) of returns is used in the calculation.

\[
VaR = -P_0(r^* - \mu),
\]

where \( P_0 \) is the initial value of the position, \( \mu \) is the mean expected return and \( r^* \) is the cutoff return for the lowest \( \alpha \% \) of returns.

In contrast, the parametric VaR assumes that the returns follow a certain distribution, which simplifies the calculation significantly if this distribution is from the parametric family. For example, for normal independently and identically distributed (niid) returns we need only the mean \( \mu \) and the volatility \( \sigma \) to estimate quantiles. Thus, VaR is calculated as follows:

\[
VaR = P_0z_\alpha \sigma,
\]

where \( z_\alpha \) is the quantile of the distribution for a given confidence level. For the parametric VaR, as can be seen from the formula, the precision of volatility estimation plays a key role for the estimated figure. This is why an immense amount of VaR models have been developed, with rather exotic names as CAViaR (Manganelli & Engle, 2004) and GlueVAR (Belles-Sampera, Guillén, & Santolino, 2014) with the focus on volatility estimation. Overall, the Generalized Autoregressive Conditional Heteroskedastic (GARCH) variance estimator has
proven to be one of the best in terms of complexity/precision/data requirements tradeoff (Danielsson, 2011; Dowd, 1998). The GARCH (p,q) variance estimator depends on both $p$ lagged squared returns $r$ and $q$ lagged volatility estimates $\sigma$:

$$\sigma^2 = \alpha_0 + \sum_{i=0}^{p} \alpha_i r_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2$$

In this study, the focus is set on the properties of VaR, assuming that the volatility is estimated with high precision.

2.2 Expected Shortfall (ES) and Tail Conditional Expectation (TCE)

A complementary and closely related measure to VaR is the average value of the loss when it exceeds the quantile $\alpha$:

$$ES_\alpha = \frac{1}{1-\alpha} \int_{0}^{1-\alpha} VaR_\gamma(P) \, d\gamma,$$

where VaR$_\gamma$ is the Value at Risk for confidence level $\gamma$, which changes from 0 to $\alpha$.

![Figure 2. Expected Shortfall and VaR. Source: own drawing.](image)

Expected shortfall, in contrast to VaR, gives information about the losses, which occur when the confidence level is exceeded and thus can potentially evaluate the extreme losses in the distribution tail.

Tail Conditional Expectation (TCE), also known as Tail VaR (TVaR), measures the expected value of losses when the realized loss exceeds VaR.
$$TCE_\alpha(P) = E[-P|P \leq -\text{VaR}_\alpha(P)]$$

It is equivalent to the Expected Shortfall for continuous distributions only, even though many authors use ES, CVAR and TCE interchangeably.

2.3 Coherency of VaR

In most cases, VaR is a coherent measure of risk, as defined by Arztner et al. (1997). As such, it possesses the following properties:

1) Monotonicity.
2) Translation invariance.
3) Homogeneity.
4) Subadditivity.

The subadditivity of VaR is one of the most discussed and criticized properties, since in some cases (especially if the returns are not niid), portfolio VaR will be higher than the sum of individual positions VaRs, which discourages diversification (Artzner et al., 1999).

2.4 Precision of VaR

P. Jorion (2007) discusses several precision aspects for estimation of VaR. First of all, the measurement errors are considered. The estimated values converge to the true ones as the number of observations approaches infinity. For the real-life small samples, the precision of estimates can be measured by sampling distributions, which can be used to obtain the confidence bands.

Second precision issue is the estimation of means and variances. The estimated mean is normally distributed around the true value, with the error term approaching zero at the rate of square root of inverse number of observations. The variance estimate is chi-squared distributed around the true value, but the distribution converges to normal for samples with 20+ observations. Overall, the variance is estimated more precisely than the mean (hence usually most of the
models focus on the volatility of returns forecasting instead of the mean. The confidence interval narrows with the increase in the number of observations.

The third issue is the estimation of the sample quantiles with the nonparametric approach. In contrast to the previous two measures, the estimates converge to their true values much slower with the increase in sample size. For 95% VaR, the confidence band for the quantile centered at 1.645 is quite large for 100 and even 250 observations, narrowing to [1.52, 1.76] for 5 years of daily observations. For higher-precision VaR estimates (with fewer observations in the tail), the confidence interval narrows only to 20% of the true value, meaning that the sample quantile estimates are very unreliable for extreme left-tail probabilities. The standard errors can be obtained by bootstrapping. For the estimation of TCE and ES, even more observations are needed in order to obtain reliable estimates, since more observations are needed in the tail extremes of the distribution.

When comparing the two approaches, the parametric method produces more precise and efficient forecasts, provided that the distribution is chosen properly – which itself is an interesting topic and would require a separate thesis to be discussed properly.

2.5 VaR in Basel Accords

BCBS has chosen VaR as a measure for minimum capital requirements calculations since the introduction of Basel II accord. VaR has to be calculated by the banks for 10-day period and 99% confidence level, after which the obtained forecast is multiplied with a factor of 3 in order to increase the confidence even more. The multiplication factor is justified by the fact that 99% 10-day VaR still allows for bank failures 1% of the time (once every 4 years on average).

Since it is hard to obtain enough observations to calculate and backtest the 10-day VaR, BCBS recommends the banks to calculate the 1-day 99% VaR and transform it into 10-day by using the square root of time rule. Furthermore,
depending on the number of violations, the multiplication factor may be increased to 4 in order to correct for model misspecifications and/or errors.

