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Value at Risk in Foreign Exchange Risk Management

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ABSTRACT

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This thesis examines the suitability of VaR in foreign exchange rate risk management from the perspective of a European investor. The suitability of four different VaR models is evaluated in respect to have insight if VaR is a valuable tool in managing foreign exchange rate risk. The models evaluated are historical method, historical bootstrap method, variance-covariance method and Monte Carlo simulation. The data evaluated are divided into emerging and developed market currencies to have more intriguing analysis. The foreign exchange rate data in this thesis is from 31st January 2000 to 30th April 2014.

The results show that the previously mentioned VaR models performance in foreign exchange risk management is not to be considered as a single tool in foreign exchange rate risk management. The variance-covariance method and Monte Carlo simulation performs poorest in both currency portfolios. Both historical methods performed better but should also be considered as an additional tool along with other more sophisticated analysis tools.

A comparative study of VaR estimates and forward prices is also included in the thesis. The study reveals that regardless of the expensive hedging cost of emerging market currencies the risk captured by VaR is more expensive and thus FX forward hedging is recommended.

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This thesis is dedicated to the memory of my father.

Helsinki, 25.4.2015

Tanja Träff

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1 INTRODUCTION

1.1 Background

Risk management is an essential concern to any participant who operates in the financial markets. Especially in the corporate world the need for a practical and accurate risk management method has increased. This is both due to internal and external requirements. The ever so volatile and interesting foreign exchange rate is the cornerstone for every corporate working in a global environment. Efficient foreign exchange risk management offers advantage to corporates over their competitors. Especially the volatile emerging market currencies cause pressure to corporates whose business is directly or indirectly reflected on their rate movements. The latest reminder from emerging market's volatile nature is the depreciation of Russian Rouble in 2014. The effects spread throughout the globe effecting immediately corporations who operate in Russia.

Various different methods to complement foreign exchange risk position calculations have been covered in the academic literature. These include Value at Risk models, stress tests and scenarios, linear programming, simulation, sensitivity analysis and various optimisation models. This thesis focuses on VaR as a risk management tool. VaR is a commonly used metric to calculate portfolio risk. VaR is designed to provide an aggregate estimate of a portfolio's risk by combining the effects of different risk factors into a single figure. It represents the lower percentile on an assumed profit and loss distribution that is based on the movements of an appropriate set of market risk factors over a given time. The popularity of VaR is based on the simplicity of the outcome, one figure.

The market risk factors in this study are the foreign exchange rates of chosen currency pairs. In this study the VaR figure is constructed with four different VaR-methods and 3 different confidence levels. This should first provide insight if VaR is useful in forecasting the foreign exchange rate movement. Second, it is observed if the VaR figures could be used when

making risk management decisions to hedge or not hedge with a foreign exchange forward.

Forward contracts have been found by many studies to be the most popular hedging method (Pramborg, 2002; Hakkarainen et al., 1996). However, especially in the case of emerging market currencies the hedging with foreign exchange forwards is considered expensive. Foreign exchange options on the other do not offer to ease the problem faced by these corporates as they are in most cases, more expensive instruments. The option not to hedge, alternatively, exposes the company to risk completely.

1.2 The research problem

The main purpose of this study is to first examine the suitability of Historical simulation, Historical bootstrap simulation, Variance-covariance and Monte Carlo simulation methods for foreign exchange rate VaR. The suitability is further divided into emerging and developed market currencies.

The second motivation is to compare the established VaR estimates to the hedging costs related to foreign exchange risk. Emerging market currencies are criticised of being expensive to hedge. The most common foreign exchange rate hedging instrument is the foreign exchange forward. The VaR results from the first research question are compared to corresponding swap points to find an answer if hedging with a forward contract is either more expensive or cheaper than the VaR estimate. The comparative analysis is divided into emerging and developed market to offer more intriguing analysis.

1.3 Motivation and contribution to existing literature

Value at Risk is widely covered in the academic literature. Several different approaches to calculate VaR have been studied and VaR has been applied to various different instruments and with different time

horizons and intervals. Despite the extensive amount of literature none of the previous studies have studied VaR with similar data and VaR models as used in this thesis. A large portion of the studies have focused on stock and index returns whereas foreign exchange and commodities have a lesser portion of the academic literature concerning VaR. Due to the similar nature of foreign exchange rates also VaR for commodities are covered in the review of existing literature.

Hendricks (1996) examined the predictive power of twelve different VaR methods. The data of the study covered eight different currencies against the U.S. dollar. The outcome of the study revealed that VaR was able to cover the risk that it was intended to cover. Giot and Laurent (2003) studied the predictive performance of commodity prices with three different VaR methods and received good results with the chosen models. Hung et al. (2008) studied the predictive performance of more complex VaR methods among commodity prices. Their study revealed good accuracy in both high and low confidence levels. Füss et al. (2010) studied different VaR methods with commodity price data and suggest that dynamic VaR models outperform traditional VaR models. The dynamic models were able to better incorporate the high volatility in the data.

1.4 Limitations of the study

There are two key limitations that should be kept in mind. The first is the fact that the number of backtesting days is limited, which means that the statistical power of the implemented backtests is restricted. The limitation is due to the short period of available and reliable data from emerging market exchange rates.

Second, the comparison between the VaR estimates and swap points is studied only for a long position in the foreign dominated currency where the risk arises from the rising of foreign exchange rates. This is due to the chosen currencies in which almost throughout the whole data horizon EUR interest rates have been lower, which results in investors gaining from a short position in forward contracts.

1.5 Structure of the study

The rest of the paper is organised as follows. The second section combines the theoretical base on which the thesis is based on with literature review about the topic. Third section explains the data, VaR methods and VaR backtesting methods used. Section 4 presents the empirical results and findings. Section 5 concludes the thesis and offers suggestion for further research.

2 LITERATURE REVIEW AND THEORETICAL BACKGROUND

This section is divided into four main parts that illustrate the cornerstones of the study. The first part covers foreign exchange risk and the second introduces its management. The third part introduces hedging and hedging instruments. The section concludes with VaR in risk management framework.

2.1 Foreign exchange risk

All companies are subject to financial risk. Financial risks are commonly divided into three different categories: credit risk, liquidity risk and market risk. Market risk consists of factors that may have an impact on the value of the company's portfolio. The measure of risk is the standard deviation of unexpected outcomes of financial assets that is also called *volatility* or *sigma* (σ). Jorion (2007) separates market risk into four subcategories:

- equity
- interest rate
- foreign exchange rate
- commodity

Foreign exchange rate (FX) risk is further divided into three types by Knüpfer and Puttonen (2009)

- transaction risk
- translation risk

- economical risk

Losses that a firm may face depend both on its exposure to these different sources of market risk and on the level of the underlying volatility of the financial assets that the firm is holding.

Transaction risk refers to the adverse movements of the exchange rate from the time foreign currency denominated transaction is initiated till the time of its final settlement. The risk arises when the foreign exchange rate at the payment date differs from the time of the agreement. This type of transaction can be, for example, account receivable or payable.

Transaction position is always denominated in a relation to the company's home currency. A company operating in Finland does not include EUR cash flows in its transaction position. But, for example, if the Finnish company receives cash flows from Sweden the SEK cash flows to the Finnish parent company are counted in the Finnish company's transaction position. Transaction risk is primarily a short term exposure that can be hedged using financial derivatives. The hedges should reduce the volatility of cash flows and consequently the volatility of company value.

Translation risk arises from the financial accounting statements of foreign affiliates that are translated into the currency of the parent company. Unlike transaction gain or loss of foreign transactions, which has cash flow effects, the translation adjustment arising from consolidating financial statements have no cash flow effects and are of "paper gain" or "paper loss" nature.

Economic risk is the risk which reflects the firm's present value of future operating cash flows from exchange rate movements. Economic risk is concerned with the effect of exchange rate changes on revenues both earned from domestic sales and exports and operating expenses that is the cost of domestic inputs as well as imports. It is said that it is the change in value of the company due to unanticipated change in the

exchange rates. The unanticipated comes as an unforeseen risk. (Srivastava, 2013)

There is no general agreement as to which of these risks is the most important or which risk needs to be emphasised to management. However, empirical studies from U.S. and UK suggest that most companies tend to concentrate more on transaction risk than the other two risks. Belk and Edelshain (1997), Duangploy et al. (1997) and Khoury and Chanf (1993) in their research on U.S. corporations found that majority of the corporations held day-to-day management of transaction risk as the centrepiece of their FX risk management.

2.2 Exchange rate risk management

Modigliani and Miller (1958) presented their classic theory that risk management is irrelevant for the company. They argued that it does not make a difference which one is managing the risk; the company or the shareholder. The simplifying assumption behind this theory is that the capital markets are frictionless. However, in the real world the capital markets are far from frictionless; taxes and agency costs to name a few. Since then several studies have argued their theory and several studies have proven the importance of risk management in a corporation and the value-adding feature of risk management.

Géczy et al. (1997) noticed, in their study among 500 U.S. corporations, that the balance of cash flows was seen as useful within companies with high growth possibilities. Froot et al. (1994) also point out the importance of corporate risk management to ensure that financial risks such as foreign currency rates changes have no effect on the investment opportunities of a firm by cutting down the cash flow. A survey made by Marshall (2000) investigated the practices of foreign exchange risk management in U.S., UK and Asia Pacific companies. The results showed that in every geographical area investigated the majority of respondents ranked foreign exchange risk management as an important activity.

Martin and Mauer (2004) studied the economies of scale in hedging among U.S. companies. A large portion of the corporations doubted that shareholders would have similar opportunities to hedge. The lack of effectiveness faced by the shareholder includes for example access to market and hedging costs.

Whether translation should be actively managed has been widely debated. Many textbooks (see Shapiro (2008) amongst others) present the view that translation exposure should not be managed as it is purely an accounting concept not related to cash flows. However, Rodriguez (1980) and Collier et al. (1992) confirm that USA and UK companies do manage translation exposure. The decision on the hedging translation exposure is influenced by the financial reporting requirements at play in the reporting country. (Hakkarainen et al., 1998; Marshall, 2000).

Glaum (1990) and Kohn (1990) emphasise that economic exposure management is the most important concept in foreign exchange management. However, although many companies seem to recognise the importance of economic exposures they have not systematically managed them. Blin et al. (1981) observe that less than a third of companies in their survey indicated that some internal adjustments for economic exposure were undertaken. This research seeks to establish the emphasis placed by MNCs in different regions on each of these risks and whether there is a regional variation. (Marshall, 2000)

2.3 Hedging

Hedging has been divided into two fundamental ways in which the corporation can manage exchange rate exposure - operational and financial hedges. The ways of hedging are presented in this chapter in respective order.

2.3.1 Operational hedging

Operational hedging is also referred to as natural hedging. It means that the company makes operational decisions that reduce their exposure to exchange rate changes. For example, if a company has a debt in foreign currency it could establish a receivable in the same amount in the foreign currency it has hedged its exposure to foreign exchange rate devaluations. Any foreign exchange gain (loss) on the accounts receivable would be offset by a loss (gain) on the accounts payable.

Another technique of operational hedging is to locate production facilities countries where significant foreign currency sales are expected, then fund foreign operations with foreign borrowings and diversify import and/or export markets to countries whose currencies do not closely track each other. (Logue, 1995)

Operational hedging is commonly used in long term hedging. In comparison to derivatives, (financial hedging) excluding long term currency swaps, it simplifies the company's risk management and reduces basis risk through a reduction in the duration differential. The simplifying aspect arises from the cost and complexity of monitoring and managing short term derivatives. The reduction on the basis risk arises from the more accurate match of duration with the exposure and the hedge. Clark and Judge (2009)

Allayannis et al. (2001) studied a selection of nonfinancial firms during 1996-1998, and found that operational hedging is not an effective substitute for financial risk management.

2.3.2 Financial Hedging

Financial hedging is a defensive strategy that reduces or eliminates the risks associated with exchange rate changes with the use of financial instruments, derivatives. Derivatives derive their value from an underlying

variable, in this case the foreign exchange rate. Derivative contracts include futures, forwards, swaps and options.

2.4 Futures, Forwards and Swaps

A forward contract is an agreement to deliver specified quantity of an asset or commodity at a specified future date, at a price to be paid at the time of delivery. A forward contract is agreed between two parties, the buyer (long position) and the seller (short position). The terms of the contract define the asset in question, quantity, price and the date of delivery. The buyer of the contract agrees to pay the forward price and the seller agrees to deliver the asset or commodity specified in the contract. A forward contract is usually traded over-the-counter because of the non-standardised nature of it. Over-the-counter refers to the private agreement between the parties. Because of the non-standardised nature of the contract, forwards are usually held to maturity and the contract is then settled. From the point of view of a hedger forwards are extremely useful as they can offer a full hedge if so needed.

Futures and forwards with the same price and same delivery date can be considered equal. Futures are like forwards but with few differences. Futures contracts are standardised in their quantity, price and date of delivery. The standardisation is necessary because futures are traded on public exchange. As the contract is traded on an exchange and there is a liquid market for these instruments, futures are usually not held to maturity. The settlement of the futures contract is daily.

A foreign exchange swap is a contract between two parties where different currencies are exchanged by combining foreign exchange spot and forward contracts. The spot contract refers to an agreement to change the predetermined currencies at the beginning of the contract with a spot rate of that day. The rest of the foreign exchange swap contract is a forward contract where the same principal amount is exchanged with a spot rate plus swap points. The example below clarifies the transactions in a foreign exchange swap contract. (Hull, 2011)

A survey done by Marshall (2000) points out that currency swaps are better for hedging against translation risk, while forwards are better for hedging against transaction risk.

2.4.1 Forward pricing

Because of the similar nature of forwards and futures there are no substantial differences in their pricing or prices in the short term, they are considered as substitutes. According to the interest rate parity theorem, the forward rate F_0 of a currency forward or futures contract is as follows (Hull, 2011):

$$F_0 = S_0 e^{(r-r_f)^T} \tag{1}$$

Where S_0 is the spot exchange rate at time *0*. The holder of the foreign currency has the opportunity to earn interest at the risk-free rate r_f prevailing in the foreign country for time *T.* The variable r is the home currency risk-free rate for the same time period *T.* The $r - r_f$ in the equation is the cost of carry. It is the relationship between the spot and forward rate. In actual markets the interest rate parity does not always prevail as the capital markets are not considered as efficient.

The forward rate is determined in the market as an exchange rate. It can be quoted in two different ways: outright and swap. The outright quotation is the banks quote on buying (bid) and selling (ask) rates. The swap quotation is divided into spot rate and swap points. These swap points are either added to or subtracted from the spot rate in order to obtain forward rate. These swap points are the cost of entering into the foreign exchange forward agreement. (Baker and Riddick, 2013)

2.5 Options

An option gives the option buyer, or holder, the right to buy (call option) or sell (put option) a set quantity of foreign currency at a predetermined exchange rate called the exercise or strike price if it is in the holder's best

interest. If the spot rate at the maturity of the option is more favourable, the option holder can let the option expire without exchanging the currencies. Thus, an option gives the holder the right, but not the obligation, to take delivery or to deliver a predetermined amount of foreign currency at a predetermined price. Options are divided into American and European options regarding the exercise period. American options can be exercised at any time up to the maturity date, whereas European options can only be exercised on the maturity date. Most commonly the foreign exchange options are European options. Options can be traded on exchange like futures contracts and similarly the options are standardised. However, most of the option trading is in the over-the-counter markets.

