

The accuracy of Value-at-Risk estimates - The effect of the amount of historical data used

Bachelor Thesis in Finance

Stockholm School of Economics, Department of Finance

Supervisor: Michael Halling

Johan Engvall
22227@student.hhs.se

May 30, 2013

Abstract

Value-at-Risk(VaR) has become the leading risk measurement technique in finance. It's important both from a regulatory and internal perspective that the calculated VaR measures are accurate and therefore they should be backtested with appropriate methods. This thesis reviews the effect that the number of historical returns used to calculate VaR measures have on the accuracy on the measurements. Two methods are considered, the parametric normal method and the historical simulation method. The accuracy is reviewed by backtesting, primarily by the Kupiec test.

The thesis shows both that it is important to choose an appropriate time window and to adapt the time window used to the method and asset class used as the effect is very different between these.

Keywords : Value-at-Risk, backtesting

Contents

1	Introduction	1
1.1	Background of VaR	1
1.2	Problem discussion	1
2	Theoretical framework	3
2.1	Risk measures	3
2.2	Definition of VaR	3
2.3	Empirical methods	4
2.4	Backtesting	5
3	Data	7
3.1	Equity indices	7
3.2	Individual stocks	7
4	Method	8
4.1	Backtesting with the Kupiec test	8
4.2	Analyzing the clustering	9
5	Results	10
5.1	Descriptive statistics	10
5.2	Indices	12
5.3	Stocks	14
5.4	Clustering	16
6	Conclusions	17
7	Further research	18
	References	19
A	Data	20
A.1	Indices	20
A.2	Stocks	21
B	Calculations of abnormal probabilities	22
B.1	Indices	22
B.2	Stocks	24

1 Introduction

1.1 Background of VaR

During the last decades there have been a lot of focus on financial risk management. The measure that have become leading is the Value-at-Risk(VaR). Holton (2002) writes that measuring risk in a similar way to the modern VaR dates back to 1922. Holton also claims that it was during the 1990's that the VaR-measure was universally adopted as a measure of risk. Since then it has become the core for the regulation of financial firms in many countries for example in Basel III(2010).

Despite it's widespread use the method is also frequently criticized for not accurately measuring risks. Measurement of VaR relies on forecasting future asset prices using historical asset prices. Also every model used to estimate VaR makes simplifications and assumptions about the future asset prices. Therefore it is important to evaluate the accuracy of the models used, this is done by comparing the estimation of the model to the actual outcome. This will be done in the thesis. Another possible problem with VaR is that people sometimes regard it as a worst possible outcome, but for many commonly used VaR measures a loss higher than the VaR is expected multiple times per year.

While there is some criticism of VaR there are no real competing quantitative financial risk measure. There exists others, for example Conditional Value-at-Risk, but the use is not widespread. Even though it is liked by some academics because of the nice theoretical properties it have. That VaR is so widely used makes it very interesting to study different aspects of it. What makes it even more interesting is that it have indisputable problems but that it's anyway almost universally used.

1.2 Problem discussion

While there is much research comparing and testing different ways to calculate VaR. There is not much research focusing on the other important aspect of the VaR calculation, how much data should be used to calculate the VaR for different assets and different methods. If too much data is used then the estimations of the future asset prices is based on too much old and irrelevant information on the other hand using too little data will cause unreliable estimations. This thesis will focus on this issue. The thesis will specifically study the following questions:

- How is the accuracy of the VaR calculations affected by how many days that is used to calculate it?

and also:

- Is this different for different confidence levels of the VaR and different methods for calculating the VaR?

2 Theoretical framework

2.1 Risk measures

To understand what Value-at-Risk is and why it's important we must first think about what is risk and more importantly how do we quantify it. Artzner et al. (1999) describes the three properties a risk measure should have, a risk measure for the asset described by the random variable X denoted $\rho(X)$ should have the following three properties:

Normalization:

$$\rho(0) = 0$$

Translativity:

$$\forall a \in \mathbb{R} \quad \rho(X + a) = \rho(X) - a$$

Monotonicity:

$$\text{If } X_1 \leq X_2 \text{ then } \rho(X_1) \geq \rho(X_2)$$

A coherent risk measure also have the following two properties for portfolios X_1 and X_2

Subadditivity:

$$\rho(X_1 + X_2) \leq \rho(X_1) + \rho(X_2)$$

Positive homogeneity:

$$\forall a \in \mathbb{R} \quad \rho(aX_1) = a\rho(X_1)$$

That a risk measure is coherent is not necessary for it's ability to be used quantitatively to measure risk but it gives some important results, mainly that the effect of diversification cannot be negative as it can for a risk measure that is not coherent.

2.2 Definition of VaR

The VaR is given by a confidence level and a period. A n-day $(1 - p)\%$ VaR is given by the probability:

$$\underset{VaR}{\text{minimize}} \quad P(L > VaR) \leq p$$

Where L is the loss after n days. The VaR satisfies the three properties of a risk measure but it does not satisfy the property of subadditivity and it's

therefore not a coherent risk measure. This means that diversification can affect the VaR negatively. From an academic point of view this is a large drawback of the VaR, but regardless it's widely used in practice. A coherent risk measure that is sometimes used is the Conditional Value-at-Risk, but the VaR is much more common.

2.3 Empirical methods

To calculate the VaR historical returns of the asset is used. Either a parametric or non-parametric method can be used. For a parametric method the asset prices is assumed to follow a probability distribution which is then modeled, for example a normal distribution. With a non-parametric method nothing is assumed about the distribution of the asset prices instead the VaR is calculated directly from the historical returns. In this thesis I will use one of the simplest methods from each, the non-parametric historical simulation and the parametric normal method.

Historical simulation approach

To calculate the VaR using the historical simulation approach the sample of the losses are first sorted:

$$L_1 \geq L_2 \geq \dots \geq L_n$$

The VaR is then the empirical quantile of the sorted losses:

$$\widehat{VaR} = L_{[n*p]+1}$$

Where $[n * p]$ is the integer part of $n * p$. The strength of this approach is that nothing is assumed about the distribution of the returns.