2.6 Backtesting
Regardless of the model used to estimate VaR, it can be compared to other models by backtesting it on the realized returns and provide evidence on the precision of the forecasts. Usually, part of the sample data is used for estimation (estimation window), and the forecasts are tested on the rest of the observations. If the observed loss on a given day is higher than the one predicted by the model, the violation is recorded. Depending on the confidence level, we would expect violations in 5% and 1% of observations for 95% and 99% VaR respectively.


At the end of the backtest, the number of observed violations is compared to the number of predicted violations. This gives the violation ratio for the model:

\[
\text{Violation Ratio} = \frac{\text{Number of observed violations}}{\text{Number of predicted violations}}
\]

Ideally, the ratio should be as close to one as possible, values above one mean that the model underestimates risk (more violations than predicted turn up during the backtesting) and values below one are a sign of over-conservative model (overestimated risk, less violations than predicted). The estimation and
backtesting lead to the question of data availability for high-confidence level VaR forecasts for time horizons longer than 1 day. For example, for 99% daily VaR we expect around 2-3 trading days in a year (1% of 252) with losses higher than forecasted. This means that to confirm that the model performs well we need on average 20 observations with no violation for 95% VaR and 100 observations with no violation for 99% VaR.

2.7 Time horizon and the square root of time rule

For the case of niid returns, the VaR formula can be written in a general form for a selected time horizon:

\[ \text{VaR} = P_0 z_{\alpha} \sigma \sqrt{\Delta t} \]

Where \( \Delta t \) is the time horizon. The square-root of time rule states that the volatility increases with the square-root of time, hence it can be applied to calculation of VaR for longer time horizons. We can calculate the 1-year VaR by multiplying the 1-day VaR forecast, obtained by using daily returns, by the time adjustment factor \( \sqrt{252} \approx 16 \). In fact, this is the method BCBS recommends for calculating the 10-day VaR.

2.8 Copulas

Copulas provide the means of assessing the joint multivariate distribution of assets in a portfolio, while allowing for different types of dependence throughout the distribution. Sklar’s theorem states that for any joint density \( f_{12} \) there exists a copula \( c_{12} \) that links the marginal densities \( f_1 \) and \( f_2 \):

\[ f_{12}(x_1, x_2) = f_1(x_1) \times f_2(x_2) \times c_{12}[F_1(x_1), F_2(x_2); \theta] \]

The copula contains all the information on the nature of dependence, only one parameter for bivariate density – the correlation coefficient \( \theta \), but it does not
contain the marginal densities. Thus it provides convenient separation of marginal densities and dependence. Often, normal copula is used, because it simplifies the calculations, even though it may only poorly approximate the reality.

2.9 Extreme Value Theory (EVT)
Most of the statistical methods focus on the entire distribution. EVT, in contrast, focuses only on the tails of the distribution – extremely rare events. EVT has long been used in natural sciences, and it was adapted for use in finance in the 1990’s. It is especially useful for calculation of high-confidence level VaR, which reflects the extremely rare losses in the distribution tail. Key inputs for the EVT model are the tail index and the inverse of the tail index (shape) parameters. Usually for risk calculation, one of the three types of tails is considered: finite endpoint, normal and fat-tailed (Student-t).

Figure 4. Types of distribution tails (left tails depicted). Source: based on Danielsson (2011).
3. Literature review

The purpose of this section is to provide an overview of the current literature on VaR in the risk management field. The focus is set on the methodology development and the main sources of information about VaR as risk management tool for risk professionals. Also the publications which are pointing out the dangers of using VaR in practice and regulation are taken into account. This literature would provide a basis for the discussion in section 4.

The technical document on VaR, released by RiskMetrics (1994), has made it available to the public and the measure quickly has gained popularity among risk management professionals. The widespread adoption though did not follow until the fundamental work of P. Jorion in 1997 came out. Until today, three editions of the book have been published, each one incorporating the latest developments in the risk management field. Since its first publication, it has remained one of the most comprehensive sources of VaR methodology and it established itself as a risk analyst’s handbook. His main points are that VaR is an excellent tool, which improves the ability of managers to assess the risks across different categories, while providing a simple figure which can capture the risks of taking complex financial positions and decisions. The author analyses the potential difficulties in calculating VaR for both risk management and regulation purposes. Another quantile risk measure is discussed as complementary to VaR – Expected Tail Loss (ETL), also known as Tail Conditional Expectation (TCE). Requirements for more observations and thus lower precision are pointed as the biggest drawbacks against using ETL instead of VaR.

of the main topics is risk forecasting for derivatives and decision-making based on VaR – the author argues that it is not a universal method and a high degree of managerial discretion is required for effective implementation. The book also criticizes the BCBS multiplication factor of 3 as an arbitrary number, but this issue is addressed by Jorion in a more recent edition of his book, by explaining that the multiplier accounts for the error in estimation of quantiles. The overall focus is on practical implications for financial and non-financial institutions, with analysis of possible caveats of using VaR and how to avoid them.

There, however, have been numerous studies and discussions on whether VaR is able to deliver what it promises. Pritsker (1997) examines the precision of VaR estimates for derivatives using Monte Carlo simulation methods, and finds low accuracy for deep out-of-the-money options. The study stresses the importance of the trade-off between accuracy and computation time, as well as the importance of specifying the distribution of the factor shocks correctly.

Artzner et al. (1999) pioneered the term “coherent risk measures” by defining a set of characteristics which such measures should satisfy. They conclude that VaR in general is not a coherent risk measure, because it is not subadditive for all returns distributions.