There are two main aspects how foreign exchange options and forwards differ. First, by buying an option the buyer is exposed to potential maximum limit of loss. The maximum loss is the price (or premium) of the option. Second, because of the right but not the obligation, the buyer is allowed to take advantage of favourable foreign exchange rate movement. This privilege is the option price. In general, the option price depends on two factors: the intrinsic value of the immediate benefit that the option holder will enjoy by exercising the option and the time value or the future potential benefit from owning the option. (Baker and Riddick, 2013)

2.5.1 Option pricing

The option pricing model was first introduced by Black and Scholes (1973) but Garman and Kohlhagen (1983) extended the model to currency options. The Garman and Kohlhagen currency option pricing model for European call option (equation 2) and put option (equation 3) are shown below:

$$C(S,T) = \exp^{-r_p T} SN\left(x + \sigma\sqrt{T}\right) - \exp^{-r_D T} KN(x) \tag{2}$$

$$P(S,T) = \exp^{-r_D T} KN(-x) - \exp^{-r_D T} SN(-(x + \sigma\sqrt{T})) \tag{3}$$

Where

$$x = \frac{\ln\left(\frac{S}{K}\right) + \left[R_d - R_f - \left(\frac{\sigma^2}{2}\right)\right]T}{\sigma\sqrt{T}} \tag{4}$$

From equations 1 and 2 six factors affecting the foreign exchange forward can be recognised. These factors and their influence on option price are:

1. *S*, the spot exchange rate, has a positive relationship with the call price. If the exercise price remains constant, a rise in the spot price leads to a rise in the intrinsic value. The rise in the intrinsic value makes the option more attractive and leads to a higher call price
2. *K*, the exercise price, has a negative relationship with the call price. If the spot rate remains constant while the exercise price rises, the intrinsic value of the option declines. Declining intrinsic value makes the option less attractive and leads to a lower call price.
3. σ, the standard deviation (volatility) of the spot price, has a positive relationship with the call price. When the volatility of the underlying exchange rate rises, the possibility that the future spot price will exceed the exercise price also rises. This leads to a higher call price.
4. R_D, the domestic riskless interest rate, has a positive effect on the call price. When the domestic interest rate rises, the present value of the exercise price declines. A declining present value of an exercise price leads to a higher call price.
5. R_f, the foreign riskless interest rate, has a negative influence on the call price. According to interest rate parity theorem, presented in Subsection 2.4.1 (futures and forwards), a country with currency that is expected to decline offers higher interest rate to compensate for the expected decline. Thus, as foreign interest rates rise, the market expects the value of the foreign currency to decline, thereby leading to lower expected intrinsic value.
6. T, the time to maturity of the option, has a positive relationship with the call price. When the maturity of the option rises, the possibility that the future spot price will exceed the exercise price also rises

because more time is available for the spot price to move above the exercise price. The market favourably views this increased probability, leading to a higher call price.

The pricing of American options is far more complex and it is left out of the scope of this thesis. However, it should be mentioned that American options are always more expensive than European options. This is due to the value of the longer exercise period. (Puttonen and Valtonen, 1996)

The previously mentioned American and European call and put options are the simplest form of options, often called plain vanilla options. The option market is very versatile and there are many types and variations available. These exotic options are either variations of the plain vanilla options or they can be wholly different product with option-like feature in it.

2.6 Introduction to Value at Risk

Even though the mathematics of VaR lies back in the 1970's, the term "Value at Risk" became a term in 1995 when J.P. Morgan provided public access to data on the covariance's across various security and asset classes. This data consisted of securities and assets it had used internally for almost a decade. The service was called "RiskMetrics" and the term Value at Risk was to describe the risk measure that emerged from the data. The immediate attention of commercial and investment banks was caught and during the last decade non-financial firms have started to exploit VaR as well. In the banking environment VaR became a standard market risk measure since the adoption of the Basel Committee of on Banking Supervision 2006. (Cheung and Powell, 2012)

VaR was originally designed for measuring the market risk originating from the fluctuations in asset prices in a way that captures both a company's exposure to the risks and the underlying volatility. Nowadays, VaR is a widely spread risk management technique. It is suitable for any institution that finds the management of financial risk crucial to its business. It has become a benchmark methodology thanks to its easily understandable

way to determine risk. VaR is a single number summarizing the total risk in a portfolio. VaR gives an institution the answer to a question: What is the most I can lose in on this investment. VaR tries to provide the answer within reasonable bound. For example, is a company's daily VaR is stated as EUR 10million with a 99% confidence level, the probability of facing a loss that exceeds EUR 10million the next day should be 1%. (Jorion 2007, Haas 2001)

Following Jorion (2007), in mathematical terms, for a portfolio whose value at the end of a period is given by

$$W = W_0(1 + R) \tag{5}$$

where W_0 is the initial portfolio value and R the portfolio's rate of return, there is a distribution of future portfolio value $f(W)$ and the VaR for the portfolio is defined as

$$1 - c = \int_{-\infty}^{W*} f(W)\, dw \tag{6}$$

where c is the specified confidence level and $W*$ is the end of period portfolio value when the worst portfolio return with given confidence level is realised.

Consequently, assuming that asset returns are normally distributed (ie. $(W) \sim N(0,1)$) VaR is calculated as follows:

$$VaR_c = \alpha * \sigma * W_0 \tag{7}$$

Where α is the normal deviate associated with the confidence level $(1 - c)$, σ is the portfolio volatility and as before, W_0 is the initial value of the portfolio. It is important to remember to use consistent time horizons in estimating the figures for return and its volatility with respect to the VaR time period. For example, if a portfolio's VaR value is EUR 50million and

the annual volatility of its returns is 15%, a 1-day VaR 95% confidence level would be as follows:

$$VaR_{95\%} = -1.65 * \sqrt{\frac{1}{250}} * 15\% * 50\text{m} = -0.78\text{m} \tag{8}$$

The value of α can be read off from standard normal distribution tables and the annual volatility is converted into daily volatility by $\sigma_t = \sigma\sqrt{T}$, where T is time horizon expressed in years.

As stated before, VaR is a fairly simple and intuitive concept in theory, and it is one the main reasons for its popularity among financial practitioners. However, its implementation in practise is hardly a straightforward process - at least not for portfolios that contain a large number and different kinds of securities - and measuring VaR is actually a demanding statistical problem. Following Jorion (2007), measuring VaR can be divided into two categories: nonparametric (historical simulation) approach and parametric approach. The parametric approach assumes normal distribution whereas nonparametric approaches make no assumption on the distribution. Monte Carlo method on the other hand simulates multiple random scenarios. The academic literature also recognises another perspective to classify measuring VaR: local valuation and full valuation. The local methods measure the risk by valuing the portfolio once (parametric approach) whereas the full valuation method measures the risk by fully reprising the portfolio over a range of scenarios (historical and Monte Carlo simulation approaches). Whichever the primary categorisation each of the above-mentioned approaches/valuations contains several sub-approaches. It should be mentioned that the different methods yield somewhat differing results. Further, using same model gives naturally differing measures depending on the practical implementation of the model. The differences between the models arise from their approach to estimating the changes in value of the portfolio. Nevertheless, what the models have in common is that they all try to account for the empirical findings about the financial

markets that were first documented already a half-century ago by Mandelbrot (1963) and Fama (1965). These can broadly be summarized as follows:

- Financial return distribution are leptokurtic (ie. the returns have fatter tails than in the normal distribution)
- Equity returns are typically negatively skewed (ie. the left side of the distribution is longer than the right side)
- Volatility is typically clustered in time so that large changes in asset values are followed by other large changes, and small changes are often followed by small changes

An overview of the different VaR models is presented in the subsequent chapters of this section and the models employed in this study are more comprehensively presented in Section 4.

2.7 Parametric methods

As the name suggests, parametric models are based on parameterisation of the behaviour of financial instruments' price changes. More explicitly, these models require making an assumption about the statistical distribution of asset returns from which data is drawn. Parametric approach can be perceived as fitting curve across the data and then reading off the VaR measure from that fitted curve. This is also the primary advantage of parametric models: computing requires relatively little information and so the practical implementation is less burdensome than with the other models. Furthermore, since parametric VaR figure is simply a multiple of the standard deviation of the distribution multiplied by an adjustment factor that depends on the confidence level and holding period length, normality enables simple rescaling of VaR figures for differing confidence levels and holding periods through changing the adjustment accordingly (Dowd, 1998). However, the problem with parametric models is that the chosen statistical distribution may not reflect accurately the actual distribution, which leads to either under- or overestimation of the

actual risk. This is especially problematic for portfolios that contain options or other instruments whose pay-off is highly asymmetric as this adds to the skewness and the kurtosis of the distributions which again leads to more extreme price variations and, consequently, to increased probability of more extreme losses (Jorion, 2007).

The normal distribution is a simplification which has been argued by many researchers as the risk factor values are usually not normally distributed. Jorion (2012) suggests that the multiplier α could be taken from a distribution with fatter tails (Student T for example) if the risk factor values are symmetric. Several different parametric approaches have been developed, each of them forecasting the standard deviation in a different way Cabedo and Moya (2003).

2.7.1 Variance-covariance method

Variance-covariance approach (also referred to as delta-normal method) is one of the basic VaR computing methodologies in the class of parametric models. The key step in variance-covariance VaR method is the computation of the standard deviation of changes in portfolio value. The portfolio VaR is obtained multiplying the standard deviation by the normal deviate and risk factor weights as shown in the previous chapter. However, even if the basic idea is very simple, the practical implementation can become challenging as the standard deviation of a portfolio depends both on the standard deviations of the portfolio's individual instruments and on the correlation between them. As a result the total number of required parameters grows rapidly as the number of instruments increases (Linsmeier and Pearson, 1996).

2.8 Non-parametric methods

Even though parametric methods are attractive because of their theoretical simplicity, Barone-Adesi and Giannopoulos (2001) point out that the parametric methods have materially underestimated the size and frequency of substantial losses due to the fact that normal distribution fails

to accurately describe the actual distribution of portfolio returns. Unlike the parametric models, non-parametric methods do not make any distributional assumption about portfolio returns.

2.8.1 Historical simulation

Historical simulation is a very popular way of estimating VaR within the class of non-parametric methods due to its simplicity. The approach uses past data in a very direct way as a guide to what might happen in the future. The VaR of the portfolio is the maximum loss in this distribution, associated with the required statistic likelihood percentile. Because the distribution of risk factors, such as asset returns, is often fat-tailed, historical simulation might be an improvement over parametric VaR approaches which assume that the risk factors are normally distributed. In historical approach the empirical distribution is derived from the price changes over the period before the time of calculation. Therefore the advantage of historical simulation is that it pays attention to periods of non-normal trading, like financial crisis and it can be used for all types of financial instruments. (Cabedo and Moya, 2003; Jorion, 2007)

Even though historical VaR does not make explicit distributional assumptions, it still contains an implicit assumption that the distribution of returns stays unchanged within the historical estimation time window (Engle and Manganelli, 2001). This assumption leads to a few problems. First, if returns within the estimation window are assumed to have the same distribution, it means that all returns of different time series have to be independent and identically distributed. The assumption on independency of returns implies that the magnitude of price movement in one period of time would not influence the price fluctuations that occur during subsequent time periods. Further, if the returns were identically distributed, or stationary, through time, it would imply that the probability of a given loss was the same for each day. This is empirically false as volatility has a tendency to cluster so that large price fluctuations are followed by further large changes. In practise this entails that during

periods with higher volatility one would also expect losses that exceed usual level. Consequently, using a constant volatility model such as basic historical simulation could be misleading as it underestimates risk during highly volatile market conditions, which is documented by Van den Goorberg and Vlaar (1999) and Vlaar (2000). Second, choosing a proper length for the time window is not a trivial task: if it is too short, it is not possible to obtain statistically significant figures, and if it is too long, the market fundamentals may have changed since the beginning of the period and observations from the past - with either too low or high volatility - may dominate the VaR estimation yielding either excessively low or high VaR figures (Dowd, 2007). For instance, Hendricks (1996) finds that longer historical sample periods result in less variability in VaR estimates, but that they also result in absolutely larger estimates.

2.8.2 Historical bootstrap simulation

The historical bootstrap method is a step up from the basic historical approach. It uses the concept of bootstrapping to efficiently estimate the statistics of the underlying unknown population distribution of the risk factor. Following Babu and Singh (1983), the bootstrap sampling distribution resembles that of the population as the number of resamples increases to infinity. For detailed instructions on how to implement historical and historical bootstrapping VaR see Cheung and Powell (2012)

2.8.3 Monte Carlo simulation

Monte Carlo (MC) simulation is widely used to develop estimates of VaR. MC is a highly flexible method for computing VaR as it is capable of simultaneously accounting for various risk sources and it can deal with time variations in volatility and nonlinear price exposure arising from complex pricing models (Jorion, 2007). Consequently, as pointed out by Agiakloglou and Agiropoulos (2013) Monte Carlo simulation is the most powerful method to obtain VaR estimates, because it has the ability to increase accuracy of determining VaR.

Implementation of MC simulation begins with identifying the important market factors and assigning suitable stochastic processes for these factors. Then a future distribution of portfolio returns is created through simulation of price paths for the instruments, and different confidence level VaR figures are drawn from this distribution (Wiener, 1999).

Even though the MC simulation uses parametric inputs, such as volatility in Geometric Brownian Motion that is used for describing the dynamics of stochastic price process, the future distribution cannot be described by an analytical function and thus the model can be interpreted as a non-parametric method. Hence, for instance Dowd (2007) categorizes MC simulation as a semi-parametric method.

MC has also attracted criticism. Barone-Adesi and Giannopoulos (2001) point out that the model's multivariate properties of the risk factors are based on historical correlations and the correlations tend to increase rapidly during crises, which may lead to underestimation of risk. Moreover, MC is often criticised because of the time-consuming and computer-intense implementation. This problem, however, is gradually mitigated as the computing capacity as well as the efficiency of simulation methods are evolving constantly. For detailed instructions on how to implement Monte Carlo Simulation see Cheung and Powell (2013).

2.9 VaR criticism

Heffernan (2005) and Kudinska (2003) listed the positive attributes of the model as follows:

- Easy to understand
- Easy to apply calculating different complexity levels and portfolios, also can be applied for risk concentration valuation according traders, markets instruments
- Valuates differently even very complex movements of related instruments, at the same time estimating risk decrease because of diversification

- Applicable for limits determination because links loss value with probability
- Results are easily compared, allowing to measure activity effectiveness of traders

Despite the positive aspects, the model also has its weaknesses. For the sake of providing a comprehensive perspective on VaR, also some of the model's shortcomings are discussed in the following chapter.

Artzner et al. (1999) have proposed a list of desirable properties that a risk measure should have in order to be considered as "coherent" risk measure. These include:

- Monotonicity: if a portfolio A yields in every possible situation better than portfolio B, then portfolio B should be assigned with a higher risk.
- Sub-additivity: the combined risk of two portfolios cannot be higher than the sum of separate risk.
- Positive homogeneity: if the size of the portfolio is doubled, the risk should double as well
- Relevance: the risk of holding no assets is zero

It is known fact that VaR fails to meet the requirement of sub-additivity, which means that using VaR might discourage diversification. Moreover, it could possibly lead to regulatory arbitrage in the sense that if the capital requirements of an institution depend on its VaR figure, by splitting its assets into separate subsidiaries a company would be able to appear less risky than it actually is.

Furthermore, while the conceptual simplicity is perhaps the main reason why VaR has become such a widespread method for risk measurement, it is also one of its fundamental shortcomings. As all available information is condensed into a single easy-to-comprehend figure it is evident that some relevant information will be lost. For instance, two positions with different risk characteristics beyond the VaR confidence level can still have the

same VaR figure. This is due to the property of VaR that it provides no information regarding the losses that exceed the VaR estimate, and why it is often said that VaR fails to account for the “tail risk”. Consequently, VaR figures solely do not provide sufficient estimate of the risks that an entity daces. A recent illustration of the “tail-risk” is the USD 2 billion mark-to-market loss suffered by JPMorgan in May 2012, while its daily average VaR in the first quarter of 2012 was reported to be USD 67 million. This incident has indeed fuelled the debate about the reliability of VaR as a risk measure especially when it was first introduced by JPMorgan.