Parametric normal approach

For the parametric normal approach a maximum likelihood estimation is used to approximate a normal distribution to the sample of historical losses the VaR is then:

$$\widehat{VaR} = 1 - \exp(\hat{\mu} + \hat{\sigma}\Phi^{-1}(p))$$

Where $\hat{\mu}$ and $\hat{\sigma}$ are the maximum likelihood estimations of the mean and volatility of the log-returns and Φ^{-1} is the inverse of the cumulative distribution function of the normal distribution. The main weakness with this method is that it makes strong assumptions about the distributions of the log-returns, for example that the distribution is symmetric. Also the tails are often not fat enough.

2.4 Backtesting

To evaluate how accurate the VaR calculations is for a given method the method have to be backtested. There are several approaches to do that, one approach is to define a time series of VaR-breaks as:

$$I_t = \begin{cases} 0 & \text{if } L_t \leq VaR_t, \\ 1 & \text{if } L_t > VaR_t, \end{cases} \quad (1)$$

Christoffersen (1998) then defines two properties that the sequence (1) must satisfy:

1. Unconditional Coverage: That the probability to receive a loss larger than the $(1-p)\%$ VaR should be exactly $p\%$.
2. Independence: That the probability to receive a VaR-break is completely independent of historical VaR-breaks. If this property is not fulfilled the VaR-breaks are said to be clustered.

This is equivalent to that the random variables I_t should be independent and identically distributed(iid) and come from the following distribution:

$$I_t \in Be(p)$$

To test the first property the the sum of VaR-breaks $Y = \sum_{t=1}^N I_t$ can be formed, the sum will in turn come from the following distribution:

$$Y \in Bin(N, p)$$

A confidence interval for the numbers of outcomes of the known distribution is the created and then compared to the actual number of VaR-breaks in a time series. This test was first proposed by Kupiec (1995) and is therefore called the Kupiec test. The null hypothesis of the test is:

$$H_0 : Y \in Bin(N, p) \quad \text{against} \quad H_1 : Y \notin Bin(N, p) \quad (2)$$

However this test does not test that the variables are iid, an early approach for testing this property using Markov Chains is given by Christoffersen (1998). Another way to backtest VaR proposed by Christoffersen and Pelletier (2004) is to instead form a time series of the number of days between two consecutive breaks which should be $\frac{1}{p}$ for a $(1-p)\%$ VaR. In this thesis only the test by Kupiec will be used. The hypothesis (2) is the main hypothesis used in the thesis and most of the results will be drawn from that.. However to check if there seem to be any clustering some calculations with inspiration

from Christoffersen (1998) will be used.

The idea behind the Markov chain approach is that the random process (1) should be a Markov chain with known transition probabilities. This gives as a result that the conditional probabilities should be the same regardless if the previous was a VaR-break or not. With the definition given in (1) this gives for a $(1 - p)\%$ VaR:

$$\begin{aligned} P(I_t = 1|I_{t-1} = 1) &= P(I_t = 1|I_{t-1} = 0) = p \\ P(I_t = 0|I_{t-1} = 1) &= P(I_t = 0|I_{t-1} = 0) = 1 - p \end{aligned} \tag{3}$$

Where the probability $P(I_t = 1|I_{t-1} = 1)$ is the most interesting, because this is the probability that will most likely deviate much from the correct probability incase that the model is not correct. This is the probability that after a VaR break there will be another the following day. This test also have the weakness that it only test the transition in one step, a complete test should incorporate the whole history. But this test will capture most of the VaR-models that have a problem with clustering. In this thesis i will use a abnormally high probability of two consecutive hits as a sign of VaR break clustering.

3 Data

3.1 Equity indices

To evaluate the VaR as a risk measure for equity indices, the log-returns of major national equity indices is used. All indices used are given in the appendix in section A.1. The indices that is used is all that is described as major by Yahoo finance for which there were more than 15 years of market data, the data is also collected from there. An exception is made for US equity indices where only the most commonly followed indices are used. For example the Russell 2000 is used instead of the S&P 600, because the results would probably be quite similar for those.

The data is all trading days 1982-2012 except where the available history was shorter, then it's all available history. Both because the stock exchanges are open different days in different countries and because I didn't get closing prices all the way until 1982 for all indices the number of log-returns are different for most of the indices.

3.2 Individual stocks

To evaluate VaR as a risk measure for stocks, the log-returns of the current components of Dow Jones Industrial Average(DJIA). The stocks and their tickers are shown in the appendix in section A.2. The reason for choosing these stocks is that I wanted stocks with a long history as listed companies. One problem with choosing the stocks in this way is that there is a form of survivorship bias, but as the aim is just to compare different methods this is not a major problem but it does however somewhat effect the conclusions that is possible to draw. The stock data is downloaded from the CRSP database and the log-returns are calculated corrected for dividends and splits. The price data is all trading days 1982-2012, except for stocks which have a shorter history in that case it is all their available history.

4 Method

4.1 Backtesting with the Kupiec test

To create the time series in equation 1 in section 2.4 the time series of log-returns described in section 3 is used. Then for a given window size n the empirical VaRs described in section 2.3 are calculated for a time t by using the the log-returns:

$$R_{t-n}, R_{t-n+1}, \dots, R_{t-1}$$

For each time series this is done for all t larger than the window size n . With N log-returns this gives $N - n$ comparisons for the given window size n , this is then done for different window sizes. For each window size and asset the hypothesis 2 in section 2.4 is tested, the hypothesis is tested with 95% and 99% significance.

The time windows that are tested between 100 and 1000 days in steps of 100 days. The reason for this is that a commonly used number of days is 500 which makes this a large enough window around it. It would of course be better to use a shorter time step, but due to time limits and lack of enough computational power this is not possible.

The VaR levels that will be tested are the most commonly used which are 95% and 99%. Another common level is 99.9%, that is not considered in this thesis. The reason for this is that the methods used are not advanced enough to give a good enough estimation of that level. For the historical simulation method at least 1000 trading days have to be used, more to give a reasonable estimate. For the normal approximation the fit of the tail will not be good enough and the problem with the tails not being fat enough will be very big.

The hypothesis will be tested with significance 95% and 99% because they give a lot of interesting information on the validity of the VaR models. If the hypothesis 2 can be rejected on a 95% it is a strong indication that the model is not correct and 99% gives a very strong indication that the model is not correct. To test on a higher significance not give that much information for example 99.9% would not give that much information as a rejection on with a 99% significance is such a strong rejection.