Dowd and Cotter (2007) analyze the precision of quantile-based risk measures. They suggest Monte Carlo simulation as the best method for estimating the precision of such measures. They also conclude that the samples typically available are too small for the estimates to be normally distributed (asymptotic normality). The final finding is that the characteristics of the underlying distributions, especially excess kurtosis, have significant impact on the precision of estimates.

During the interview for Derivatives Strategy (1996), Nassim Taleb has criticised VaR for its shortcomings, later saying that this interview has given a start to his
“war against “Value at Risk” (Taleb, 2007). He argued also in "Roundtable: The Limits of VaR" (Derivatives Strategy, 1998) that VaR creates a false sense of security by giving seemingly precise estimates for risks which cannot be captured by conventional statistical methods. According to him, the risk managers who use VaR get too confident in the calculations and trust more the numbers than their experience. He states that VaR cannot capture the correlations between returns and cannot measure the complexity of events that occur in the modern world.

Daniélsson (2002) examines the limitations of the modern risk models both for risk management and regulation. In particular, he studies the precision of the models at different confidence levels and finds that in terms of precision, GARCH and RiskMetrics models are the best at 95% level, but their performance diminishes at 99%. The BCBS capital requirements based on VaR are criticized as arbitrary and ineffective. The author believes that when VaR is targeted by institutions in order to meet capital requirements, it poses risks of manipulation of the measures and escalates the losses in times of crises. He also proposes a corollary of Goodhart's Law applied to VaR:

“A risk model breaks down when used for regulatory purposes”

The scaling of VaR for different time horizons and distributions has been addressed in another paper by Daniélsson and Zigrand (2006), where the authors conclude that the square-root-of-time rule leads to underestimation of risk. This bias is very small for the 10-day period (which coincides with the requirements of BCBS), but increases at an increasing rate for longer horizons.

In his book on financial risk forecasting, Daniélsson (2011) has combined the methodology of VaR with the versatility and processing power of modern software (R and MATLAB). The comprehensive guide on implementation of risk forecasting models is complemented with a thorough analysis of the theory. The
issues of precision and interpretation are addressed as in the author’s earlier articles. The author stresses on the importance of the assumptions made for each model and the critical interpretation of results. For the calculation of high-confidence VaR, EVT methodology is used to calculate VaR in the extreme regions of the distribution tails. This approach mitigates the underestimation of risk, since the distribution of returns in the tails is better captured by the EVT. The endogenous prices in financial markets are pointed out as the cases, when the RMPs need to utilize common sense and intuitive understanding of risk measures to be able to make rational decisions.

Nocera (2009), in the Risk Mismanagement article, presents us with an excellent discussion of opinions from VaR opponents and advocates. The main arguments presented in the article against VaR are that it cannot predict extreme risks and that it is valid for distributions which are not common for financial returns. The responses of the VaR proponents are suggesting that the mistakes in risk management were primarily in the managerial decisions and not in the models. Risk management experts share in the interviews with the author, that VaR measure has been manipulated by managers in order to create “asymmetric risk positions”, which increased the losses that were not captured by the models. VaR also did not capture the effects of leverage. The author concludes that the latest crisis has shown once again the critical need for better understanding of risk.

Guégan and Tarrant (2012) resent in their paper theoretically the insufficiency of up to four risk measures combined in order to capture the risk from peculiar, although possible, loss distributions. Since the measures can produce the same risk estimates for different distributions, the proposed solution for assessment of risk profile is to use 95% and 99% VaR and TCE in combination with Maximum Loss (ML). The authors suggest that the banks should be required to submit multiple risk measures to the regulatory bodies.
McAleer, Jimenez-Martin, and Perez-Amaral (2013) analyse different methods for calculating VaR and the daily capital charges for authorized deposit-taking institutions. The study found that there is no single best model, but each model performs best at certain time periods (stages of the economic cycle). Before the GFC, GARCH is the best in terms of days with minimized capital charges. Riskmetrics model performs best in the beginning of the crisis, until September 2009. Exponential GARCH with shocks following the Student-t distribution performs best until the end of 2009. The authors conclude that the institutions should use multiple risk models in order to minimize the capital charges and thus the penalties from VaR violations.

In the “BlackRock: The monolith and the markets” (2013), a concern on the widespread use of same risk models in the financial markets is presented. The BlackRock’s risk-management system popularity can be compared with the wide-spread use of VaR since the RiskMetrics release and its implementation in the Basel accords. The main concern is connected to the limitations of the models, also as pointed out by Danielsson (2002), which are used by the increasingly large groups of people. Even the systems much more sophisticated than VaR, like the BlackRock’s “Aladdin”, raise concerns when used by large group of market participants.
4. Discussion

This section aims to provide a discussion of theoretical and empirical studies of VaR. The ambition of the study is to provide an overview of caveats and strengths of VaR use in risk management practice, as well as to provide some suggestions for mitigation of possible issues with the use of this risk measure.