However, it is possible to partially overcome this shortcoming by using a so called “conditional VaR” method that measures the expected loss given that the VaR is exceeded. This method is also known as the expected shortfall or expected tail loss and it is gradually gaining more popularity. It should be pointed out that while expected shortfall is based on value at method, it is coherent measure of risk while VaR is not. Also, it is expected that expected shortfall will take VaR’s position as regulatory measure in the future as the Basel Committee on Banking Suprevision has recently state that under the prospective Basel III the market risk capital requirements would be based on expected shortfall rather than VaR measurements. However, even though it is coherent risk measure and hence theoretically better than VaR, it also has its limitations. For instance, the challenges in its implementation exceed those of VaR, and if the calculation method used in expected shortfall is the same as in VaR, i.e. based on bootstrapping data from the past 250 days, it does not make a significant difference which method is used.

Another general VaR criticism has been the model’s intrinsic feature of merely considering the loss at the end of the estimation period, which, as for example Boudoukh et al. (2004) and Kritzman and Rich (2002) point out, becomes a problem with longer estimation horizons. For instance, certain investors, such as insurance companies and money managers, are interested not only in their long-horizon VaR but also in what happens in the interim: VaR horizon and hence the actual losses could become

substantially worse than predicted by VaR. Kritzman and Rich (2002) propose using “continuous VaR” in which the normal end-of-horizon probability of loss is transformed into intra-horizon path dependent loss.

Furthermore, all VaR methods are at least partially dependent on historical data, and as is well known, history does not predict future very well. All in all, regardless of how VaR is computed, it is far from being a perfect tool for risk management. As a result, other risk management techniques are required in addition to VaR estimates. These include stress tests and scenario analysis together with various sensitivity analyses with respect to different risk factors.

2.10 VaR backtesting

The usefulness of a VaR model for generating risk estimates is dependent on the model’s ability to accurately predict future losses. The precision of a VaR model can be backtested by comparing actual losses to corresponding VaR estimates. There are a few different viewpoints that can be taken into account when determining the goodness of a VaR model. When determining whether the model in question is accurate or not, some kind of definition for accuracy is needed. For example, accuracy could refer to the ability of the model to measure a particular percentile of the profit and loss distribution, or it could mean the model’s capability of predicting the size and frequency of portfolio losses. For that reason there is no one single test that provides a correct answer. This chapter offers a brief overall view over commonly used backtesting methods, while a more detailed description of the statistical framework of backtesting and specific backtests applies in this study are in Sections 3.3 - 3.5.

Following Christoffersen (1998), the evaluation of a VaR model’s accuracy can be reduced into studying the *unconditional* and *conditional* coverage properties of the exception sequence generated by the model. Hence, most backtesting methods can be divided into tests of unconditional coverage and into tests of conditional coverage.

Unconditional coverage tests measure the frequency of VaR exceptions over a specified time period. In short, these tests compare the actual failure rate with the model's theoretical failure rate. For example, when using a 95% confidence level for daily VaR computing, one should expect to face losses greater than the model has predicted five times during 100 trading days on average. Therefore, even the estimates generated by a sound VaR model are breached occasionally but it is the number of those exceptions, or violations that counts. Consequently, the most obvious determinant of a model's validity is the number of occasions when the actual loss for the observed period exceeds the model's respective forecast.

While unconditional coverage tests mainly focus on the number of VaR violations, the tests of conditional coverage account also for the time variation of the occurred exceptions. This is because a sound VaR model is expected to generate an acceptable number of exceptions that are also evenly distributed in time. If a model generates an acceptable number of exceptions during a given backtesting period, the model could still be deemed deficient in case the exceptions suffer from clustering, which could be a sign of the model's poor ability to capture changes in market volatility and correlations.

Third way of testing is to utilize the information provided by the size of the exception through applying a loss function that penalizes a model that has provided a worse estimate of the loss given that the VaR figure is estimated. Consequently, an expected shortfall figure is needed to use loss function based evaluation, and hence, the test provides indirect insight about the quality of a VaR model through studying the tail of the distribution used in the given model rather than the hit sequence the model generates.

3 DATA AND METHODOLOGY

This section starts with a presentation of the data employed in this study, and then continues with a description of the VaR methods utilized in creating the monthly VaR estimates. The section concludes with an illustration of the methodologies utilized in backtesting the VaR methods.

3.1 Data

The data used in this study consists of monthly foreign exchange rate data between 31st January 2000 and 30th April 2014 from Thomson Reuters Eikon. The exchange rate is the months' last trading days' "mid price" quote. "Mid price" is the average of bid and ask (buy and sell) quotes. For the VaR calculating purposes the foreign exchange rates have been transferred to monthly natural logarithmic returns following the next equation,

$$r_t = ln\left(\frac{X_t}{X_{t-1}}\right) \tag{9}$$

where X_t is the monthly closing value of the interest rate on month t.

The total amount of monthly returns is 172 for each currency pair. Two portfolios of the exchange rate returns were constructed. Due to the writers own interest all exchange rates are in respect to Euro. Therefore the start of the observation period was limited to the beginning of Euro. Therefore the observation period can be considered rather short for this kind of research, which is naturally a limitation. This limitation might reflect the results; a longer period could give different results among the different models, or perform more reliably. The chosen currencies and the portfolios constructed are presented below:

Emerging market portfolio:

- EUR/RUB

- EUR/ZAR
- EUR/TRY

Developed market portfolio:

- EUR/USD
- EUR/GBP
- EUR/AUD

Each currency pair is equally weighted in the portfolio to capture the characteristics of each currency in the portfolio. The currencies to the EM portfolio were chosen on the basis of the length of reliable market data. Thus, currencies with the longest reliable historical data were chosen to present the characteristics of emerging market currencies. Fortunately these currencies present large geographical areas and different political and economic backgrounds. The DM portfolio was constructed to present large geographical areas and influential nations.

Using a historical rolling window of 113 monthly returns in VaR estimation, there are 58 monthly observations left for back testing. The mechanism of the rolling window is such, that the first window is placed between 1st and 113rd data points. The window contains the historical data for our first VaR calculations, which will be calculated for the 114th observation. Then the window is moved by one observation ahead to 2nd and 114th to obtain the forecast for the 115th observation etc.

In addition to foreign exchange rate data, swap point data is required to perform the comparative analysis in Section 4.3. Monthly swap point data of the previously mentioned currencies is from Thomson Reuters Eikon, and covers the time span from 31st June, 2007 to 30th April, 2014. The swap point data is the “mid price” quote of the last day of the month. The swap points have also been constructed into portfolios equal to the foreign exchange rate data, with equal weightings. The swap point data is the

actual price data, not returns. There is in total 58 swap point observations for the comparative analysis.

3.1.1 Descriptive statistics

EM and DM exchange rates during the data horizon have faced both bull and bear markets, and the observations include the financial crisis which began in 2008. The time series returns of both portfolios are presented in Figures 1 and 2. The figures help to point out the features of the portfolios. The volatility of the EM portfolio is notably higher than the DM portfolio as expected. The financial crisis of 2008 is observable in both portfolios but the DM portfolio hit the crisis harder within one month. However, excluding the crisis in 2008 the DM portfolio is performing with less volatility throughout the observation period. The EM portfolio faced several volatile periods in 2001-2002 and finally the financial crisis 2008. The volatility in 2001 and 2002 is due to the strengthening of Euro that was caused by the gradual growth of Euro-area interest rates.

Figure 1:

Emerging market portfolio monthly returns

The figure shows the monthly returns for the emerging market portfolio under the observation period between January 31, 2000 and April 31, 2014.

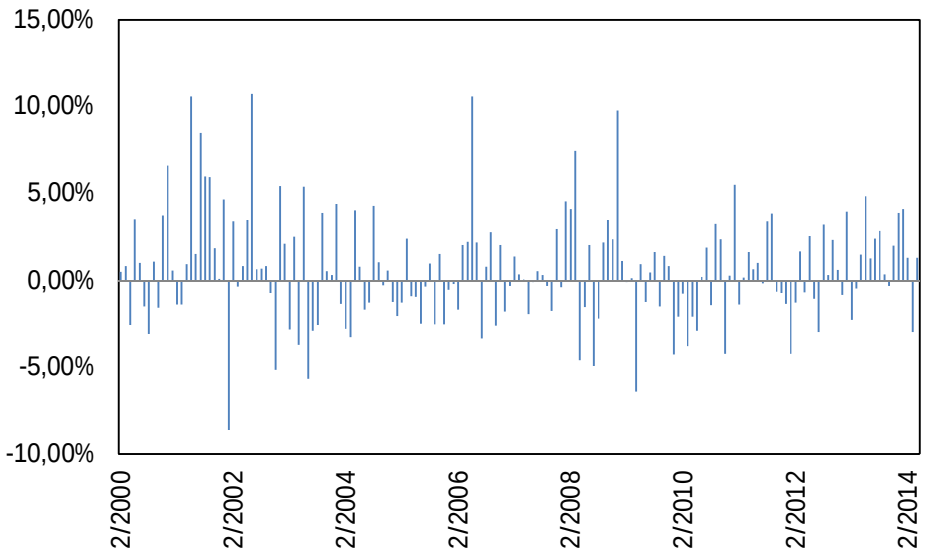
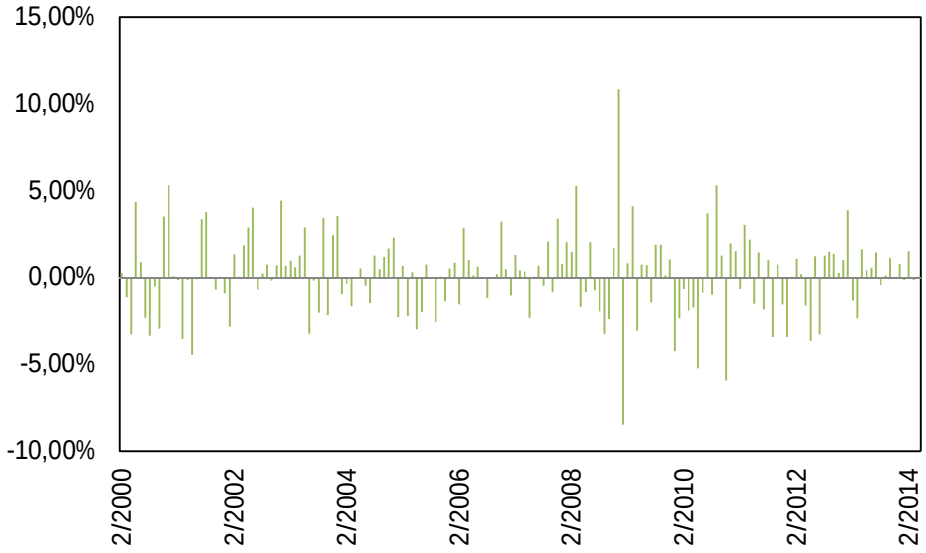


Figure 2:

Developed market portfolio monthly returns

The figure shows the monthly returns for the developed market portfolio under the observation period between January 31, 2000 and April 31, 2014.



The nominal exchange rates for EM and DM portfolios are presented Figures 3 and 4, respectively. The figures provide more insight to the actual performance of the individual rates. Throughout the observation period, all emerging market currencies have depreciated in respect to Euro. TRY has depreciated with equal pace from the beginning of the observation period starting from 0.4 to 2.9. Both ZAR and RUB faced the first depreciation period starting 2001. This was due to the natural strengthening of Euro. However the RUB continued to depreciate until 2004 while ZAR appreciated back to previous levels in 2002. It is common in emerging market currencies that while one EM currency starts to depreciate the other EM currencies start to follow the trend but return back to their normal level after a while. Both ZAR and RUB was affected by the financial crisis, but the depreciation of the ZAR began already in the beginning of 2008 whereas the RUB depreciation took place in the last quarter of 2008 along with Euro. Until the end of 2008 RUB was artificially too strong and thus the financial crisis had such a drastic effect on RUB.

The observation period before the financial crisis was a bull market for the Euro against all developed market currencies. However, the effect of the financial crisis caused the Euro to depreciate with a rather high pace and the rates depreciated in respect to the Euro. The depreciation was especially drastic with USD and AUD as the market was afraid of the financial crisis in Southern Europe. The GBP depreciation was more gradual and less drastic as Great Britain was experiencing its own banking crisis as well.

Figure 3:

Emerging market exchange rates

The figure shows the development of exchange rates for EURRUB, EURZAR and EURTRY under the VaR estimation period between January 31, 2000 and April 31, 2014.

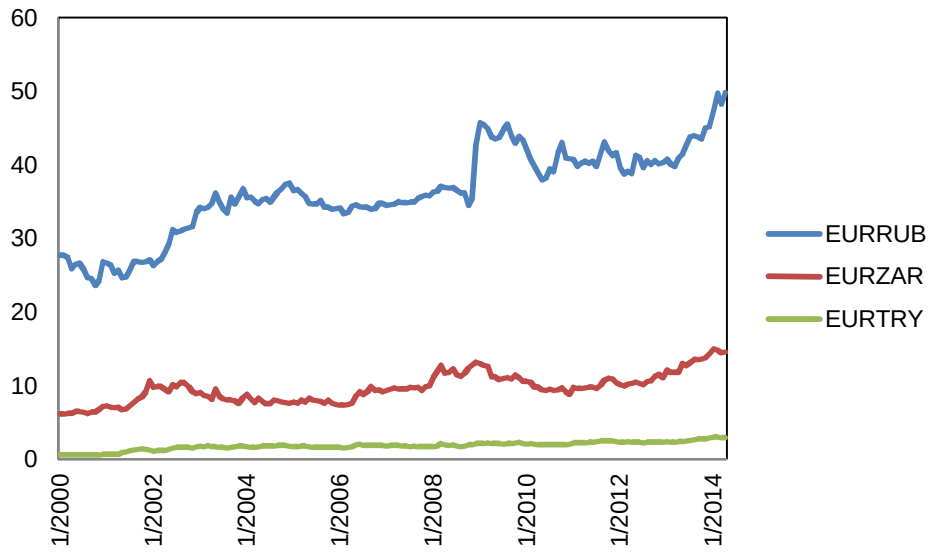


Figure 4:

Developed Markets exchange rates

The figure shows the development of Exchange rates for EURRUB, EURZAR and EURTRY under the VaR estimation period between January 31, 2000 and April 31, 2014.

The summary statistics of natural logarithmic returns for both EM and DM portfolios are presented in Table 1. The mean of both portfolios is positive indicating that the trend of the observation period, on average, is that either the Euro is strengthening or the variable currency is weakening. The mean of the EM portfolio (0.006) is substantially higher than the DM portfolio (0.001) indicating that the changes in the EM portfolio are higher than in the EM portfolio. This verifies the assumption that EM currencies are more volatile than DM currencies. The minimum and maximum values of both portfolios are somewhat similar. However, the minimum and maximum values of the DM portfolio are restricted to a few observations in the beginning of the financial crisis 2008, whereas the EM portfolio has faced values close to maximum and minimum throughout the observation period. The standard deviation of the EM portfolio (0.031) is higher than DM portfolio (0.023) indicating the DM portfolio to be more stable. However both statistics are can be considered rather mild. Within individual currency pairs only EUR/USD (0.031) from the DM portfolio is

able to exceed the lowest standard deviation of EUR/RUB (0.029) in the EM portfolio.

Regarding VaR calculation the figures of kurtosis and skewness are in great interest, as the variance-covariance VaR -model assume the series to be normally distributed. In statistics generally, terms of normality are met, when skewness is close to 0, and kurtosis is close to 3. The exchange rate data of EURRUB, EURTRY and EURGBP fail to meet these requirements, but both of the constructed portfolios are near or within the limits. The EM portfolio is suffering slightly from skewness whereas the DM portfolio is suffering slightly from kurtosis. However, as mentioned before the normal distribution assumption concerns only the variance-covariance method.