The results of these tests will be plotted in figures 1-4 in section 5. For each of the different asset classes the number of assets for which the hypothesis is rejected is plotted. The plots will be done separately for both the two VaR levels and show the number of rejections of both significances of the

hypothesis testing in the same plot. From these plots the main conclusions regarding the unconditional coverage will be drawn.

4.2 Analyzing the clustering

To see if there is any tendencies for clustering the conditional probability given in table (3) is calculated for all time steps, assets, methods and probability levels. From this the abnormal probability to receive a VaR-break the day after another VaR break will be calculated by subtracting the target probability. As no formal theoretical framework is used to analyze the abnormal probabilities, no conclusions can be drawn from their absolute size. However it is possible to compare between both different time windows for the same asset, method and VaR level and between different methods for the same asset, time window and VaR level.

5 Results

5.1 Descriptive statistics

Indices

The descriptive statistics for the log-returns of the indices are shown in Table 1.

Table 1: Descriptive statistics for the log-returns of the equity indices

Ticker	Observations	Mean(%)	Standard Deviation(%)	Skewness	Kurtosis
AEX	6327	0.03196	1.544	-1.249	46.65
AORD	7188	0.02613	1.01	-3.833	100.2
ATX	4980	0.02316	1.389	-0.3854	10.53
BFX	5495	0.01315	1.18	-0.003208	9.747
BVSP	4867	0.1607	2.442	0.4796	12.56
DJIA	6596	0.04109	1.052	-2.345	61.58
FCHI	5781	0.01188	1.433	-0.02321	7.446
FTSE	7261	0.02303	1.125	-0.3756	11.29
GDAT	6464	0.01743	2.13	-0.3009	291.4
GDAXI	5593	0.02973	1.465	-0.09732	7.629
GSPC	7818	0.03137	1.162	-1.202	29.96
GSPTSE	7142	0.02318	1.006	-0.9219	17.4
HSI	6463	0.03369	1.763	-2.383	59.0
IXIC	7818	0.03501	1.395	-0.2365	11.27
KLSE	4706	0.01063	1.545	0.4016	54.49
MERV	4001	0.0394	2.183	-0.2802	8.49
MXV	5285	0.06486	1.589	0.0191	8.633
N225	7129	0.0006464	1.453	-0.2772	11.5
RUT	6380	0.02531	1.348	-0.5914	11.77
SSEC	5675	0.05502	2.413	5.568	155.4
SSMI	5589	0.0285	1.18	-0.1189	8.959
STI	6263	0.02149	1.281	-0.1298	11.51

The first thing we see is that except for N225 the mean returns is of the same order. The standard deviation is also quite similar across the different indices. We further see that most have a negative skewness but for most it's not that big. The kurtosis is positive and relatively big for all assets meaning that the distributions will have a high peak. The high kurtosis will make the fit to the normal distribution bad especially far out in the tails.

Stocks

The descriptive statistics for the log-returns of the stocks are shown in table 2.

Table 2: Descriptive statistics for the log-returns of the DJIA stocks

Ticker	Observations	Mean(%)	Standard Deviation(%)	Skewness	Kurtosis
AA	7831	0.02238	2.332	-0.2681	12.66
AXP	7818	0.05023	2.33	-0.2044	13.51
BA	7818	0.0485	1.938	-0.2088	8.922
BAC	7818	0.03672	2.597	-0.3685	30.8
CAT	7818	0.04198	2.065	-0.3389	9.748
CSCO	5763	0.09676	2.847	-0.05119	8.241
CVX	7818	0.0466	1.662	-0.1287	11.65
DD	7818	0.03984	1.768	-0.2813	8.878
DIS	7818	0.05289	2.019	-0.8476	22.36
GE	7818	0.04799	1.791	-0.123	11.77
HD	7818	0.09348	2.341	-0.8016	18.7
HPQ	7818	0.03196	2.451	-0.127	11.53
IBM	7818	0.04182	1.752	-0.3764	16.1
INTC	7818	0.06024	2.67	-0.3073	8.709
JNJ	7818	0.05257	1.516	-0.4162	12.38
JPM	7818	0.03935	2.433	-0.1033	16.79
KO	7818	0.06037	1.576	-0.4926	22.75
MCD	7818	0.05726	1.619	-0.2214	9.002
MMM	7818	0.04629	1.529	-0.9938	26.22
MRK	7818	0.04959	1.727	-0.9747	21.98
MSFT	6759	0.08715	2.279	-0.6024	17.5
PFE	7818	0.05137	1.799	-0.2674	7.736
PG	7818	0.0529	1.544	-2.755	76.64
T	7283	0.04469	1.665	-0.2489	16.31
TRV	7818	0.04479	1.788	0.08192	16.35
UNH	7111	0.0839	2.802	-0.8704	24.68
UTX	7819	0.05419	1.749	-0.9452	23.56
VZ	7280	0.04356	1.595	-0.01973	11.47
WMT	7818	0.0718	1.821	0.04488	6.348
XOM	7818	0.05552	1.531	-0.5047	23.45

The descriptive statistics of the individual stocks look very similar to those of the equity indices except that the standard deviations are a little bit bigger.

5.2 Indices

In the figures 1-2 the results for the hypothesis testing for the indices is shown. For the historical simulation method the dependency of the time window is not entirely clear but for both levels of the VaR and both levels of the hypothesis there seems to be least rejections with the time window 400 days.

For the parametric normal method, firstly the method does not perform good enough for any of the indices calculating the 99% VaR so no conclusions can be drawn there regarding the time windows. This is a result of the high kurtosis of the log-returns. For the 95% VaR the method seem to perform worse with shorter time windows.