4.1 VaR as a measure for non-normally distributed returns.

Assumption of normality is crucial for some methods of calculating VaR. This is quite similar to many other financial models, since normality greatly simplifies the calculations of dependencies which otherwise can become incomprehensively complex. Since the normal distribution can be described by only 2 moments – the mean and the standard deviation, the VaR calculation is the simplest when the assumption of normality holds. But the methodology does not break up when the returns are not normally distributed, even though VaR may lose some desirable properties (Artzner et al., 1999)

One of the main critiques of VaR is that it relies on parametric distributions, which can be a poor fit for the market data. Danielsson (2011) emphasizes in his book the stylized facts about financial returns:

Volatility clusters
Fat tails
Nonlinear dependence
Figures 5 and 6 clearly show the differences between normally distributed returns and the distribution of S&P500 data. The real probability is higher-than-normal near the mean of the distribution, it is lower when the distance from the mean increases, and it is again higher-than-normal in the tails of the distribution, which is a very important fact for risk analysis.
The stylized facts bring up some important considerations for calculating VaR:

- Volatility estimation models have to be flexible enough in order to capture the clusters – high/low volatility has to be followed by high/low volatility forecast.

- The model has to account for the probability of extreme events higher than in normal distribution.

- Linear dependency can approximate the joint movements in the centre of the distributions, but it becomes progressively less precise for extreme events.

The obvious choice and common practice for calculating VaR in the case of non-normally distributed returns is the Historical Simulation, Nonparametric VaR. But such approach raises another question, whether it is realistic to assume that the history repeats itself and as such whether the past contains enough information for prediction of future events. There is also a trade-off between the size of the estimation window (the number of observations used to forecast VaR) and the speed at which the forecasts will adjust to new information. The years of returns data before the first part of 2008 (before the GFC) are clearly a poor fit for the VaR forecast of returns in the second part of 2008. The HS VaR is a relatively simple and precise tool when there are no or very little structural changes in risk, like in the years before the GFC (Danielsson, 2011).

To account for non-normality of returns while allowing for losses that are higher than the ones from the estimation window, either a parametric distribution of choice (e.g. Student-t) should be used, or the Generalized Pareto Distribution applied to model the distribution in the tails, while accounting for skewness and kurtosis of the data.

In order to incorporate risk changes quickly and precisely into VaR forecasts, more complex models need to be used. A popular approach is to use the models...
with time-dependent volatility to forecast $\sigma$ for use in VaR calculation (Dowd, 1998; Jorion, 2007; Danielsson, 2011).

Nassim Taleb criticizes VaR methods for using past return data (HS) and relying on normal distribution (parametric methods), concluding that VaR cannot predict extreme events (“Black Swans”) and is harmful because it creates a false sense of security and confidence in RMPs. The obvious counter-argument is that the non-parametric and parametric methods should be used in the context of the market situation. This is where the managerial discretion is important – it is up to the risk manager to choose the best appropriate method. The choice of distribution for calculation of VaR is also important and the normal distribution should not be used to simplify calculations at the cost of precision. Existing methods are sufficiently precise given that the choice of method is justified by the data and market conditions (Danielsson, 2011; Jorion, 2007). By definition, VaR gives the maximum loss for a given confidence interval, given normal market conditions (when the markets are abnormal, VaR estimates are not valid). The limitations of models also have to be taken into account and the manager’s understanding of these models and the risks they forecast is crucial for the quality of VaR forecasts.

Given the reality of the modern financial markets, it is unrealistic to assume normal distribution of financial returns, meaning that more sophisticated VaR methods should be used by RMPs, combined with improved risk understanding. Using of HS in order to capture the non-normality should be done in the context of the fact that such calculations do not provide sufficient information about the future volatility (Fong Chan & Gray, 2006; Pérignon & Smith, 2010).

4.2 The quality of high confidence level VaR forecasts – 95%, 99% VaR and higher.

Due to the nature of VaR as a quantile risk measure, the precision of the estimates degrades with the increase of confidence level. This tendency arises from the fact
that in the extreme regions of the tails there are progressively fewer observations which can be used to estimate VaR, as well as from the fact that the financial data distribution has fat tails. The problem is even worse for estimation of ES, since the measure itself is not a quantile, but the mean of all the quantiles beyond \( \alpha \). This is confirmed by the empirical findings of Giannopoulos & Tunaru (2005) and Yamai & Yoshiba (Yamai & Yoshiba, 2005). There are several most common ways of overcoming such limitations in practice:

1) Gathering more data
2) Obtaining more observations by using simulations
3) Bootstrapping
4) Applying EVT to model the tails of the distribution (99%+ VaR)

Gathering more data can be problematic, and the trade-off between the estimation window length and speed of adjustment to new information is an important concern. Daily VaR is a commonly calculated measure, and gathering more daily data may not be very challenging in most situations. But if the weekly, 10-day or even monthly VaR needs to be calculated, it can be impossible to obtain enough observations in order to get sufficiently precise estimates.

If the available data is limited, bootstrapping can provide more precise estimates of VaR, ES and their standard errors, without any assumptions about the distribution of returns. The observations are drawn randomly with replacement from the collected sample. This method also adjusts slowly to new information in the sample and relies on the assumption that the history repeats itself, but improves on HS by providing more precise estimates. Pritsker (2006) confirms that bootstrapping is superior to HS by analysing the returns of the exchange rates of 10 currencies versus the USD.

If the distribution of returns can be approximated and defined in the simulation software, then increasing the number of simulations should give more precise
estimates. The results will vary depending on the quality of the random number generator, the number of simulations, and the quality of the transformation method. The transformation method is the way of converting the randomly generated numbers into the random numbers from the distribution of interest. Since the number of calculations can be very high for a big financial institution, pseudo-random number generators can be used. These produce a pre-defined sequence of “random” numbers, which allows the simulation to converge faster and produce accurate results with fewer simulations. Even with these tweaks, Monte Carlo (MC) is the most computationally demanding method.