Table 1:

Exchange rate summary statistics

The table presents summary statistics of monthly changes in exchange rates during the observation period between January 31, 2000 and April 31, 2014. The changes are measured as log-returns and are presented as percentage changes.

	RUB	**ZAR**	**TRY**	**Portfolio**
n	172	172	172	172
Mean	0,003	0,005	0,010	0,006
Std	0,029	0,046	0,054	0,031
Kurtosis	9,323	0,868	18,233	1,444
Skewness	1,782	0,488	2,810	0,585
Min	-0,056	-0,122	-0,142	-0,086
Max	0,186	0,162	0,412	0,107
	USD	**GBP**	**CAD**	**Portfolio**
n	172	172	172	172
Mean	0,002	0,002	0,000	0,001
Std	0,031	0,024	0,028	0,023
Kurtosis	1,242	7,876	0,287	2,829
Skewness	-0,306	1,272	0,027	0,241
Min	-0,102	-0,082	-0,082	-0,085
Max	0,096	0,148	0,082	0,109

In addition, characterisation of non-normal distribution of EM and DM portfolio returns is presented in the quantile-quantile (QQ) plots in Figures 5 and 6, respectively. The QQ plot is a graphical way to observe departures from normality. The quantiles of an empirical distribution are plotted against the standard normal quantiles. The QQ plot is a scatter plot of the transformed empirical and the standard normal quantiles. If the returns have excess kurtosis, the probability of large negative or large positive values is greater than under the corresponding normal density function. Hence, the lower quantiles are less than the normal quantiles, and vice versa. If the distribution of the returns is normal, the QQ- plot should be close to linear. Fat tails show up as deviations above this line at the lower quantiles, and below the line at upper quantiles. The findings from the QQ plots continue to confirm the non-normality of the returns in both portfolios.

Figure 5:

Emerging market portfolio QQ plot

The figure shows the monthly returns for the emerging market portfolio under the observation period between January 31, 2000 and April 31, 2014.

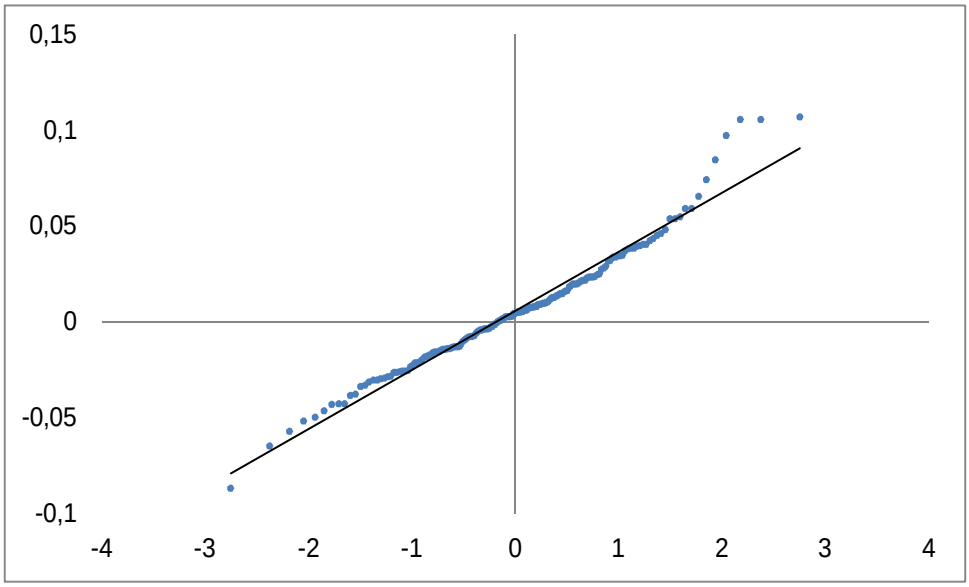
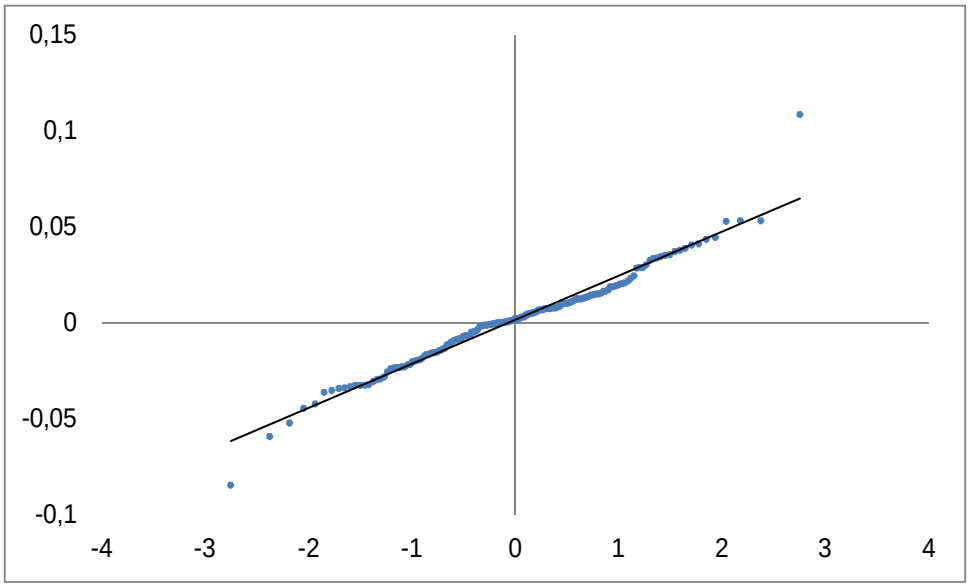


Figure 6:

Developed market portfolio QQ plot

The figure shows the monthly returns for the developed market portfolio under the observation period between January 31, 2000 and April 31, 2014.



The swap point data required to perform the comparative analysis in Section 4.3 is presented next. The figures are actual swap points instead of returns. The development of the swap points in EM and DM portfolio currency pairs are described in Figures 7 and 8, respectively. Throughout the observation period all EM currencies swap points have been positive. As previously explained in Subsection 2.4.1 the forward pricing and thus the swap point is the cost of hedging. Therefore the positive swap point data indicates a cost for an investor with a long position in the EM currencies. Within the DM currencies there is some variation through observation period. The swap points in respect to all three currencies turn negative in 2011. EUR/USD turns negative for over 18 months as EUR interest rates rose temporarily increased. At the end of the observation period EUR/USD trend turns negative once again.

Figure 7:

Emerging market swap points

The figure shows the development of swap points for EURRUB, EURZAR and EURTRY under the VaR estimation period between June 31, 2009 and April 31, 2014.

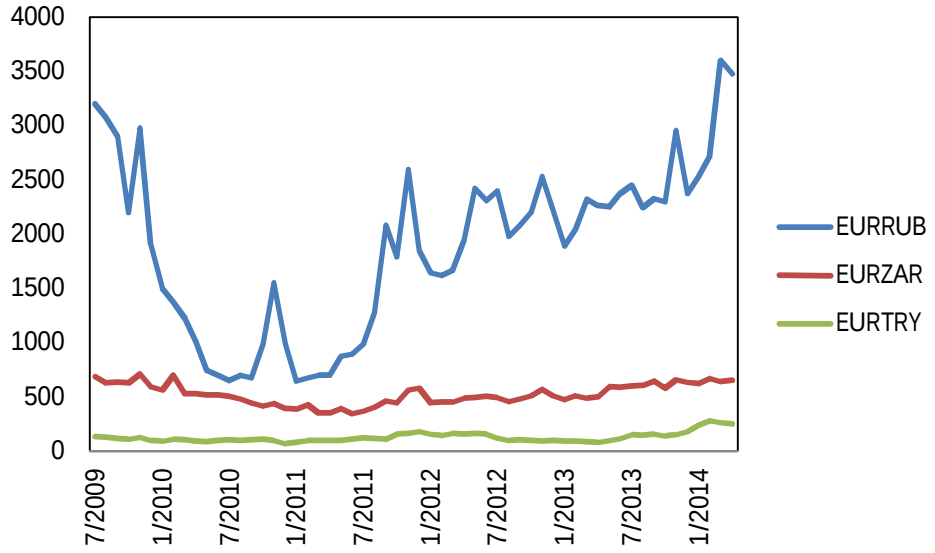


Figure 8:

Developed market swap points

The figure shows the development of swap points for EURUSD, EURGBP and EURAUD under the VaR estimation period between June 31, 2009 and April 31, 2014.

Table 2 presents the summary statistics of the swap point data. The minimum and maximum values of the swap points between EM and DM

portfolios differ to great extent. The maximum, minimum and mean of the EM portfolio are in a whole another dimension compared to DM currencies. This is a vivid implication of the hedging cost of foreign exchange forward contracts within EM currencies in general.

Table 2:

Swap point summary statistics

The table presents summary statistics about changes in swap points during the observation period between June, 31 2009 and April 31, 2014. The changes are measured in absolute terms and presented in basis points.

	RUB	**ZAR**	**TRY**	**Portfolio**
n	58	58	58	58
Mean	1858,749	523,341	128,029	794,030
Std	825,632	96,526	45,482	299,405
Kurtosis	-0,599	-0,881	3,134	-0,659
Skewness	-0,145	0,062	1,740	-0,102
Min	650,000	345,140	71,000	144,440
Max	3600,000	711,600	284,270	1412,897
	UDS	**GBP**	**CAD**	**Portfolio**
n	58	58	58	58
Mean	-0,495	1,440	6,749	2,565
Std	4,100	1,963	5,261	3,425
Kurtosis	1,987	1,624	-1,436	-0,006
Skewness	-1,482	-1,239	-0,406	-0,750
Min	-12,605	-4,327	-2,415	-6,449
Max	4,550	5,355	14,600	8,168

3.2 VaR estimation

This study employs four different VaR estimations for generating a backtesting sample that is used to find an answer to first research problem. The VaR methods used in this study are from two teaching studies presented by Cheung and Powell (2012) and Cheung and Powell (2013).

In VaR computation the following four methods are used:

- historical simulation
- historical bootstrap simulation
- variance-covariance
- Monte Carlo simulation

The historical observation period is 172 monthly natural logarithmic returns. Hence, the moving time frame is 113 observations. The VaR figure is computed for every last day of the month starting from June 31, 2009 until the end of the data set April 30, 2014, resulting to 58 VaR figures for both long and short positions. The VaR figures are estimated using 90%, 95% and 99% confidence level and risk horizon of 1 month. For computational reasons, it is assumed that the hedged position is opened and closed on a monthly basis.

3.2.1 Historical simulation

Historical simulation is implemented by generating different scenarios using the observed historical changes in exchange rates. VaR estimate with historical simulation by Jorion (2012): Current value of the asset or portfolio is P_t, which is a function of N current risk factors at time t, $P_t = P\left[f_1, f_2, \dots, f_{N,t}\right]$. The changes in risk factor movements from the historical distribution are sampled without replacement. The first change $k = 1$ comes from yesterday's movements $j = t - 1$, second from the day before, and so on,

$$\Delta f^k = \left\{\Delta f_{1,j}, \Delta f_{2,j}, \dots, \Delta f_{1N,j}\right\} \tag{10}$$

Accordingly, a distribution of 113 profit and loss figures is achieved from which the 1%, 5% and 10% quantile (for VaR 99%, 95% and 90% confidence level, respectively) is drawn.

3.2.2 Historical bootstrap simulation

The historical bootstrap method improves the historical simulation by resampling the data with replacement many times in order to generate an empirical estimate of the entire sampling distribution of statistic. The model structure is same as in the historical simulation, but the historical changes in the exchange rate are randomly selected and then resampled 1000 times using the time scenario sampling technique. The mean, standard deviation and the VaR of 1%, 5% and 10% are calculated of each bootstrap sample and then plot the distribution of the 1000 statistics. The resampling mimics the random process of the system.

3.2.3 Variance-covariance method

In the variance-covariance method the historical data is used to specify a probability distribution that characterises the likely values of the exchange rates. The distribution obtained from the mean and standard deviation of the historical data is normally distributed. Therefore, the calculation of 1%, 5% and 10% VaR values are the left and right tails of the normal distribution.

3.2.4 Monte Carlo simulation

The equation for Monte Carlo simulation is as follows (Jorion, 2012):

$$\Delta f^k \approx g(\Delta f; \theta) \tag{11}$$

The factor movements are sampled from a predetermined distribution. In the Equation 11 g is the joint distribution and θ the parameters. k is the simulated scenario which can be run unlimited number of times, each case revaluing the entire portfolio. VaR is then computed from the distribution of changes in portfolio values. In this study we use 10.000 iterations for each VaR figure.

3.3 Backtesting

Next subchapters explain the methodology of backtesting. The different VaR models are evaluated with conditional and unconditional tests based on the information provided by the number and frequency of VaR exceptions. Backtesting should answer research problem 1 by providing insight whether the used models are suitable for measuring exchange rate VaR.

3.3.1 The statistical framework of backtesting

The most commonly used and straightforward method for measuring the quality of a given VaR model is to count the number of times when the actual portfolio losses exceed the mode's respective estimates: if the number of exceptions goes above the limit indicated by the used confidence level, the model could be too optimistic in the sense it might underestimate the actual risk. The model may also overestimate risk, if the number of exceptions is less than predicted by the confidence level. Both of the previously mentioned scenarios indicate that the quality and hence the estimates of the model might be questionable. The number of exceptions is a random variable. Thus, the decision whether the number of exceptions is acceptable or not should be based on study of appropriate statistical analyses.

Statistical tests provide valuable insight into VaR model quality estimation a systematic approach to decision making when assessing the validity of VaR model. In the test of unconditional coverage a VaR model's *failure rate* is used as a basis for statistical analyses when assessing the quality of the model. The failure rate is based on the "hit" sequence of historical losses that have exceeded the respective VaR estimates over a given observation period. According to Campbell (2005), when the daily profit and loss figure of the portfolio denoted as x_{t+1} the hit function can be presented as follows:

$$l_{t+1}(\alpha) = \begin{cases} 1, x_{t,t+1} \leq -VaR_t(\propto) \\ 0, x_{t,t+1} > -VaR_t(\propto) \end{cases} \tag{12}$$

The failure rate is defined as the number of violations divided by the total number of obsevations T. Hence, the hit ratio is an unbiased estimator of the probability of observing a violation so that

$$\frac{1}{T} l(\alpha) = \hat{\alpha} \tag{13}$$

where the number of exceptions is

$$l(\alpha) = \sum_{t=1}^{T} l_t(\alpha) \tag{14}$$

When the sample size increases so that $\hat{\alpha}$ converges to α, the following relation should hold for an accurate model:

$$\alpha = 1 - c \tag{15}$$

where c denotes the chosen confidence level. Thus, for example when using 99% confidence level, α should equal 1%. Hence, the backtesting process resembles a Bernoulli trial in which an action with two possible outcomes is repeated numerous times and in which each outcome is independent from the prior outcomes. Therefore, the number of violations follows binomial probability distribution as follows:

$$f\big(l(\alpha)\big) = \binom{T}{l(\alpha)} \alpha^{l(\alpha)} (1 - \alpha)^{T - l(\alpha)} \tag{16}$$

With sufficiently large sample size, the binomial distribution can be approximated with the normal distribution so that

$$z = \frac{\sqrt{T}(\hat{\alpha} - \alpha)}{\sqrt{\alpha(1-\alpha)}} \approx N(0,1) \tag{17}$$

The hypothesis test could then be conducted based on the known sample distribution z.

However, when conducting statistical analysis either accepting or rejecting a null hypothesis, there is always a tradeoff between type I and type II errors. When validating soundness of a given VaR model, the null hypothesis refers to the goodness of VaR model, type I error stands for a rejection of a sound model, and type II error, respectively, refers to not rejecting a deficient model. In the field of risk management, incurring type II errors can be very costly and therefore a high threshold should be applied when accepting validity of a VaR model.