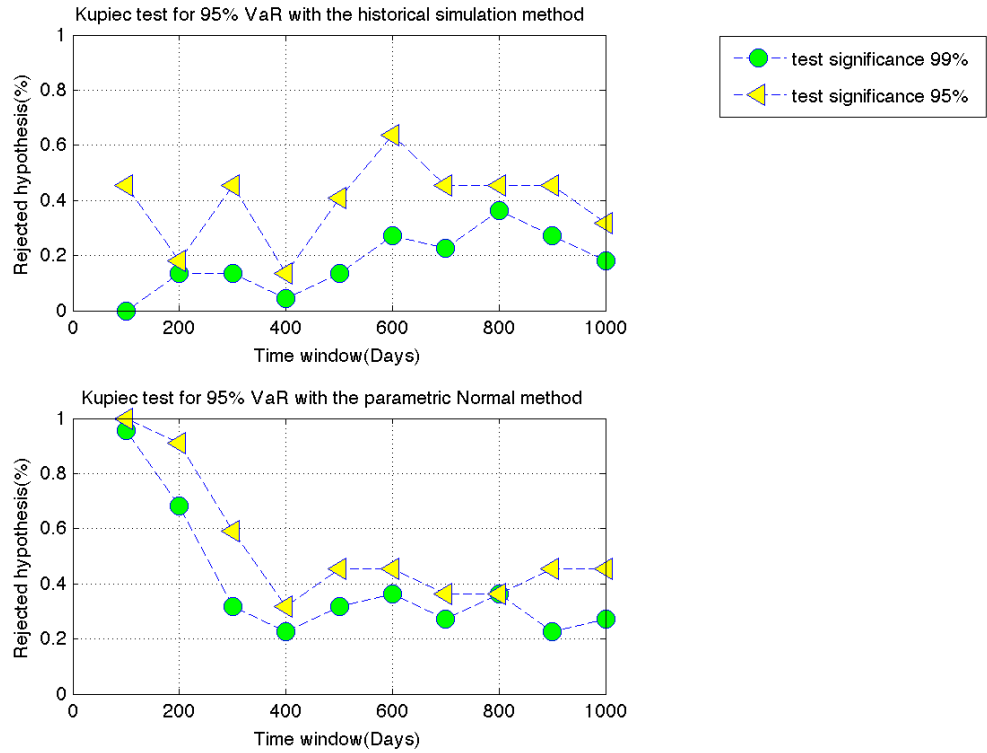


Figure 1: The percentage of indices for which the hypothesis is rejected on with 95% and 99% significance for the 99% VaR for the two different methods

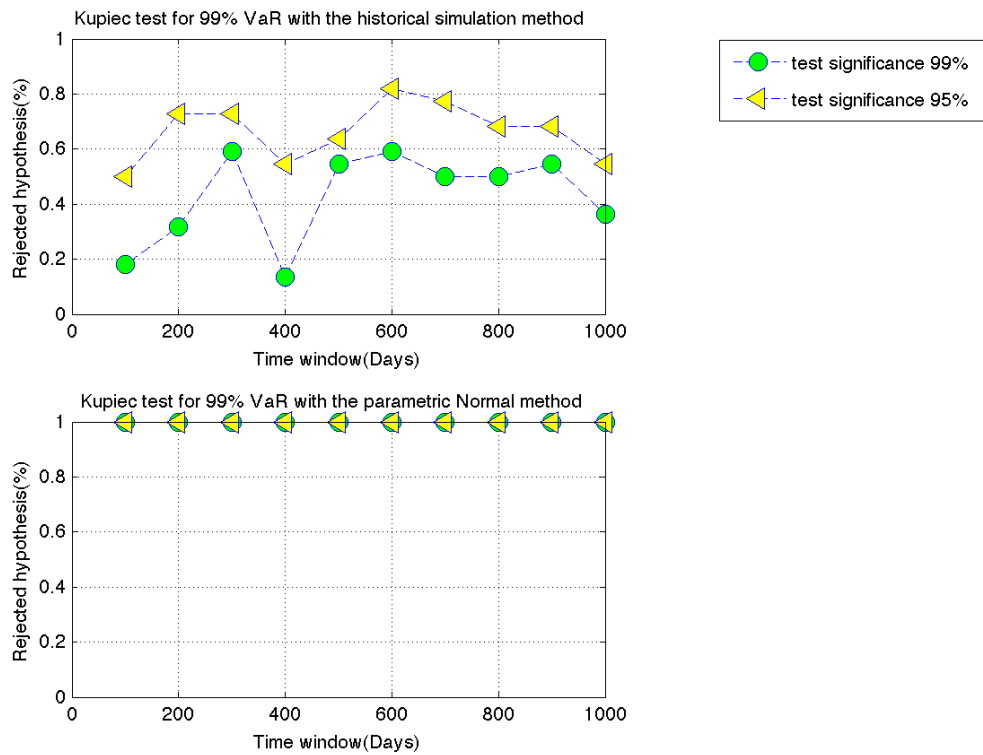


Figure 2: The percentage of indices for which the hypothesis is rejected on with 95% and 99% significance for the 95% VaR for the two different methods

5.3 Stocks

In the figures 3-4 the results for the hypothesis testing for the individual stocks are shown. The historical simulation method shows some unexpected results for both the 95% and 99% VaR, the method seem to perform worse with longer time windows. For both VaR levels and test levels of the hypothesis the method seem to perform best when a very short time window is used.

For the parametric normal method no conclusions can be drawn from the 99% VaR as it doesn't perform good enough for any time window or stock. As for the indices this is an effect of the high kurtosis of the log-returns. For the 95% VaR however the method seem to perform better with longer time windows.