Another way to speed up simulations and VaR calculation is to use factor models. Such models assume that the changes in risk are driven by changes in one or several risk factors. Each position is modelled according to its exposure to these risk factors, thus only a handful of factors need to be simulated by using MC.

For calculation of high-precision VaR with confidence levels above 99%, the EVT can be applied. It accounts for the shape of the tail of the distribution, usually producing more precise estimates. EVT should be used with caution, since the precision of the estimates is even more sensitive to the underlying distribution of returns in comparison to lower confidence level VaR. Danielsson (2011) suggests using EVT with sample sizes above 1000 and for confidence levels of 99,6% and higher. (Lin & Shen, 2006) also provide evidence on improved performance of VaR when calculated based on student-t or EVT modelled tails, in comparison to normal distribution tails for confidence level of 98,5% and higher. An easy approximation would be to use normal or student-t tails up to 95% confidence level, and use student-t for 99% or when the number of observations does not allow to implement EVT efficiently.

There is no method superior to others in all situations (although usually MC can better forecast the tails of returns distributions at the cost of computation time),
the choice should be made by the RMP based on market conditions, purpose of the forecast and fundamental understanding of the models and nature of risk.

4.3 VaR as an aggregate measure of risk.

VaR can be used to calculate risk from different exposures and then it can be aggregated to obtain the measure of the overall risk. In contrast, summing up two volatilities of exposures in different currencies does not make sense, but aggregating VaRs across different positions can produce a total risk exposure for a company. This quality of VaR as risk metric has made it attractive in the past decades with the rise of enterprise risk management. In the same way as different risk exposures can be aggregated into individual VaR numbers, different positions in a portfolio can be aggregated to produce portfolio VaR. The caveat in risk aggregation is that the overall risk is not simply equal to the sum of individual component measures, because VaR is not sub-additive. Either parametric (analytical) or non-parametric (simulation) methods should be used in order to account for the benefits of diversification when calculating the aggregate VaR.

The simplest way of summing up the individual VaRs produces very crude estimates and disregards any benefits of diversification, thus the resulting number is sometimes called Undiversified VaR. It assumes that the individual positions are perfectly correlated.

\[
VaR_{12} = \sqrt{VaR_1^2 + VaR_2^2 + 2VaR_1 \times VaR_2} = VaR_1 + VaR_2
\]

Another approach is to estimate the sensitivities of different exposures to the changes in the underlying risk factors. A simple and in most cases sufficiently precise method is to estimate the linear correlations between risks and use the correlations in the aggregate VaR computation:
\[ \text{VaR}_\alpha = \alpha \sigma_P P = \alpha \sqrt{w_1^2 \sigma_1^2 + w_2^2 \sigma_2^2 + 2w_1 w_2 \rho_{12} P} \]

Where \( P \) is the portfolio value and \( w_1 \) and \( w_2 \) are the weights of individual positions and \( \rho_{12} \) is the correlation coefficient. This approach allows to calculate aggregate VaR while accounting for the benefits of diversification across different types of risks. According to the study made by Perignon et al. (2008), large banks typically overstate the VaR figures they report and are conservative in the VaR reductions from diversification.

The assumption of linear dependence is not very realistic for financial markets, since the negative returns tend to have stronger impact than the positive returns, which is also pointed out as a stylized fact of non-linear dependence by Danielsson (2011). Linear correlation only approximates the dependency between random variables (returns) sufficiently until a certain point. Taking into account the typical VaR confidence levels (95% and 99%), it is not surprising that at such levels the correlations will differ from the predictions of the above mentioned model. In recent years, the research has been concentrated on using copulas in order to model joint multivariate distributions and improve VaR forecasts for aggregate risk measurement (Gendron & Genest, 2009; Manner & Reznikova, 2012). Copulas are able to capture the non-linearity of the relationships between random variables in the extreme regions of the distributions. Using the conditional copula-GARCH model, Huang et al. (2009), find the method to be robust and allowing flexible distribution, which is an improvement on the traditional methods like HS and MC, when applied to highly volatile market returns. But even such robust models will be useless if the chosen copula does not approximate the real dependencies accurately, which is the choice risk manager has to make.

Another method of calculating aggregate VaR is the full revaluation – calculation of returns for different exposures and positions by using pricing models, and
calculation of VaR based on the aggregate returns. This requires a lot of computational power, especially if combined with MC simulations, when for each position there have to be calculated around 10000 simulations in order to get precise estimates. McKinsey in the Working Paper on Risk # 32 (2012) point out the computational requirement as a big challenge for institutions, with calculations taking 2-15 hours to complete. Another striking fact is that 75% of financial institutions relied on HS methods, which are inferior to MC, since the latter can better predict occurrences in the tails of a distribution. The models used by the majority of institutions provide fast and easy to understand (simulations are perceived as a “black box”) measures, but this simplicity comes at a cost, which has been seen in the extreme losses the companies have suffered during the GFC.

The advantages that VaR provides as an aggregate measure of risk are especially pronounced for financial institutions (for calculation of capital requirements and enterprise risk management) and for clearing houses (for calculations of margin requirements). Financial institutions use VaR to estimate the losses from all business units and calculate the capital requirements (both for regulatory and internal risk management purposes) in order to be able to absorb such losses when they occur. Clearing houses use VaR to calculate the margin requirements for traders based on the positions that they (traders) have taken and not only on their historical performance or credit scores.