3.4 Test of unconditional coverage

The tests of unconditional coverage determine whether the hit sequence generated by VaR model satisfies the unconditional property i.e. the aim is to study if the sequence contains a tolerable amount of exceptions or not. In this study the unconditional test is the proportion of failures introduced by Kupiec (1995).

3.4.1 Proportion of failures test

The idea behind the tests of unconditional coverage is to test whether the observed failure rate is consistent with the expected failure rate indicated by the confidence level. A commonly used test based solely on the failure rate and the confidence interval is a proportion of failures (POF) test proposed by Kupiec (1995). In the POF- test it is assumed that the number of violations follows the binomial distribution, and the null hypothesis for a correct model is

$$H_0: \alpha = \hat{\alpha} = \frac{l(\alpha)}{T} \tag{18}$$

Respectively, the null hypothesis tested against an alternative hypothesis H_A:

$$H_A: \alpha \neq \hat{\alpha} \tag{19}$$

Consequently, the test aims to provide an answer to the question whether the observed failure rate significantly differs from the expected rate and it can be performed as a likelihood-ratio test that expresses how many times more likely the observed data are under the null model compared to the alternative model. More specifically, the ratio to be investigated is the maximum probability of the observed result under the null hypothesis divided by the maximum probability of the observed result under the alternative hypothesis. The logarithm of computed ratio is assumed to be asymptotically chi-square (X^2) distributed with one degree of freedom and thus the obtained test statistic is compared to a critical value obtained from X^2 distribution. The smaller the ratio is, the higher the value of the test statistic becomes, which leads to rejection of the null hypothesis if the critical value is exceeded.

The POF statistic is as follows:

$$LR_{POF} = 2log\left(\frac{1-\hat{\alpha}^{T-l(\alpha)}\hat{\alpha}^{l(\alpha)}}{[1-(\alpha)]^{T-l(\alpha)}\alpha^{l(\alpha)}}\right) \tag{20}$$

While calculating the log-likelihood ratios is purely quantitative exercise, the chosen confidence level should balance the probability of committing type I and type II errors. For example, 95% test confidence level implies that the model will be rejected only if the evidence against is fairly strong, and with 99% confidence level the evidence against a given model should be very strong before it is rejected. The model implied in this thesis is with the 95% confidence level.

While the POF- test is relatively simple to implement, it suffers from two major shortcomings. First, the test is not statistically powerful with small

sample sizes. While the sample size decreases, the probability of rejecting an inaccurate model becomes harder (Table 3). Second, the test does not account for time variation in the observed exceptions. This implies that a supposedly accurate model that generates an acceptable amount of exceptions could still fail in capturing market volatility and correlations.

Table 3:

Non-rejection ranges for Proportion of Failures -test

The table shows non-rejection ranges for a VaR model with different chosen VaR confidence and test confidence levels with sample sizes of 250 and 1 000. Probability level α is the expected proportion of failures, or exceptions, under a given VaR confidence level.

		Non-rejection range for number of exceptions y			
	Test confidence level	95 %		99 %	
VaR Confidence Level	Probability Level p	T = 250	T = 1 000	T = 250	T = 1 000
99 %	1 %	0 ≤ y ≤ 6	5 ≤ y ≤ 16	0 ≤ y ≤ 7	4 ≤ y ≤ 19
95 %	5 %	7 ≤ y ≤ 19	38 ≤ y ≤ 64	5 ≤ y ≤ 22	34 ≤ y ≤ 68
90 %	10 %	17 ≤ y ≤ 34	82 ≤ 119	14 ≤ y ≤ 38	77 ≤ y ≤ 125

3.5 Test of conditional coverage

While the POF test use the ratio of observed exceptions as the only input, tests of unconditional coverage are designed to account also for the time variation of the exceptions. Christoffersen and Pelletier (2004) emphasize that clustering of VaR violations should receive more attention since successive large losses are more likely to lead to a bankruptcy. Thus, if the VaR violations are clustered in time and also across different banks, as Berkowitz and O'Brien (2002) find, it may be significant source of systematic risk. Therefore, it can be argued that the clustering of VaR exceptions could also be used as a basis for rejecting a given VaR model.

Probably the most widely known test of conditional coverage has been proposed by Christoffersen (1998), also referred to as *bunching*. He uses the same log-likelihood testing framework as Kupiec, but extends the test

to include also a separate statistic for independence of exceptions. In addition to the correct rate of coverage, his test examines whether the probability of an exception on any day depends on the outcome of the previous day. The testing procedure described below is explained, for example, in Jorion (2007), Campbell (2005), Dowd (2007) and in greater detail in Christoffersen (1998).

The test is carried out by first defining an indicator variable that gets a value of 1 if VaR is exceeded and value of 0 if VaR is not exceeded:

$$l_t = \begin{cases} 1 & if\ violation\ occurs \\ 0 & if\ no\ violation\ occurs \end{cases} \tag{21}$$

Then define n_{ij} as the number of days when condition j occurred assuming that condition i occurred on the previous day. To illustrate, the outcome can be displayed in a 2 x 2 contingency table:

	$l_{t-1} = 0$	$l_{t-1} = 0$	
$l_t = 0$	n_{00}	n_{10}	$n_{00} + n_{10}$
$l_t = 1$	n_{01}	n_{11}	$n_{01} + n_{11}$
	$n_{00} + n_{01}$	$n_{10} + n_{11}$	N

In addition let π_i represent the probability of observing an exception conditional on state i on the previous day:

$$\pi_0 = \frac{n_{01}}{n_{00} + n_{01}}, \tag{22}$$

$$\pi_1 = \frac{n_{11}}{n_{10} + n_{11}} \quad and \quad \pi = \frac{n_{01} + n_{11}}{n_{00} + n_{01} + n_{10} + n_{11}} \tag{23}$$

If the model is accurate, then an exception today should not depend on whether or not an exception occurred the previous day. In other words, under the null hypothesis the probabilities π_0 and π_1 should be equal. The relevant test statistic for independence of exceptions is a likelihood-ratio:

$$LR_{ind} = -2ln\left(\frac{(1-\pi)^{n_{00}+n_{10}}\pi^{n_{01}+n_{11}}}{(1-\pi_0)^{n_{00}}\pi_0{}^{n_{01}}(1-\pi_1)^{n_{10}}\pi_1{}^{n_{11}}}\right) \tag{24}$$

By combining this independence statistic with Kupiec's POF-test a joint test is obtained, which examines both properties of a good VaR model, the correct failure rate and independence of exceptions, i.e. conditional coverage:

$$LR_{cc} = LR_{POF} + LR_{ind} \tag{25}$$

LR_{cc} is also x^2 (chi-squared) distributed, but in this case with two degrees of freedom since there are two separate LR-statistics in the test. If the values of the LR_{cc}-statistic is lower than the critical value of x^2 distribution, the model passes the test. Higher values lead to rejection of the model.

Christoffersen's framework allows examining whether the reason for not passing the test is caused by inaccurate coverage, clustered exceptions or even both. This evaluation can be done simply by calculating each statistic, LR_{POF} and LR_{ind}, separately and using x^2distribution with one degree of freedom as the critical value for both statistics. Campbell (2005) reminds that in some cases it is possible that the model passes the joint test while still failing either the independence test or the coverage test. Therefore it is advisable to run the separate test even when joint test yields a positive result. In this study the tests are utilised separately.

3.6 VaR and swap point analysis

As VaR offers an investor the expected loss of the portfolio it is most often calculated as an amount of loss. However in the case of foreign exchange

rates the value of expected loss can be presented as basis points of the foreign exchange rate.

The empirical study regarding VaR and foreign exchange rate hedging with forward contracts is a comparative study between the VaR estimates received and the corresponding swap points. The VaR estimates offer the maximum and minimum level of the foreign exchange rate after one month with a chosen confidence level. The corresponding swap point is the cost of hedging at that time. The comparative analysis gives the investor insight if the hedging of the foreign exchange is cheaper or more expensive according to VaR.

This thesis focuses on the long position investor who faces losses if the exchange rate rises. The rise of exchange rate in this case refers to the strengthening of euro or weakening of the variable currency. Due to the performance of the data within the observation period the short position observation is left out of the scope.

4 RESULTS

This section presents the empirical findings of this study. The section starts with an overview of the VaR estimation results and then proceeds to more detailed assessment of the differences between the tested models and concludes with comparative analysis between VaR estimates and swap points.

4.1 VaR results

The first research problem was to investigate if the VaR is suitable for exchange rate risk management. The results are presented as foreign exchange rates instead of EUR value, for which VaR is commonly used.

Graphical illustrations of the results are presented in Figures 9-16. They have been divided by VaR method and portfolio type. A closer look at the figures show, that in with both EM and DM portfolios the Monte Carlo simulation's performance is the worst. The method seems to follow the spot rates in a visibly slower trend than historical simulation and historical bootstrap simulation methods. In addition to slower reaction to changes to the underlying spot rate, as Figures 12 and 16 shows, the difference between different confidence levels is almost non-existing. Variance-covariance method is performing visibly poor as well, but with a slight better forecasting power than MC simulation and there is visible difference between the different confidence levels. Both historical simulation and historical bootstrap simulation methods have visibly rather similar results and the spot rates seem to stay in the boundaries of the VaR figures even with the 90% confidence level. The worst periods with both portfolios and all four VaR methods are the years 2009-2010 when the both portfolios rate decreases, DM portfolio even more drastically due to financial crisis that had begun in 2008.

A more detailed assessment is presented in the next subsection when the models are systematically evaluated.

Figure 9:

Historical simulation estimates - EM portfolio

The estimates given by the Historical simulation method with 90%, 95% and 99% confidence levels are shown with the actual spot rate during the backtesting period.

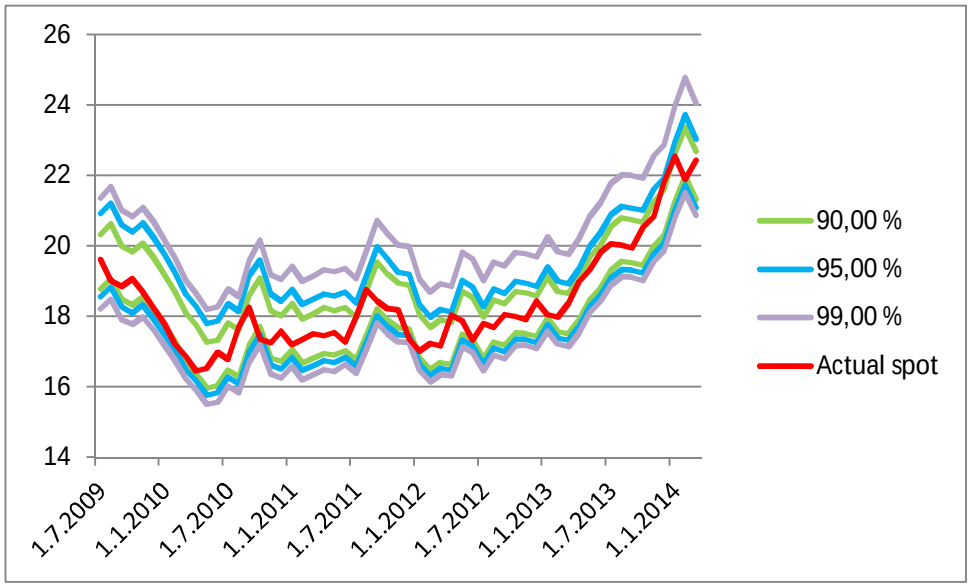


Figure 10:

Historical Bootstrap simulation estimates – EM portfolio

The estimates given by the Historical simulation method with 90%, 95% and 99% confidence levels are shown with the actual spot rate during the backtesting period.

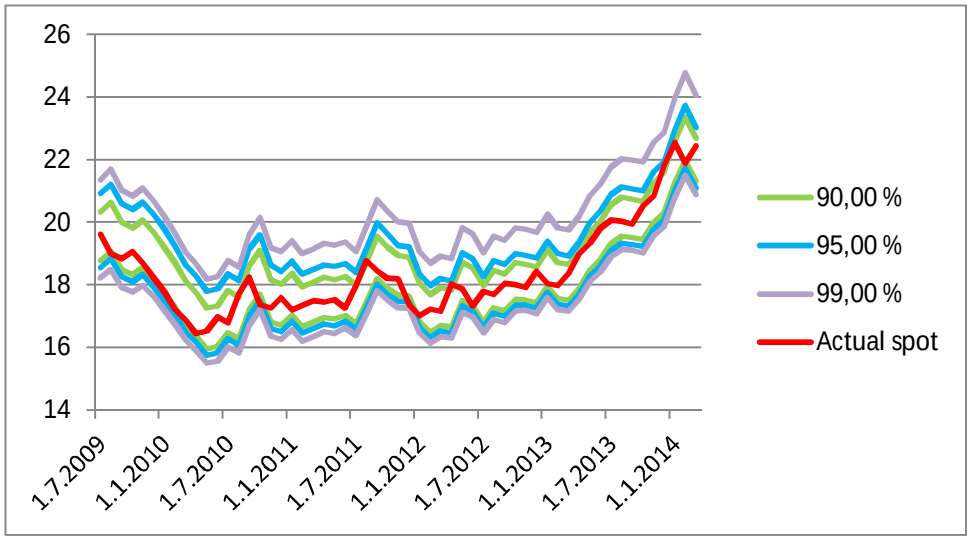


Figure 11:

Variance-covariance method estimates - EM portfolio

The estimates given by the Historical simulation method with 90%, 95% and 99% confidence levels are shown with the actual spot rate during the backtesting period.

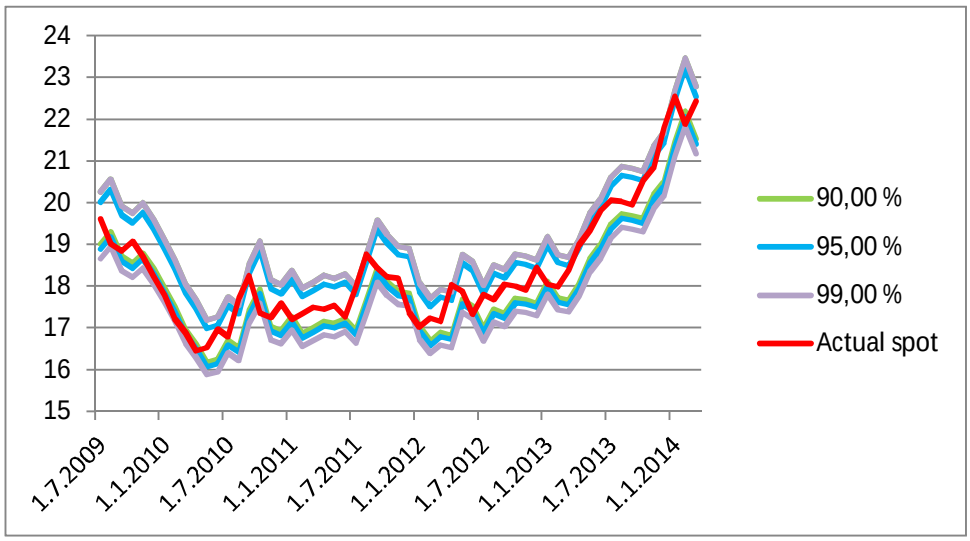


Figure 12:

Monte Carlo simulation estimates - EM portfolio

The estimates given by the Historical simulation method with 90%, 95% and 99% confidence levels are shown with the actual spot rate during the backtesting period.