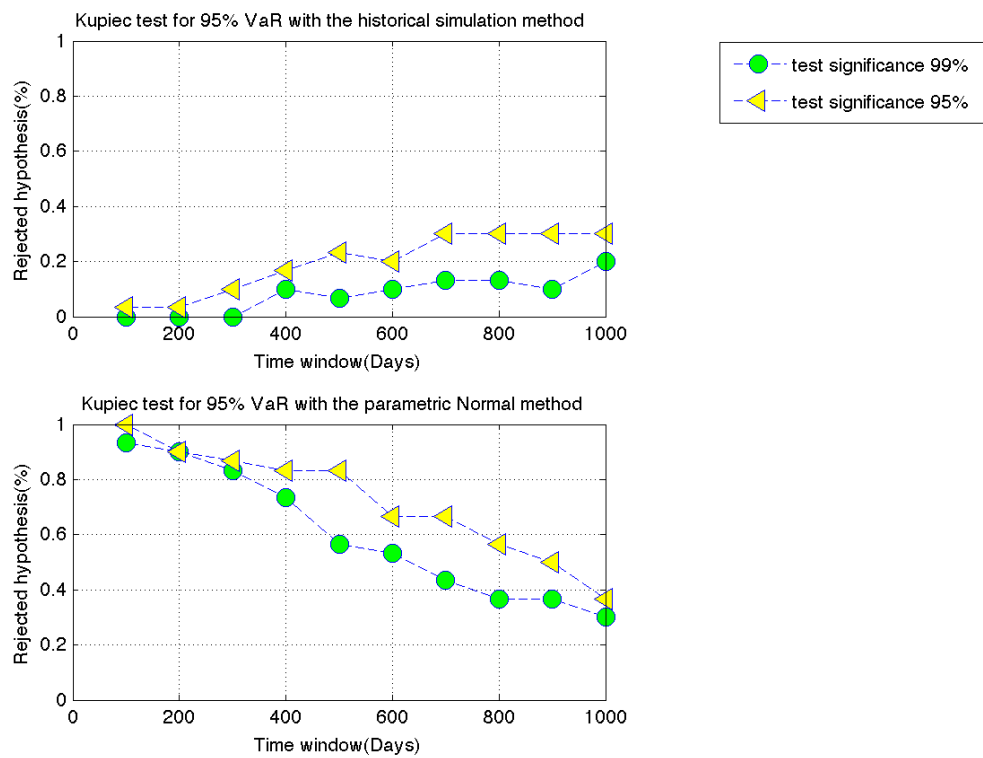


Figure 3: The percentage of DJIA stocks for which the hypothesis is rejected on with 95% and 99% significance for the 99% VaR for the two different methods

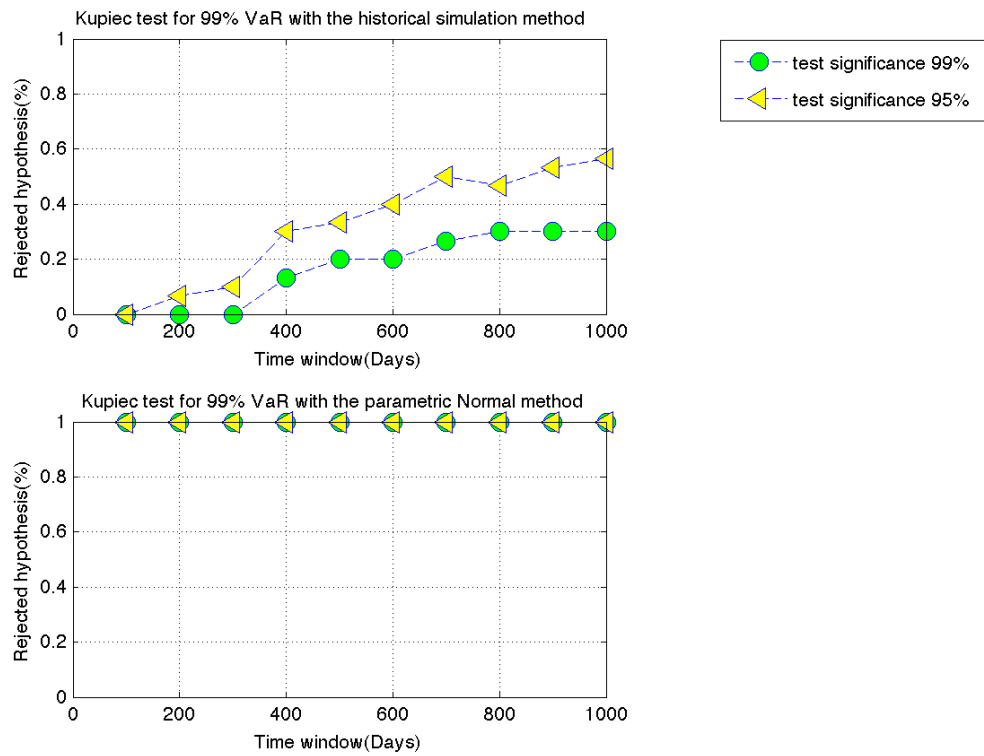


Figure 4: The percentage of DJIA stocks for which the hypothesis is rejected on with 95% and 99% significance for the 95% VaR for the two different methods

5.4 Clustering

In the table 3 means of the abnormal probabilities to receive adjacent VaR breaks is calculated for different time windows, methods, assets and confidence levels are shown. The full results is shown in the appendix in section B. First of all we see that there are serious tendencies for clustering for all time windows, methods, assets and confidence levels. There also seem to be a positive correlation between the length of the time window and the abnormal probability. This seem to be stronger for the historical simulation method than for the parametric normal method.

The reason that the problem with clustering is higher for longer time windows is that is the well known phenomena of volatility clustering, for example described by Mandelbrot (1963). This is that "large changes tend to be followed by large changes-of either sign-and small changes tend to be followed by small changes". This has the effect that there are periods with high volatility followed by periods of low volatility. When a longer time window is used the volatility will not increase or decrease fast enough with changing market conditions, which will create more VaR-breaks in volatile markets and less VaR-breaks in calm markets.

Table 3: Table of the means of the abnormal probability to have a VaR-break after another VaR-break for for the different methods and levels for the VaR. The historical simulation method is denoted hs and the parametric normal method pn

	100	200	300	400	500	600	700	800	900	1000
95%VaR hs, indices	0.01599	0.03406	0.05042	0.05182	0.05813	0.06254	0.06327	0.06532	0.0698	0.07468
95%VaR pn, indices	0.0401	0.04161	0.05301	0.05729	0.06227	0.06602	0.06621	0.06891	0.07786	0.09055
95%VaR hs, stocks	0.02528	0.03807	0.04184	0.04412	0.04669	0.05121	0.05282	0.0608	0.06544	0.06661
95%VaR pn, stocks	0.03551	0.03673	0.03766	0.03854	0.04197	0.0469	0.04712	0.0468	0.04915	0.05041
99%VaR hs, stocks	0.048	0.05364	0.05849	0.06286	0.06685	0.06853	0.068	0.07006	0.07093	0.072
99%VaR pn, stocks	0.04481	0.04155	0.04542	0.04755	0.05052	0.05492	0.05265	0.05363	0.0542	0.0549
99%VaR hs, indices	0.04549	0.06428	0.07439	0.07806	0.08461	0.09463	0.09621	0.09933	0.09886	0.1047
99%VaR pn, indices	0.04985	0.05321	0.06129	0.0632	0.07152	0.07094	0.07028	0.07073	0.0778	0.08408

6 Conclusions

The results in this thesis points towards the parametric normal methods seem to have a better unconditional coverage for longer time windows when calculating a 95% VaR, this however come at the cost of a higher degree of clustering of the VaR breaks. So when using the parametric normal method the time window that should be used is a consideration between a better unconditional coverage that the parametric normal method gives and the lower clustering that a shorter time window gives.