The real strength of VaR as an aggregate measure of risk may lie not in the end product of the calculations – the portfolio VaR, but in the measures which are used to calculate it. Component VaR and Marginal VaR can give invaluable insights into how certain positions impact the overall risk. Component analysis can aid the managers in the selection of projects in addition to the NPV analysis by giving them the idea of how a project is contributing to the project portfolio risk in the company.
It is clear that VaR is a very important tool in risk management. It is the industry standard for measuring of aggregate risk exposure, which arises from multiple positions. At the moment there is no better alternative than VaR for aggregating the risk across the institution. Arguments can be made in favour of the ES, but for this measure both the precision and computational requirements prevent its widespread adoption. Clearly, the banks cannot rely on daily full revaluation methods if they take 15 hours to compute. But even with such speed, there would be no difficulty for them to make these calculations once per week in order to check the validity of the simplified calculations. The quality of data and models are as important as the experience and competence of the RMPs using them to make decisions. The knowledge of differences in models and their limitations are crucial for successful risk management.

4.5 VaR use for stress testing

(Malz, 2011) discusses VaR in the context of stress testing as a tool for calculation of changes in values of risk factors in a portfolio. VaR shocks are calculated as a product of marginal volatility of a position in portfolio and a multiplier for the quantile (based on the normal distribution). The value of a VaR shock corresponds to maximum loss for the selected confidence level, which for stress
scenarios is usually higher than for daily VaR calculations. These amounts are then compared to the predicted losses from the stress test scenarios in order to capture the magnitude of tail events which could not have been predicted by the models that assume normality of returns. Since, by definition, VaR measures the loss during the normal market conditions, stress testing can give the RMPs more information about the risks in the cases when markets are abnormal. The biggest challenge in stress testing methods remains the choice of scenarios and assigning the probabilities to them.

The GFC has shown the failure of the modern stress-testing techniques to predict systemic failures in financial sector. The critique is mainly related to the limited number of scenarios, and inappropriate methods (N. N. Taleb, 2012). Taleb (2012) proposes a heuristic method, which is a scalar measure that contains the information about “the fragility of volatility in the stresses”. The fragility represents the disproportionately higher losses which occur when the stress increases. The heuristic is calculated by performing additional stress tests around the main scenarios by using multiples of mean deviation for scenario variables.

However, Sorge (Sorge, December 2004) argues that the VaR methodology implemented with macroeconomic stress-testing can account for both the extreme shocks and the endogenous prices in the financial sector. If additionally the shocks are calculated for the tests around the main scenario as proposed by Taleb, it can give the RMP the necessary information about the changes in VaR arising from shocks.
One such scenario could be the shift of the loss distribution caused by the endogenous reaction of market participants to a severe shock.

It can also be argued, that with the information about VaR changes, the heuristic will be redundant. The changes in VaR can give a good representation of risk exposure and which factors have the biggest impact on it. Therefore, in stress-testing, the process of VaR calculation is even more important than in other areas. Of course, this process may provide numerical estimates of losses for low-probability high-impact scenarios, but the quality of the estimates will largely depend on the closeness of the hypothetical stress scenarios to the realized movements in risk factors. On the other hand, the process itself will give the manager more information about the relationship between risk factors in extreme cases, which can help develop strategies for risk mitigation. Such information can allow RMPs to act on the early signs of adverse movements in risk factors and thus reduce their total impact on the portfolio.

The use of stress testing can improve on the VaR methodology by relaxing the assumption of exogenous market prices, for which VaR has been criticized (Danielsson, 2011). There are, however, many important issues that need to be considered. First of all, the stress test horizon has to be carefully selected: one day...
may not be very useful for assessment of stress impact, but one quarter horizon may involve too many uncertainties. Second, the factors which could affect the prices should be identified and principal component analysis may be used in order to decrease the computational needs. Third, a limit to the number of combinations of such factors should be selected, since it may not always be realistic to assume that there will be maximum adverse changes in all risk factors at the same time. Exactly how realistic it is is definitely not an easy question, since this is the Taleb’s (N. Taleb, 2010) “Black Swan” event scenario. Thus even though the VaR calculations can provide parametric methods for estimation of losses during stress-testing, the inputs for the tests remain key factor for the precision and quality of the tests. These inputs need to be chosen based on knowledge, experience, risk and business understanding of the RMP.

4.6 VaR as a widely adopted measure of risk for financial institutions

It is natural for a good risk measure to be quickly adopted by many market participants and few models have had such wide-spread adoption as VaR. Even though there are many different ways/models of calculating it, most of the time only several models are used. Every model has flaws, and as Danielsson (Danielsson, 2002) argues, most of the models perform much worse than expected. When the markets are heterogeneous and investors are using many different models when making decisions, it is likely that the model errors will impact only a small portion of market participants and will not have any significant impact on the market as a whole. When a large portion of investors is using the same (or very similar) models, then the markets can get dangerously homogenous. In such situation an error in the model can have very big impact on the system: the investors find the same positions attractive, which increases the demand for these positions and drives the prices up, at the same time the investors find the same positions unattractive, which drives the prices of these position down. The key factor is the magnitude of demand changes, which is
driven by the use of similar models. Such changes would produce accordingly big changes in prices, and since most of the models assume that the prices are exogenous (not affected by the market transactions), this can create a dangerous feedback loop of sell-offs and price drops.