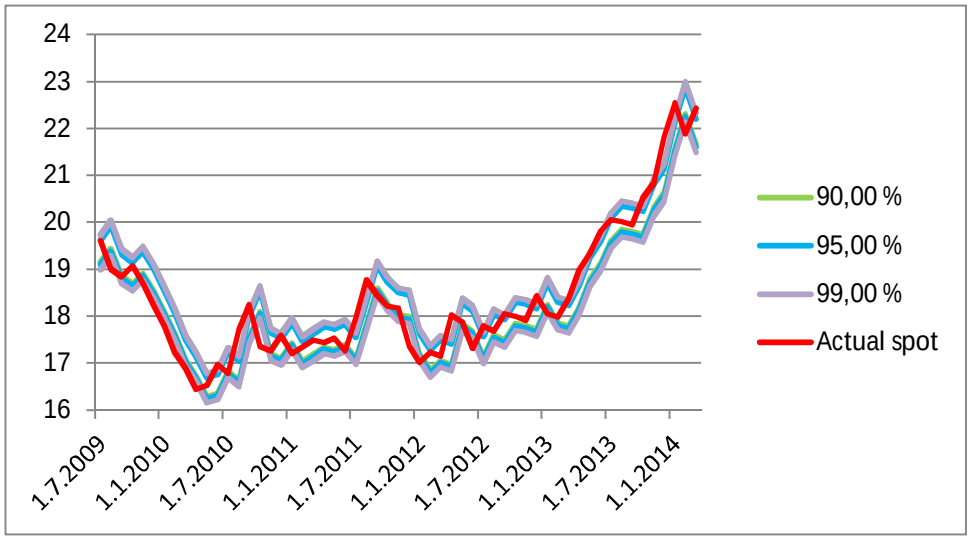


Figure 13:

Historical simulation estimates - DM portfolio

The estimates given by the Historical simulation method with 90%, 95% and 99% confidence levels are shown with the actual spot rate during the backtesting period.

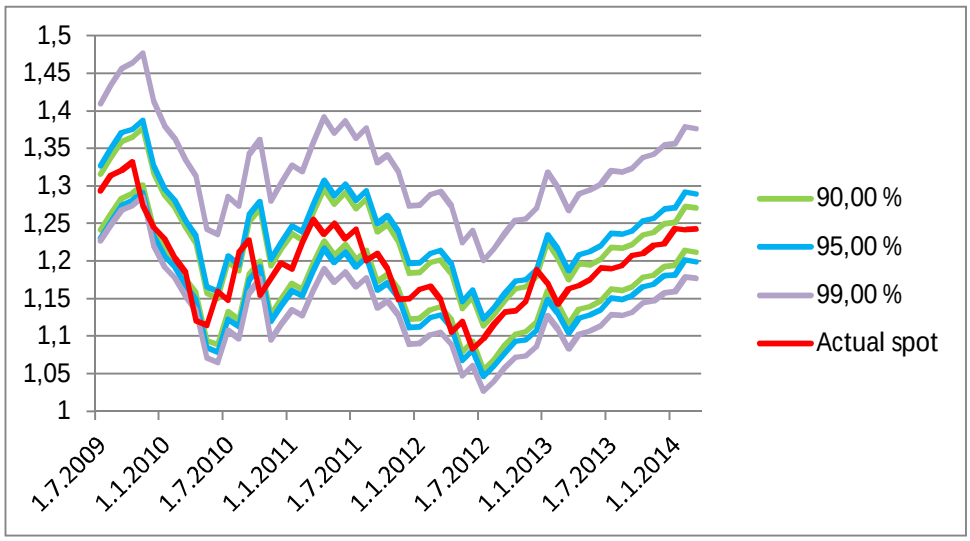


Figure 14:

Historical Bootstrap simulation estimates - DM portfolio

The estimates given by the Historical simulation method with 90%, 95% and 99% confidence levels are shown with the actual spot rate during the backtesting period.

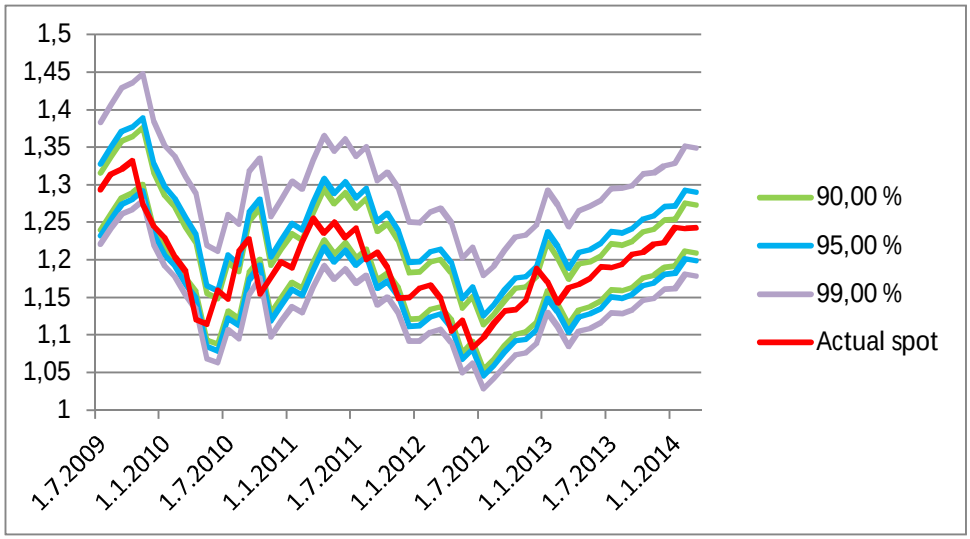


Figure 15:

Variance-covariance simulation estimates - DM portfolio

The estimates given by the Historical simulation method with 90%, 95% and 99% confidence levels are shown with the actual spot rate during the backtesting period.

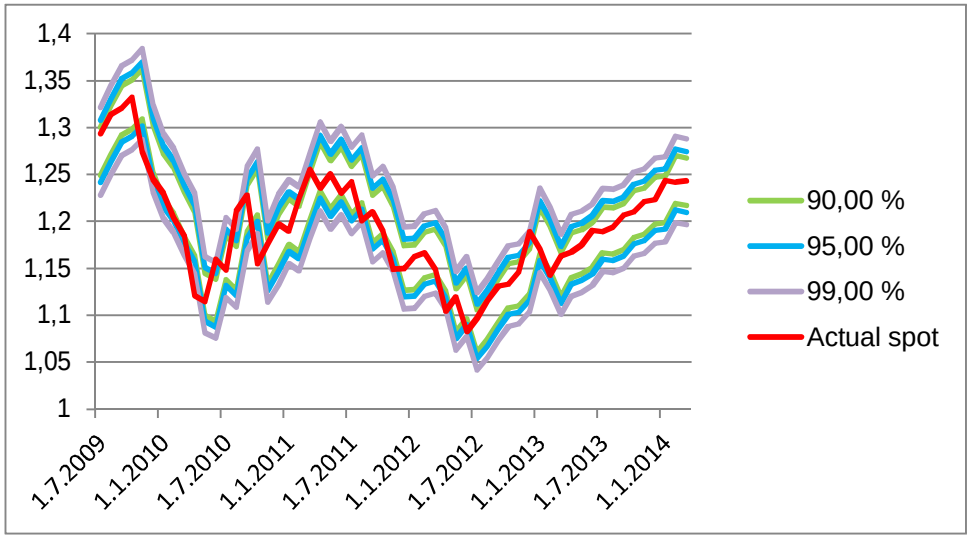
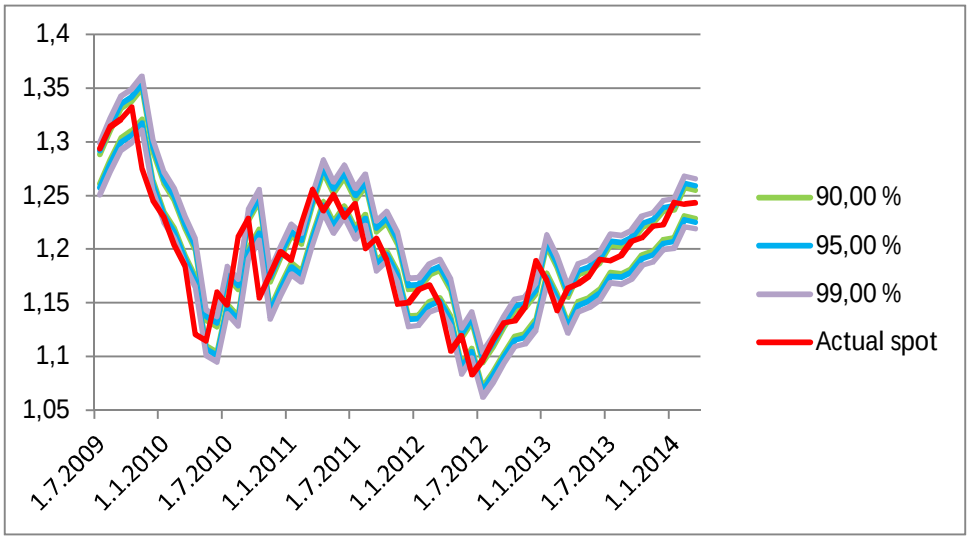


Figure 16:

Monte Carlo simulation estimates - DM portfolio

The estimates given by the Historical simulation method with 90%, 95% and 99% confidence levels are shown with the actual spot rate during the backtesting period.



4.2 VaR backtesting results

Binominal Distribution backtesting results are presented in Table 4. With a 5% confidence level all Monte Carlo simulation results in both portfolios and with all three VaR confidence levels are rejected. The graphs from the previous chapter reveal the Monte Carlo methods even with the 99% confidence level facing a great amount of exceptions and therefore the binominal distribution results are as expected. The Variance-covariance method with 99% confidence level is accepted, but rejected with the 95% and 90% confidence level. The level of the acceptance is not too high and the relevance of the method should be doubted.

The best results according to binominal distribution method were with HS and HBS. Both models were accepted with 99% and 95% confidence level VaR's in both portfolios. The level of acceptance with the 99% VaR was full 100% in the emerging market portfolio in both historical simulation and historical bootstrap simulation. The acceptance levels were slightly lower in the developed market portfolio with 99% VaR and significantly lower with 95% VaR.

However, as stated in the methodology chapter of backtesting, rejecting a sufficient model or not rejecting an insufficient model especially in risk management purposes can have disastrous outcomes. Therefore the models are backtested with several backtesting models.

Table 4:

Binominal distribution backtest statistics

The table presents the binominal distribution results. The confidence level of the binominal backtest is 5% and the result of the backtest should exceed 5% to be accepted. Accepted values are underlined.

Portfolio	**Emerging market**			**Developed market**		
VaR confidence level	**1 %**	**5 %**	**10 %**	**1 %**	**5 %**	**10 %**
Historical simulation	1,00	0,93	0,01	0,82	0,06	0,03
Historical bootstrap simulation	1,00	0,93	0,01	0,82	0,11	0,03
Variance-covariance	0,34	0,00	0,00	0,34	0,01	0,00
Monte Carlo simulation	0,00	0,00	0,00	0,00	0,00	0,00

The POF- test by Kupiec applied to the VaR estimates is presented in Table 5. The confidence level of the POF test is the 95th % -quantile of the Chi-Squared distribution with one degrees of freedom, which is approximately 3.84. The Variance-covariance method along with Monte Carlo simulation estimates possesses extremely high number of exceptions. With the exception of 99% confidence level in variance-covariance method they all fail the Kupiec's test. There is no valuable difference between the emerging and developed market results either as they both fail the test.

The historical method performs significantly better with failing the test only in the 90% confidence level VaR of the emerging market portfolio. The POF test results in Table 5 and and exceptions presented table 6 reveal that the limit of not being rejected is 10 exceptions. The 90% confidence level VaR in EM portfolio for both historical simulation and historical bootstrap simulation is barely above the limit with 11 exceptions. The results between historical simulation and historical bootstrap simulation methods in the emerging market portfolios are the same due to the same amount of exceptions occurring with all three VaR confidence levels.

In the developed market portfolio there is a slight difference between the both historical methods as there are less exceptions occurring in the historical bootstrap method and due to before mentioned the Kupiec results are better aswell. However, the difference is not significant and both methods are accepted with relatively good performance.

Table 5:

Kupiec's POF test statistics

The table presents the Kupiec's POF test results. The confidence level of the POF test is 95th % -quantile of the Chi-Squared distribution with one degrees of freedom, which is approximately 3.84. Accepted null hypotheses are underlined.

Portfolio	**Emerging market**			**Developed market**		
Confidence level	**1 %**	**5 %**	**10 %**	**1 %**	**5 %**	**10 %**
Historical simulation	0,00	3,27	4,23	1,57	1,79	2,90
Historical bootstrap simulation	0,00	3,27	4,23	1,57	0,92	2,90
Variance-covariance	0,02	16,00	18,49	0,02	4,23	11,43
Monte Carlo simulation	61,37	77,83	77,83	13,64	53,66	86,57

Table 6:

The number of exceptions

The table presents the number of VaR exceptions occurred and the expected number of VaR exceptions. Accepted values are underlined.

Portfolio	**Emerging market**			**Developed market**		
Confidence level	**1 %**	**5 %**	**10 %**	**1 %**	**5 %**	**10 %**
Expected amount of exceptions	1	5	11	1	5	11
Historical simulation	0	2	11	3	9	10
Historical bootstrap simulation	0	2	11	3	8	10
Variance-covariance	6	17	18	6	11	15
Monte Carlo simulation	31	35	35	16	29	37

The Christoffersen backtest is also exercised. The test offers additional insight into the goodness of the VaR models by analysing the model of suffering clustering effects. The results are presented in Table 7. The results are intriguing. Regardless of the poor performance of variance-covariance and Monte Carlo simulation methods in the Kupiec test, both of the methods pass the Christoffersen test, excluding 95% variance-covariance VaR in developed market. It seems that even though with the reasonably high amount of exceptions the model is able to capture changes in the portfolio and do not suffer from clustering. The performance of both of the historical methods at 99% and 95% confidence levels in both portfolios are similar as in the Kupiec test and both methods pass the test. However, both methods fail the test in the develop market with 90% confidence level and suffer from clustering the exceptions. The emerging market data in total passes the clustering test whereas the developed market data fails the test three times. One reason for the develop market to fail the test could be the less volatile nature of the data and sudden changes, even though seldom, would result as peaks that hit the VaR limit.

Table 7:

Christoffersen backtest statistics

The table presents the Christoffersen test results. The confidence level of the test is 95th % -quantile of the Chi-Squared distribution with one degrees of freedom, which is approximately 3.84. Accepted null hypotheses are underlined.

Portfolio	**Emerging market**			**Developed market**		
Confidence level	**1 %**	**5 %**	**10 %**	**1 %**	**5 %**	**10 %**
Historical simulation	0,00	0,15	1,11	0,34	3,47	4,38
Historical bootstrap simulation	0,00	0,15	1,11	0,34	2,68	4,38
Variance-covariance	1,44	0,01	0,02	1,44	5,43	2,08
Monte Carlo simulation	0,11	0,18	0,02	0,14	0,07	0,51

As stated before, the Christoffersen test results should not be analysed separately. Instead the results should be analysed jointly with Kupiec test results. The results of the Kupiec test combined with Christoffersen and along with other backtests exercised are presented in Table 8. While analysing all results combined there appears to be very insignificant difference between the two portfolios. The historical methods pass the test almost fluently in every backtest. Hence, the historical methods with 95% and 99% confidence levels can be considered as worthy in foreign exchange risk management. The Variance-covariance method performs equally well in both portfolios with 99% confidence level and is therefore included in the category of worthy risk management tool. The Monte Carlo simulation however fails the first three tests and cannot therefore be considered in risk management. The results are slightly better for EM currencies which due to the more volatile nature of the rates. As the backtesting methods used in this thesis use the exceptions to determine the goodness of VaR the sudden changes in usually more stable DM currencies result in exceptions more easily while the EM VaR estimates are expecting more risk due to the volatile nature.