For the historical simulation method the conclusions is that shorter time windows have a slightly better unconditional coverage and a lower degree of clustering. Using these a little bit crude backtesting techniques it seem that the best results is obtained by using a time window that is as short as possible. Especially surprising is that the the historical simulation seem to perform so good for both asset classes for the 99% VaR. Which is essentially taking the last 100 days and assuming that the VaR is the biggest loss in any of these days. This is the most interesting result of the thesis.

A problem with the selection of the stocks is that the selection criteria creates some bias, because the companies are successful now but the analysis is based on past performance the results may not be fully accurate for comparable stocks in general. Because of this bias the firm specific risk are not fully accounted for. It is not improbable that for example a shorter time window would make the model adapt faster in case the return of a stock performs very poorly over a period.

7 Further research

It would be interesting to research the subject both using more advanced methods for backtesting the VaRs, for example the one outlined by Christoffersen (1998) or Christoffersen and Pelletier (2004) and more advanced methods to calculate the VaRs. Especially methods that account for volatility clustering. It would also be interesting to backtest using more different assets classes. It would be very interesting to see if the surprising result that historical simulation performs better with shorter would be the same with other more advanced backtesting methods and with other asset classes.

References

- Glyn A. Holton. History of value-at-risk: 1922-1998. 2002.
- Basel iii: A global regulatory framework for more resilient banks and banking systems. 2010.
- Philippe Artzner, Freddy Delbaen, Jean-Marc Eber, and David Heath. Coherent measures of risk. *Mathematical Finance*, 9:203–228, 1999.
- Peter F. Christoffersen. Evaluating interval forecasts. *International Economic Review*, 39:841–862, 1998.
- Paul Kupiec. Techniques for verifying the accuracy of risk management models. *Journal of Derivatives*, 3:73–84, 1995.
- Peter F. Christoffersen and Denis Pelletier. Backtesting value-at-risk: A duration- based approach. *Journal of Financial Econometrics*, 2:84–108, 2004.
- Benoit Mandelbrot. The variation of certain speculative prices. *The Journal of Business*, 36:394–419, 1963.

A Data

A.1 Indices

- AEX (AEX)
- All Ordinaries(AORD)
- ATX(ATX)
- BEL-20(BFX)
- Bovespa(BVSP)
- Dow Jones Industrial Average(DJIA)
- CAC 40(FCHI)
- FTSE 100(FTSE)
- Athex Composite Share Price Index(GDAT)
- DAX(GDAXI)
- S&P 500(GSPC)
- S&P TSX Composite(GSPTSE)
- HANG SENG INDEX(HSI)
- NASDAQComposite(IXIC)
- FTSE Bursa Malaysia KLCI (KLSE)
- Merval Buenos Aires (MERV)
- IPC(MXX)
- Nikkei 225(N225)
- Russell 2000(RUT)
- Shanghai Composite(SSEC)
- Swiss Market(SSMI)
- STRAITS TIMES INDEX(STI)

A.2 Stocks

The current stocks of the Dow Jones Industrial Average with their ticker in parenthesis:

- 3M(MMM)
- Alcoa(AA)
- American Express(AXP)
- AT&T(T)
- Bank of America(BAC)
- Boeing(BA)
- Caterpillar(CAT)
- Chevron Corporation(CVX)
- Cisco Systems(CSCO)
- Coca-Cola(KO)
- DuPont(DD)
- ExxonMobil(XOM)
- General Electric(GE)
- Hewlett-Packard(HPQ)
- The Home Depot(HD)
- Intel(INTC)
- IBM(IBM)
- Johnson & Johnson(JNJ)
- JPMorgan Chase(JPM)
- McDonald's(MCD)
- Merck(MRK)
- Microsoft(MSFT)
- Pfizer(PFE)
- Procter & Gamble(PG)
- Travelers(TRV)
- UnitedHealth Group(UNH)
- United Technologies Corporation(UTX)
- Verizon(VZ)
- Wal-Mart(WMT)
- Walt Disney(DIS)

B Calculations of abnormal probabilities

B.1 Indices

Table 4: Table of the abnormal probability to have a VaR-break after another VaR-break for 95% VaR with the historical simulation method

	100	200	300	400	500	600	700	800	900	1000	Mean
AEX	-0.01	0.004493	0.003699	0.01899	0.02704	0.05098	0.04952	0.04063	0.03706	0.06778	0.02902
AORD	0.01564	0.02529	0.04556	0.03762	0.03706	0.04618	0.05098	0.05329	0.05494	0.06353	0.04301
ATX	-0.01	-0.01	0.03	-0.01	0.01381	0.03255	0.01273	0.01326	0.01381	0.03651	0.01227
BFX	0.05349	0.08231	0.1011	0.06407	0.1032	0.13	0.1196	0.1438	0.11	0.1124	0.102
BVSP	0.01128	0.1011	0.1048	0.1381	0.09	0.1306	0.1352	0.1306	0.1352	0.1233	0.11
DJIA	0.02125	0.005625	0.004706	-0.01	0.03286	0.0311	0.01817	0.01597	0.01564	0.0141	0.01494
FCHI	-0.01	0.02175	0.04882	0.05557	0.03478	0.03412	0.03762	0.04	0.06143	0.0525	0.03766
FTSE	0.002346	0.0008696	0.02529	0.04063	0.08302	0.08091	0.05818	0.06059	0.06692	0.07955	0.04983
GDAT	-0.01	0.05667	0.06246	0.03286	0.03	0.04405	0.05667	0.04479	0.06143	0.0497	0.04286
GDAXI	0.006667	0.006129	0.005625	0.006393	0.006393	0.004706	0.005873	0.02333	0.03545	0.03478	0.01354
GSPC	0.01469	0.0141	0.03938	0.05579	0.03878	0.05818	0.04882	0.04435	0.05383	0.04618	0.04141
GSPTSE	0.07	0.04063	0.07235	0.07235	0.08756	0.07861	0.1076	0.1063	0.1312	0.1275	0.08941
HSI	-0.01	0.04405	0.04405	0.0311	0.04	0.04	0.05757	0.08524	0.08639	0.08756	0.0506
IXIC	0.001494	0.0005263	0.02191	0.02333	0.04319	0.0395	0.04263	0.05	0.0466	0.06143	0.03306
KLSE	0.04882	0.05977	0.0987	0.1063	0.115	0.05	0.09	0.1032	0.1032	0.1107	0.08857
MERV	0.04263	0.05977	0.05061	0.08091	0.07824	0.08524	0.07333	0.06895	0.06895	0.09811	0.07067
MXX	0.01	0.02704	0.0578	0.07929	0.07065	0.08677	0.08375	0.08524	0.08231	0.1032	0.0686
N225	0.03598	0.04	0.05667	0.07451	0.05849	0.04333	0.03225	0.03	0.0311	0.04	0.04423
RUT	0.01597	0.01667	0.03054	0.02333	0.04882	0.03478	0.03762	0.03762	0.0497	0.06143	0.03565
SSEC	0.02448	0.02571	0.02125	0.02175	0.01899	0.01817	0.01899	0.01632	0.01703	0.03225	0.02149
SSMI	0.005873	0.05452	0.07065	0.05557	0.1043	0.1039	0.1076	0.09345	0.09169	0.09169	0.07793
STI	0.02125	0.07219	0.1133	0.1415	0.1168	0.1522	0.1471	0.15	0.1818	0.1487	0.1245
Mean	0.01599	0.03406	0.05042	0.05182	0.05813	0.06254	0.06327	0.06532	0.0698	0.07468	0.0546