Similarly, during the GFC the financial institutions that have taken the same positions (presumably low-risk ones) had to decrease their exposure in order to meet the regulatory capital requirements when the risk estimates of these positions increased. The sell-offs triggered further decrease in the quality of these positions, which further increased VaR and triggered more sell-offs. The key problem is that even if different models are used to assess the risk internally, the need to comply with VaR-based regulations forces the market participants to take actions which could have negative impact on the whole system.

Since there is no model superior to others in all situations, and the market participants have diverse expectations about the reality of financial markets (normality, economic cycle, stationarity, trends, etc.), it is unlikely that the same model will be used by sufficiently big number of investors, unless imposed by some kind of regulation requirement. Even if the VaR is the preferred model for assessing risk, there are so many decisions that have to be made by the RMPs when implementing it, that there will be no significant effects on market prices and feedback loops will not occur. This argument, once again, shows the benefits of a free market system, and it confirms the validity of Goodhart’s law for risk measures and VaR in particular.

4.7 VaR as an instrument for regulation in Basel Accords.
One of the most debated topics on the use of VaR is its implementation in the BCBS Accords (Basel II and III) as a measure of market risk for calculation of capital requirements. The main purpose of the Basel Accords is to prevent systemic crises by requiring the financial institutions to hold a certain amount of
capital. This amount of capital depends on the positions that the institution has taken and the riskiness of these positions. Since VaR is a tool for measurement of the market risk of a financial institution, it determines the minimum amount of equity capital that this institution should hold for a given level of market risk exposure. The required capital is supposed to be sufficient for sustaining losses arising from such risk.

VaR has been a recommended measure since Basel II. Such measure change from Basel I is a step to more customized requirements, specifically tailored to each institution, according its risk exposure. Thus the institutions with higher risk appetite have to set aside more capital than the institutions with lower risk appetite. Moreover, BCBS allows the use of internal methods for estimation of VaR, so the institutions may choose from more or less conservative approaches to modelling of VaR. Aggressive approach aims to minimize the daily capital charges (the amount of capital set aside) and improves the profitability. The downside of such approach comes from the variable multiplier, which penalizes the institutions using the models which for some reason have more VaR violations then allowed by the Accords.

Such specific requirements stimulate the financial institutions to apply the best possible VaR models in order to free the capital and minimize the holding costs. Overly aggressive (low) VaR and poor models can create too many violations and lead to higher multiplier increasing the amount of required capital.

There can be identified several problems with the approach of BCBS to the measurement of capital requirements using VaR.

First of all, the multiplier can be argued to be arbitrary. Philippe Jorion (2007) elaborates on the choice by reviewing the precision of VaR estimate and concludes that the multiplier of 3 produces the maximum value of the estimate. This way, at least in theory, the required capital is calculated to cover VaR for
confidence levels much higher than 99%, implying that the institutions with such amount of capital reserves would virtually never go bankrupt. In the light of the GFC, it is clear that there is something wrong with this logic. Such approach to VaR calculations is valid for the normally distributed returns, which is not a very good approximation of reality for financial markets. Meaning that even if VaR calculations, using internal models, are made for non-normal returns, the BCBS requires multiplication to be made with the method which assumes the normality, meaning that the final figure will not be the maximum value of the estimate and will not correspond to the implied (by the BCBS) level of risk. Danielsson & Zigrand (Danielsson & Zigrand, 2006) found that there is no underestimation of VaR for 10 day period, but only when the probability of crashes (extremes of the left distribution tail) is low.

![Figure 9](image.png)

Figure 9. Illustration of the relative error (the ratio VaR[η]/(\sqrt{η}VaR[1])) from the use of the square-root of time rule, where 1/λ is the expected time to crash in years. Source: Danielsson & Zigrand (2006).

Second, because of the difficulties in calculating the high-precision VaR, the BCBS recommends the use of square-root of time rule in order to calculate the 10-day VaR. But such approach is valid for normally distributed returns, applying it to the calculated VaR will underestimate risk, which, at least in theory, the institutions would prefer, since it leads to lower amounts of their capital being locked in. The interesting fact is that the empirical findings of (Pérignon, Deng,
& Wang, 2008) show that the banks tend to overstate the VaR figures in their reports. While it can be argued that such overstatement can help mitigate the potential underestimation of losses if VaR model used is underestimating the risk on average, it creates unnecessary costs for the institution. Another potential problem may be that when the VaR reporting consistently understates the estimates, the model itself cannot be assessed properly. Minor violations caused by model deficiencies can be missed because of the overstatement and these deficiencies could prevent the bank from foreseeing the increase in risk level.

Third, as pointed out by Danielsson (2011) in his corollary of Goodhart’s law, when VaR becomes a target, it ceases to be a good measure of market risk exposure for the institutions. When the measure becomes a target, incentives for manipulation are created. Financial institutions can start tailoring the VaR figures produced by their models to match the level of capital they are willing to set aside for the risks they are taking. Because VaR is only a quantile of the distribution, financial derivatives can be used to alter the payoff at the specific point in the distribution and produce a lower risk estimate. In the subsequent steps this problem is only made worse by the use of the square-root of time rule and the multiplier, both of which assume the normality of returns.
An example of such manipulation could be writing a put option with the strike price just below the VaR and buy one put option with the strike price above the desired VaR value. This way the institution will lower the VaR amount, but decrease the expected profit on all confidence levels. There is really nothing that prevents banks from using such instruments, unless the RMP decides that this is not in line with the bank’s risk management policy. For the external observer there is no way to...
distinguish between the institution which has not used the instruments to change
VaR (lower risk) and the institution which has modified VaR (higher risk).