Table 8:

Summary of backtest statistics

The table presents all backtesting results with Pass/Fail classification and the overall performance as a percentage.

Portfolio	**Emerging Markets**			**Developed Markets**		
Confidence level	**1 %**	**5 %**	**10 %**	**1 %**	**5 %**	**10 %**
Historical simulation	100 %	100 %	50 %	75 %	75 %	50 %
Expected exceptions	Pass	Pass	Pass	Fail	Fail	Pass
Binominal distribution	Pass	Pass	Fail	Pass	Pass	Fail
Kupiec's POF test	Pass	Pass	Fail	Pass	Pass	Pass
Christoffersen's test	Pass	Pass	Pass	Pass	Pass	Fail
Historical bootstrap simulation	100 %	100 %	50 %	75 %	75 %	50 %
Expected exceptions	Pass	Pass	Pass	Fail	Fail	Pass
Binominal distribution	Pass	Pass	Fail	Pass	Pass	Fail
Kupiec's POF test	Pass	Pass	Fail	Pass	Pass	Pass
Christoffersen's test	Pass	Pass	Pass	Pass	Pass	Fail
Variance-covariance	75 %	25 %	25 %	75 %	0 %	25 %
Expected exceptions	Fail	Fail	Fail	Fail	Fail	Fail
Binominal distribution	Pass	Fail	Fail	Pass	Fail	Fail
Kupiec's POF test	Pass	Fail	Fail	Pass	Fail	Fail
Christoffersen's test	Pass	Pass	Pass	Pass	Fail	Pass
Monte Carlo simulation	25 %	25 %	25 %	25 %	25 %	25 %
Expected exceptions	Fail	Fail	Fail	Fail	Fail	Fail
Binominal distribution	Fail	Fail	Fail	Fail	Fail	Fail
Kupiec's POF test	Fail	Fail	Fail	Fail	Fail	Fail
Christoffersen's test	Pass	Pass	Pass	Pass	Pass	Pass

4.3 Comparative analysis on VaR and swap points

The comparative analysis results are rather straight forward within both portfolios. The tables are presented in Appendix A divided into comparison within each VaR method and within each confidence level. With all four VaR methods in both portfolios the VaR estimates indicating the probable loss of a short position investor, presented in basis points, is remarkably higher than the swap points for the corresponding period. From this perspective it is recommendable for the investor to hedge the foreign exchange exposure rather than carry the risk of the open position.

The interest of the comparison idea rose from the drastically higher hedging costs related to emerging market currencies in comparison to

developed market currencies, but this study suggests that at least from VaR perspective the hedging cost is not overestimated. Even with 90% confidence level the risk estimates are at such a high level that the basis points are almost marginal. However the fundamentals of this analysis are seen from the tables in Appendix B as the hedging cost and the VaR estimates are approximately from 100 to 200 times bigger within emerging market.

4.4 Empirical findings

Based on the backtesting results in Section 4.2 the recommended tools for an investor with foreign exchange risk are the historical, historical bootstrap and variance-covariance methods with 99% confidence level. In addition, the historical and historical bootstrap methods are recommended with a 95% confidence level. The emphasis is on the emerging market portfolio as the relatively more volatile portfolio seems to be more reliably estimated with these VaR methods. However, there is no significant difference between the two different portfolios and the tool can be recommended at least as an additional tool to other foreign exchange risk management tools available.

It is up to the investor to decide the confidence level used in the VaR estimation. If the investor is risk averse then a 99% confidence level seems to be a reasonable choice. However the 99% confidence level might jeopardise the possible profits by emphasizing the risk of the portfolio. However the 90% confidence on the contrary has the greater chance of underestimating the risk and unexpected losses are likely to occur.

5 CONCLUSIONS

The main research objective was to study the suitability of four different VaR models in generating foreign exchange VaR. The VaR models studied were: historical simulation, historical bootstrap simulation, variance-covariance method and Monte Carlo simulation. The performance of the VaR estimates was further studied between emerging and developed market currencies. The second objective was to compare the VaR estimates established with these different models with foreign exchange forward swap points to have insight if VaR could be used as a risk management tool when making foreign exchange hedging decisions. The implementation of the VaR models is based on teaching studies by Cheung and Powell (2012, 2013).

The backtesting results revealed that basic models: historical simulation and historical bootstrap simulation performed better than variance-covariance and Monte Carlo models. In particular it was interesting that emerging market portfolio performed better than developed market portfolio. This was explained by the more volatile nature of the EM currencies and hence VaR exceptions were avoided. However, the graphical illustrations revealed that all models at least in visible sense follow the actual foreign exchange rate and could be used as an indicative or additional risk management tool along with some more advanced tools, which is in line with Shapiro (2008).

The second objective was to study the swap point data in comparison to VaR estimates. The results were unexpected. It was expected that VaR estimates at a lower confidence level within the emerging market portfolio would have indicated that hedging with a forward contract is more expensive than the expected risk related. However, with all VaR models and confidence levels and regardless of the portfolio (EM or DM) hedging with a forward contract is substantially affordable offering a 100% hedge.

The expectations in the beginning of the thesis were in favour of remarkable differences between emerging and developed market

currencies however with the models, data horizon and currencies used there were no substantial differences between the two. The volatile foreign exchange rates in emerging market appeared not to be as volatile as expected within the observation period. This study revealed that underlining the exchange rate risk of one market over the other does not actually hold in reality. The risks are valid in both markets and the nature of foreign exchange risk enables anything to happen.

For future research it would be interesting to implement more advanced VaR methods which are already widely covered in academic literature. In addition to more advanced methods, a longer data horizon would enable a longer backtesting period which would offer more comprehensive analysis. Different data frequencies could also be evaluated as a comparative study. Overall Value at Risk offers various interesting future research options within the field of foreign exchange risk management.

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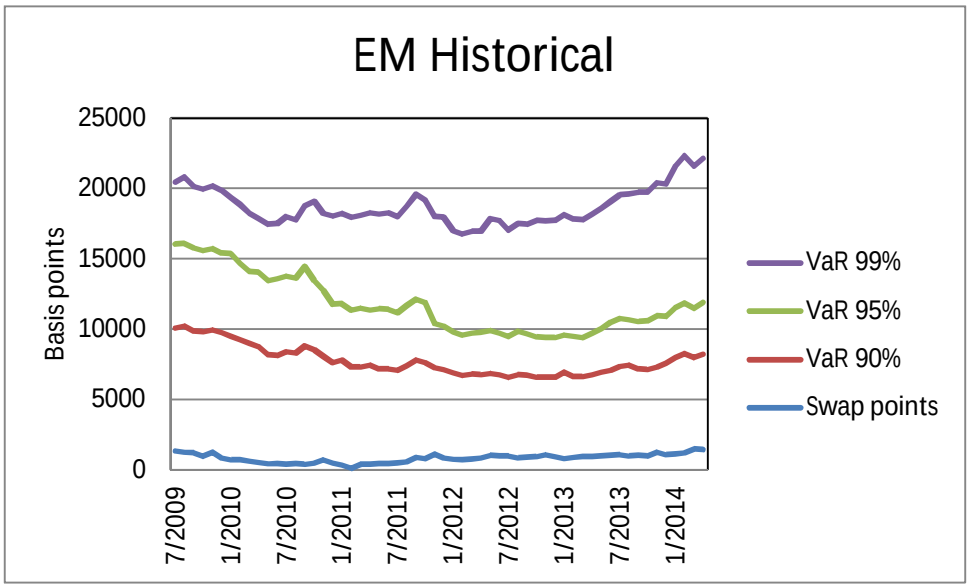
APPENDIX

This appendix provides a graphic illustration of the VaR estimate and swap point analysis. Tables 1-4 present the graphs of the swap points and VaR estimates for EM portfolio divided by VaR method. Tables 5-8 present the graphs of the swap points and VaR estimates for DM portfolio divided by VaR method. Tables 9-11 present the comparison by confidence level among EM portfolio and Tables 12-14 present the comparison by confidence level among DM portfolio.

Table 1



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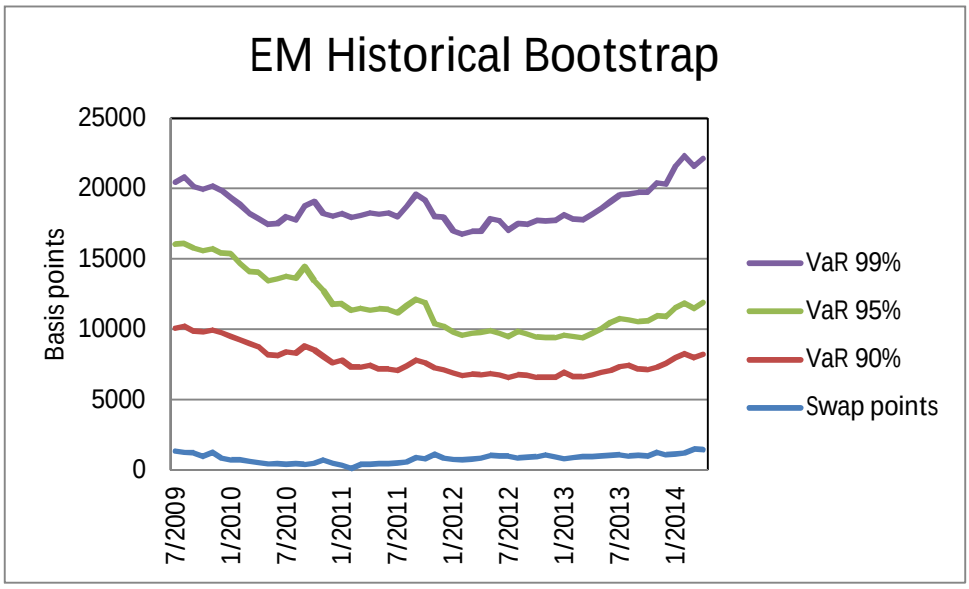

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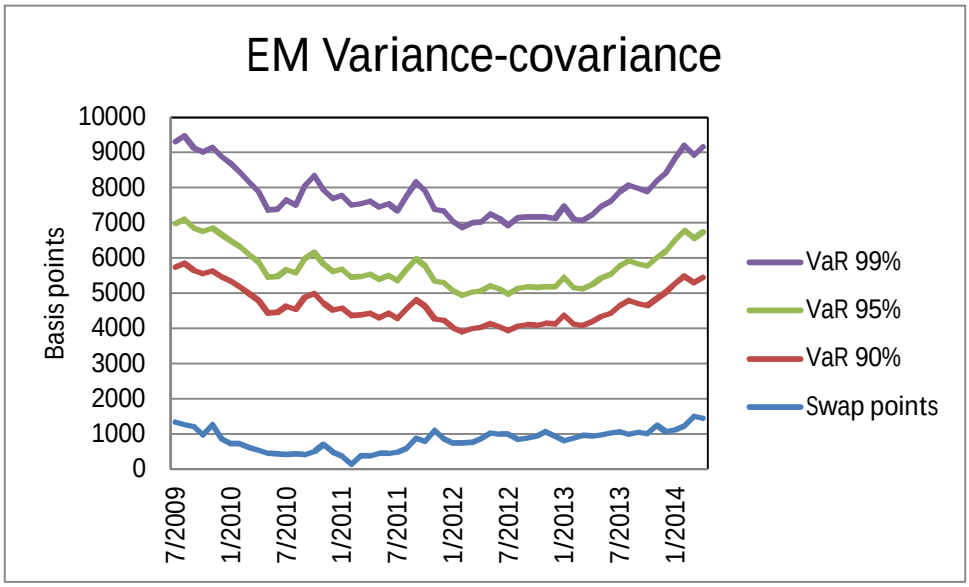

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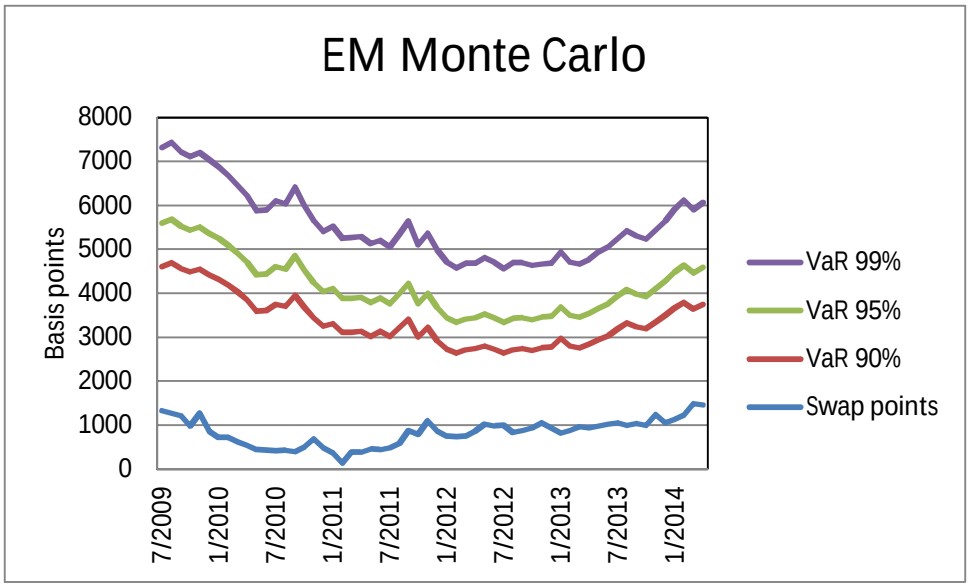

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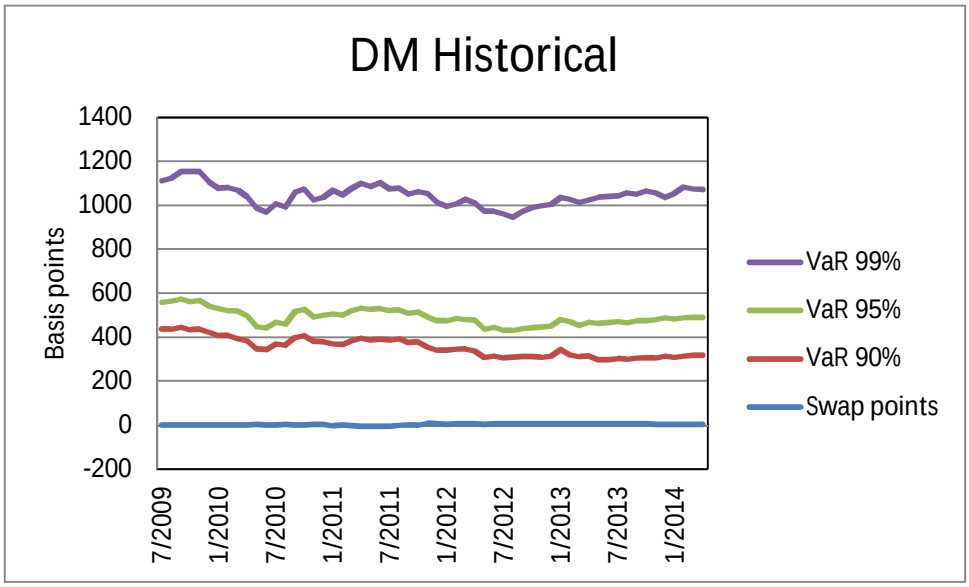