Table 5: Table of the abnormal probability to have a VaR-break after another VaR-break for 95% VaR with the parametric normal method

	100	200	300	400	500	600	700	800	900	1000	Mean
AEX	0.03545	0.0331	0.04785	0.0331	0.01344	0.02008	0.01308	0.02125	0.02077	0.1177	0.03558
AORD	0.01899	0.03237	0.0608	0.07257	0.08346	0.07929	0.08259	0.08174	0.07257	0.08804	0.06724
ATX	0.02409	0.003333	0.01941	0.03615	0.04556	0.06576	0.06576	0.06353	0.11	0.1204	0.0554
BFX	0.04556	0.05897	0.06042	0.07955	0.06895	0.1025	0.08877	0.0939	0.08639	0.1025	0.07875
BVSP	0.001765	0.002048	0.04	0.04195	0.07333	0.09526	0.09	0.1115	0.1107	0.09526	0.06618
DJIA	0.03032	0.03098	0.02906	0.05977	0.06143	0.06317	0.062	0.06519	0.1003	0.1003	0.06025
FCHI	0.02	0.03598	0.03545	0.03545	0.03494	0.03301	0.03211	0.03082	0.05931	0.05522	0.03723
FTSE	0.06246	0.0497	0.0773	0.0578	0.05897	0.05957	0.06477	0.06477	0.0785	0.09377	0.06676
GDAT	0.07594	0.05422	0.05612	0.07661	0.07661	0.06377	0.08167	0.07594	0.07871	0.07943	0.0719
GDAXI	0.01	0.01222	0.03545	0.04495	0.04263	0.04319	0.04435	0.03706	0.04682	0.05977	0.03764
GSPC	0.03046	0.01439	0.02704	0.04455	0.04882	0.04814	0.0541	0.06018	0.05857	0.06975	0.0456
GSPTSE	0.04385	0.05452	0.062	0.06937	0.09236	0.08756	0.08677	0.07333	0.08322	0.0968	0.07498
HSI	0.03511	0.02731	0.03688	0.05667	0.05207	0.04594	0.05338	0.05207	0.05383	0.06258	0.04758
IXIC	0.04422	0.03286	0.06857	0.05522	0.06947	0.07725	0.06383	0.06947	0.09692	0.1168	0.06946
KLSE	0.08783	0.07889	0.06692	0.05849	0.05173	0.08302	0.1049	0.1374	0.1264	0.1163	0.09119
MERV	0.02409	0.05593	0.05173	0.08639	0.07046	0.08783	0.08677	0.07333	0.1024	0.1166	0.07555
MXX	0.03651	0.05522	0.06813	0.06377	0.08375	0.0773	0.08091	0.07197	0.0713	0.06143	0.06703
N225	0.05154	0.06813	0.05977	0.08091	0.07547	0.05195	0.05087	0.04455	0.04357	0.03762	0.05644
RUT	0.04833	0.03167	0.04769	0.001628	0.02409	0.02614	0.02614	0.03706	0.04952	0.1084	0.04007
SSEC	0.05364	0.05931	0.03902	0.05481	0.06692	0.07594	0.07	0.06937	0.07661	0.09156	0.06572
SSMI	0.0239	0.04769	0.05061	0.02529	0.04556	0.04435	0.04155	0.05186	0.05061	0.07247	0.04539
STI	0.07824	0.07661	0.126	0.1253	0.1299	0.1214	0.1123	0.1299	0.136	0.1293	0.1165
Mean	0.0401	0.04161	0.05301	0.05729	0.06227	0.06602	0.06621	0.06891	0.07786	0.09055	0.06238

Table 6: Table of the abnormal probability to have a VaR-break after another VaR-break for 99% VaR with the historical simulation method