The biggest beneficial feature of VaR as a tool recommended by the Basel Accords
lies, as pointed out by Jorion (2007), not in the final result (VaR as a metric), but
in the process of getting it (VaR as a measure). Institutions which have to
calculate their VaR for reporting purposes have to face the risks in their portfolio
and decide whether to take any measures to mitigate those risks. The process of
calculating VaR also gives the RMPs a lot of insight into the riskiness of
individual exposures and how they contribute to the overall risk of the
institution.

Since the measures of the first two Basel Accords have proven to be unable to
ensure protection against crises, the third Accord of the BCBS has increased the
capital requirements for financial institutions. The new regulations increase the
amount of capital that the institutions would have to hold and decrease their
leverage. Apart from the increase in the institution risk-specific ratios, more
general ones like the “mandatory conservation buffer” of 2,5% of common equity
and the “discretionary counter-cyclical buffer” of 2,5% which could be required
by the national regulators. Such changes in the regulations point towards the
requirements based less on the institution-specific VaR and more on their
leverage. The transition to higher capital ratios is planned to be gradual in order
to allow institutions to adjust. For example, minimum capital requirements are
planned to be phased-in during 2014-2015 and conservation buffer – during 2016-
2019.

The increases in required capital are clearly going to impact the profitability of
financial institutions. Since the costs are likely to be transferred to the customers
(Grosen, 2011), the new Accord also is expected to have significant negative
macroeconomic impact (Slovik & Cournède, 2011). It may look as if the cost is the
only definitive aspect of the new regulations, since as with Basel II, there is no guarantee that they will prevent systemic failures, and as Grosen (Grosen, 2010) writes, the Basel accords are “the Maginot line of the banking sector”. However, the costs may be justified if we factor in the long-term costs of crises, which can be calculated as the missed GDP growth (Rangvid, 2010).

It may be reasonable to consider different alternatives to existing regulation, which may improve the stability of the financial system. Instead of requirements for the level of capital ratios, requirements for insurance of certain levels of risk could be implemented. Danielsson (2011) also argues in favour of such system, where the banks would insure and re-insure other banks. Such strategy should be considered, since as a whole the banking industry possesses enough capital to absorb the shocks. An area of future research can be to analyze how the aggregate cost of insurances will compare to the costs of the Basel regulations. Using VaR is a more precise, more efficient way of regulating the industry than imposing arbitrary capital ratios. An important tool for regulation is stress-testing, especially when it is used as a combination of different risk measures and stress-scenarios (Plesner, 2012). Another option is to abandon all capital requirements and let the institutions to be market disciplined. The role of the BCBS in such case
would be shifted towards enforcement of transparency of risk exposures. In this case, VaR and ES could be disclosed among other measures of risks for each institution to provide an overview of loss distributions. Better transparency could potentially have greater effect on the long-term stability of the financial sector, compared to the increases in the amount of required capital.
5. Conclusions and prospects for future research

This thesis aimed to assess the practical application and model properties of Value-at-Risk in the context of the GFC and recent developments in the risk management field. The main focus was set on finding out what are the caveats of using VaR, how and to what degree they can be mitigated by the existing methodology. The factors which could jeopardize the risk measure estimates are discussed together with the measures which can prevent this from happening.

The current VaR methodology is highly complex and presents many tools to the managers, which can be used to estimate precise figures for the purpose of risk measurement and mitigation. Empirical studies have shown VaR methods can produce highly accurate estimates when appropriate models are used. It is hard to overestimate the role that the risk manager plays in the choice of the methodology for VaR calculations. From the conducted analysis it is clear that the errors in VaR estimates which arise from the models are much smaller than the errors from application of inappropriate methods. Both theoretical and empirical literature support this view by providing a wide range of models which perform at their best in different market situations. And while we can easily “blame the models”, it is necessary first to assess the applicability of these models to the reality of the markets.

Another emphasis of this thesis is the failure of statistical measures to provide adequate basis for regulation. While the benefits of using VaR make it an appropriate measure for highly customized capital requirements, the consequence of such regulation is deterioration in the quality of VaR estimates caused by manipulation.

Overall, the focus of risk management should be set on the process of VaR calculation, the analysis of component risk measures and their impact on aggregate risk. In this area the most promising area is the use of simulations and
scenario analysis in combination with VaR to assess the impact of different risk factors on overall risk in both financial and non-financial companies.

After looking into the mechanics of VaR calculation and its relation to decision making processes in companies, it is clear that VaR is an important tool in the RMIP’s toolbox. The principles of risk management also apply to the measurement process itself, and portfolio of risk measures should be used in order to capture the relevant information about risks. No matter how complex the model, it would not be able to capture all this information in a single number or measure. Since this may be critical for assessment of extreme tail events, VaR analysis should be complemented by simulations and other risk measures.

Future research should be conducted for development of methods which would aid risk managers in their choice of VaR estimation methods, since this is a critical step in the estimation process. Another potential research area is the analysis of stress tests which would use the extended variables ranges as proposed by Taleb (2012) for his heuristic measure. For the regulation purposes, the alternative of insurance instead of capital requirements for banks should be further studied in the context of its ability to prevent systemic crises and its macroeconomic impact in comparison to the current regulations of BCBS.
References


*Mathematical Finance, 9*(3), 203.


Danielsson, J. (2002). The emperor has no clothes: Limits to risk modelling.

*Journal of Banking & Finance, 26*(7), 1273.


http://www.fooledbyrandomness.com/imbeciles.htm