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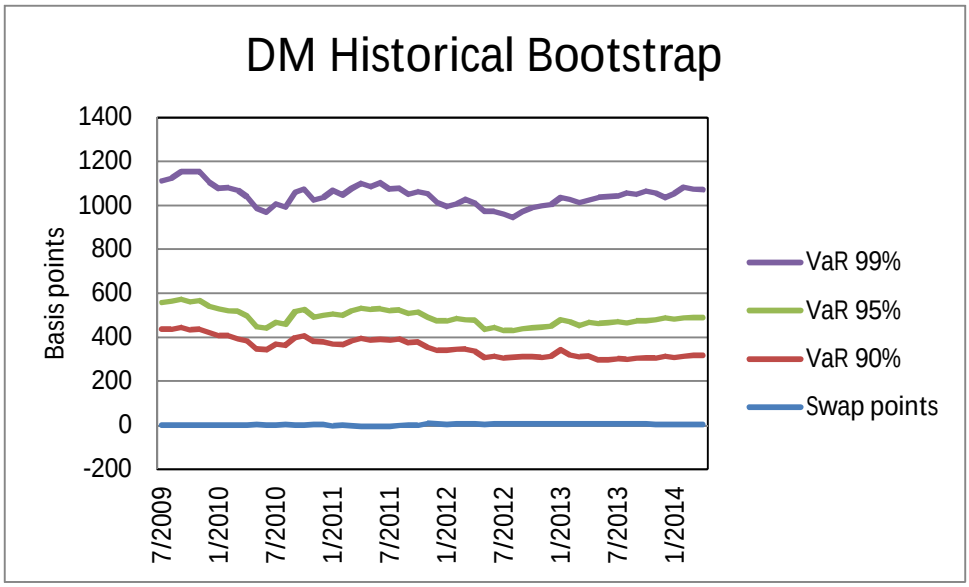

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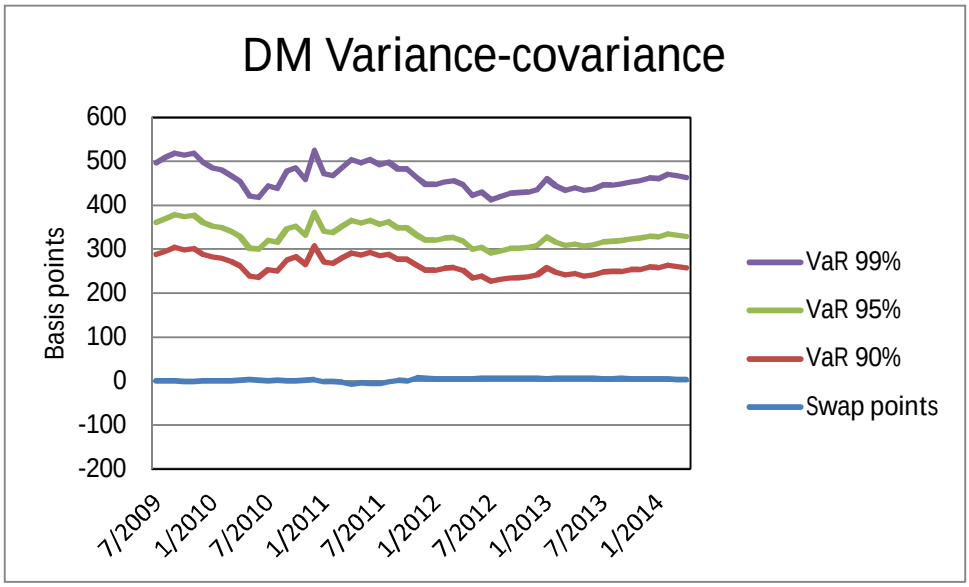

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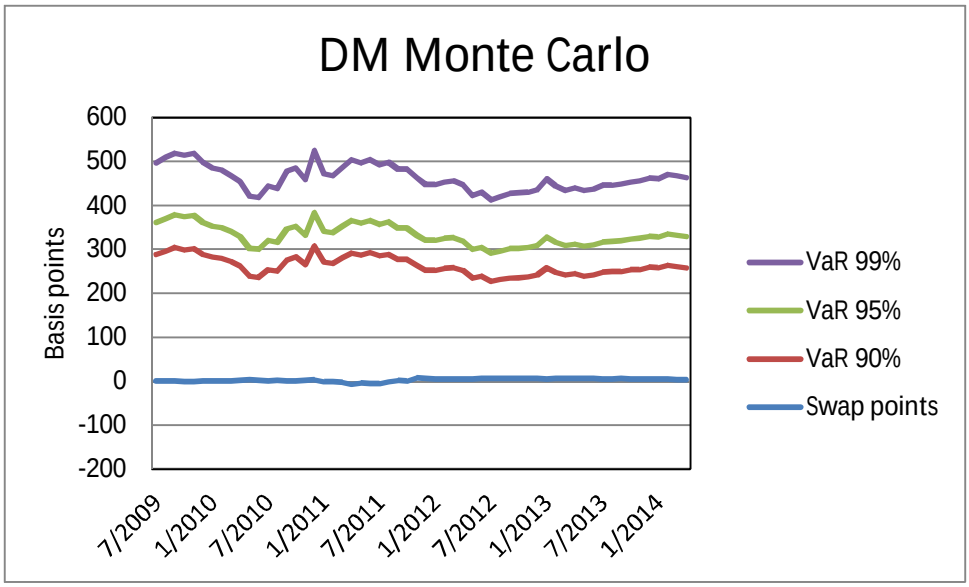

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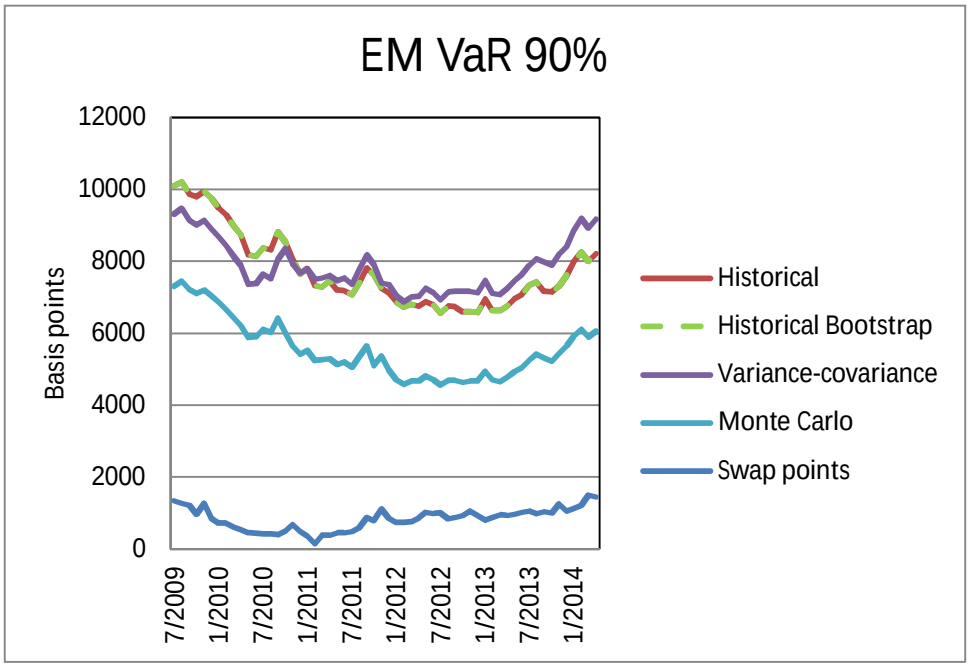

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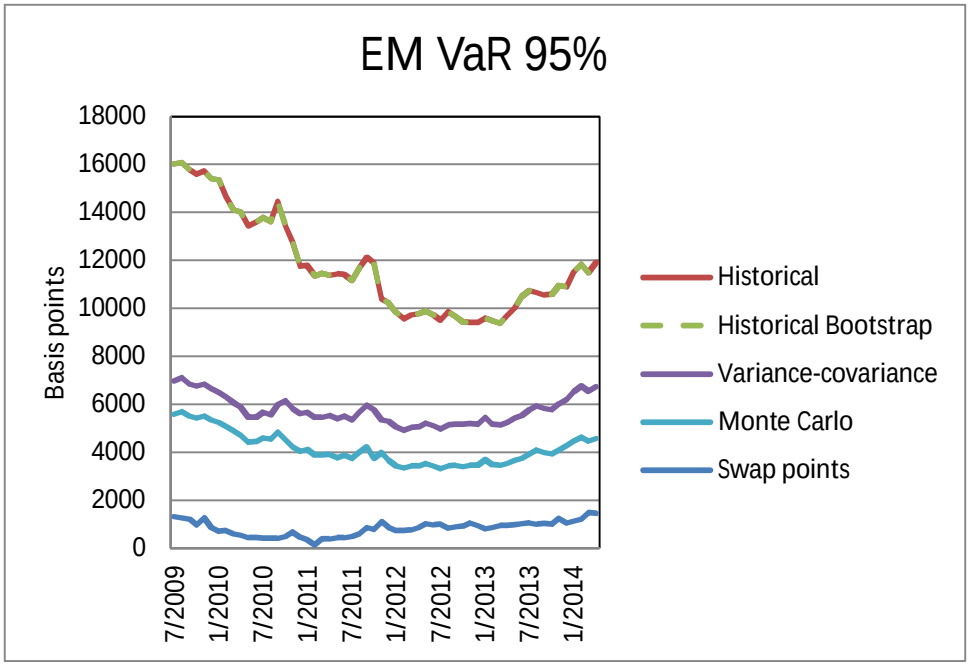

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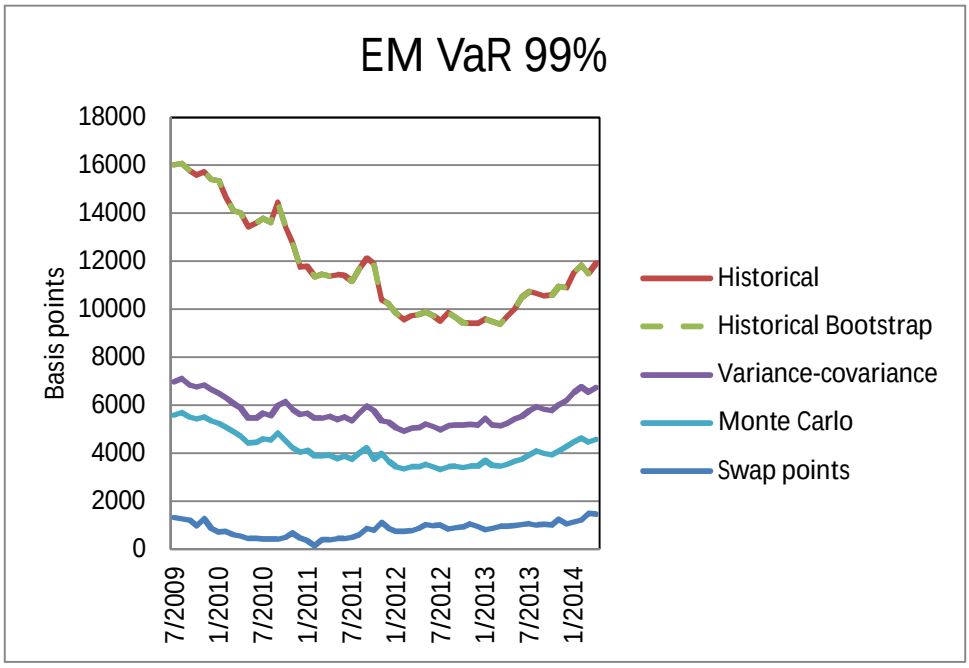

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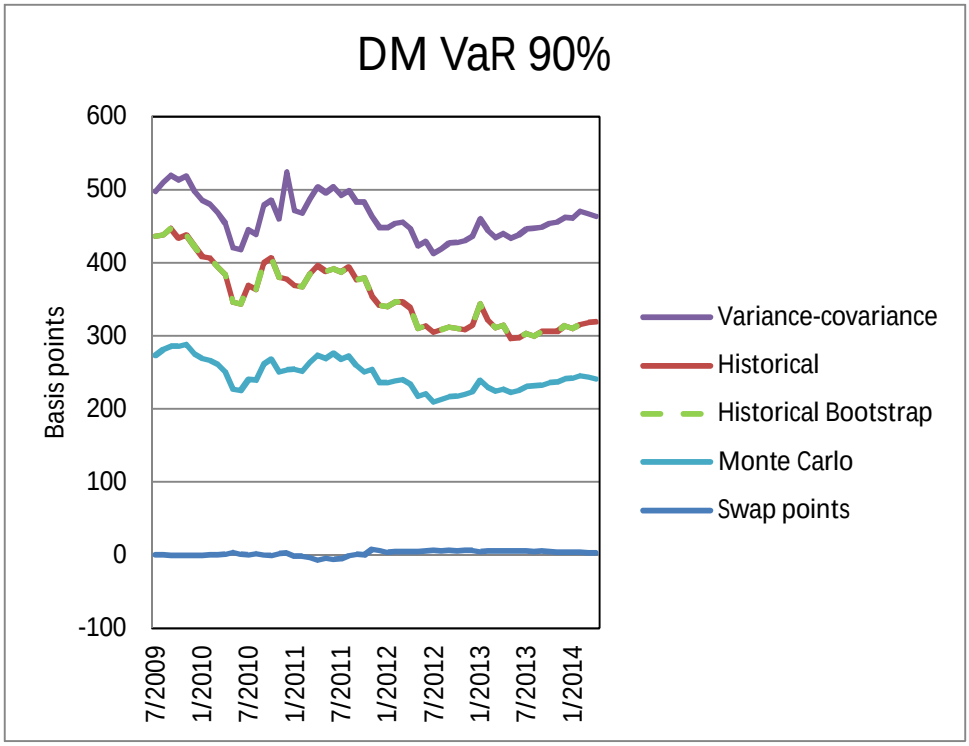

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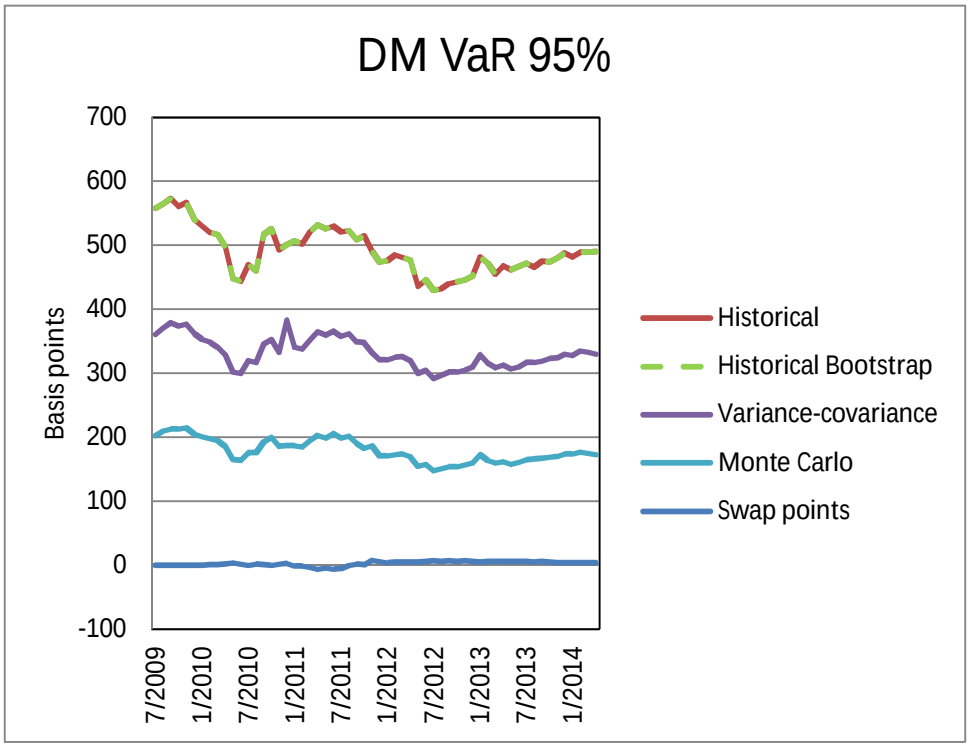

Table 14