	100	200	300	400	500	600	700	800	900	1000	Mean
AEX	0.03638	0.06579	0.06498	0.05601	0.07092	0.09286	0.09426	0.08993	0.09931	0.1057	0.07761
AORD	0.03284	0.05029	0.06816	0.0642	0.07312	0.06905	0.06621	0.06838	0.07812	0.06746	0.06378
ATX	0.04778	0.0586	0.08717	0.07136	0.07745	0.09563	0.08942	0.08084	0.0893	0.1034	0.0801
BFX	0.07253	0.09876	0.09894	0.08778	0.1077	0.1281	0.144	0.1574	0.1446	0.1569	0.1197
BVSP	0.06268	0.05698	0.06538	0.1002	0.1063	0.1352	0.1314	0.1418	0.1307	0.142	0.1073
DJIA	0.03609	0.05774	0.05959	0.05368	0.04968	0.05543	0.05759	0.06818	0.06854	0.06111	0.05676
FCHI	0.0113	0.01923	0.03032	0.03097	0.04524	0.06508	0.07134	0.06934	0.07648	0.07705	0.04964
FTSE	0.03215	0.03798	0.04483	0.04467	0.05324	0.06143	0.05651	0.06176	0.05632	0.06145	0.05103
GDAT	0.07014	0.09029	0.09286	0.1189	0.1312	0.1236	0.1257	0.1265	0.1226	0.1336	0.1135
GDAXI	-0.001613	0.02287	0.03627	0.04053	0.05246	0.04717	0.04565	0.05959	0.06737	0.0744	0.04447
GSPC	0.01933	0.02588	0.03671	0.05221	0.06653	0.07467	0.07267	0.0792	0.08299	0.08316	0.05933
GSPTSE	0.06526	0.09607	0.12	0.1011	0.1038	0.1152	0.1288	0.139	0.1403	0.1318	0.1141
HSI	0.0317	0.06842	0.08099	0.09803	0.1146	0.1207	0.105	0.1118	0.1015	0.1114	0.09442
IXIC	0.03753	0.06467	0.07	0.05556	0.07665	0.08351	0.09433	0.0966	0.09209	0.1057	0.07767
KLSE	0.149	0.131	0.1409	0.1249	0.1137	0.1423	0.1483	0.1558	0.1573	0.1555	0.1419
MERV	0.0125	0.03982	0.03642	0.05909	0.06932	0.08369	0.08812	0.09754	0.1025	0.1006	0.06896
MXX	0.06404	0.08439	0.09286	0.1243	0.1119	0.1329	0.1357	0.1287	0.1466	0.1587	0.118
N225	0.0314	0.04036	0.06144	0.05619	0.05029	0.05272	0.04877	0.04404	0.04032	0.05299	0.04785
RUT	0.05231	0.09815	0.1167	0.1065	0.09232	0.08688	0.09063	0.0951	0.08944	0.118	0.0946
SSEC	0.0254	0.05672	0.06508	0.05861	0.06191	0.07069	0.07587	0.07132	0.07545	0.0862	0.06473
SSMI	0.02925	0.06636	0.07774	0.1035	0.1077	0.1117	0.1187	0.123	0.1086	0.1014	0.09479
STI	0.08287	0.0838	0.08937	0.109	0.1253	0.1333	0.1276	0.1194	0.1044	0.1155	0.1091
Mean	0.04549	0.06428	0.07439	0.07806	0.08461	0.09463	0.09621	0.09933	0.09886	0.1047	0.08406

Table 7: Table of the abnormal probability to have a VaR-break after another VaR-break for 99% VaR with the parametric normal method

	100	200	300	400	500	600	700	800	900	1000	Mean
AEX	0.01452	0.01472	0.02167	0.02639	0.03306	0.04396	0.03042	0.03425	0.03302	0.09286	0.03449
AORD	0.07658	0.07368	0.08019	0.07684	0.08314	0.08084	0.07987	0.07541	0.0822	0.08167	0.07904
ATX	0.0314	0.05256	0.06009	0.05448	0.06579	0.05929	0.06538	0.06828	0.06538	0.09201	0.06147
BFX	0.06881	0.08127	0.08834	0.08389	0.09286	0.09226	0.09222	0.08242	0.08171	0.09208	0.08559
BVSP	0.01415	0.01926	0.02658	0.02175	0.03051	0.05127	0.04787	0.075	0.08308	0.08462	0.04541
DJIA	0.0373	0.02229	0.02477	0.02742	0.03333	0.03125	0.02837	0.02831	0.03798	0.0491	0.03201
FCHI	0.01623	0.02547	0.04449	0.03203	0.03915	0.04312	0.03974	0.02983	0.04129	0.04865	0.036
FTSE	0.03121	0.04474	0.05286	0.04792	0.05334	0.0587	0.06111	0.04459	0.05616	0.05909	0.05097
GDAT	0.08782	0.06401	0.08226	0.0877	0.09765	0.09	0.09915	0.09089	0.09828	0.1014	0.08992
GDAXI	0.01329	0.03333	0.03178	0.01615	0.03046	0.01589	0.01329	0.001948	0.02692	0.04259	0.02257
GSPC	0.02415	0.02907	0.03029	0.04453	0.05099	0.04824	0.03854	0.05025	0.0567	0.05933	0.04321
GSPTSE	0.09249	0.07392	0.0803	0.08826	0.08183	0.06905	0.07847	0.08287	0.08704	0.09343	0.08277
HSI	0.02008	0.03286	0.04199	0.06515	0.075	0.06963	0.05938	0.05972	0.05458	0.04594	0.05243
IXIC	0.06159	0.04548	0.06141	0.06051	0.08833	0.07651	0.08057	0.08975	0.1055	0.1161	0.07858
KLSE	0.1208	0.1151	0.1246	0.1239	0.1449	0.1417	0.148	0.1421	0.1452	0.1446	0.1351
MERV	0.0528	0.04744	0.03092	0.03602	0.05	0.05256	0.05053	0.06765	0.08408	0.08333	0.05553
MXX	0.04846	0.04967	0.06355	0.1044	0.1027	0.08455	0.07593	0.08636	0.089	0.08061	0.07853
N225	0.03919	0.05651	0.06111	0.05256	0.06003	0.06945	0.06888	0.06191	0.0694	0.0745	0.06136
RUT	0.05644	0.06182	0.06824	0.06913	0.08732	0.09229	0.08765	0.09575	0.1079	0.1277	0.08542
SSEC	0.04747	0.06328	0.08077	0.08846	0.08284	0.08523	0.0913	0.09234	0.09706	0.09662	0.08254
SSMI	0.04325	0.06439	0.0781	0.06157	0.06475	0.07288	0.07766	0.07664	0.08699	0.06682	0.0693
STI	0.09865	0.09985	0.1141	0.1213	0.1254	0.1321	0.1318	0.1198	0.1221	0.1167	0.1182
Mean	0.04985	0.05321	0.06129	0.06632	0.07152	0.07094	0.07028	0.07073	0.0778	0.08408	0.06729

B.2 Stocks

Table 8: Table of the abnormal probability to have a VaR-break after another VaR-break for 99% VaR with the historical simulation method

	100	200	300	400	500	600	700	800	900	1000	Mean
AA	0.03167	0.04263	0.06229	0.06692	0.09227	0.08783	0.07421	0.07889	0.1034	0.1011	0.07412
AXP	0.03	0.04747	0.03819	0.0304	0.03211	0.05452	0.06609	0.06609	0.05593	0.07081	0.04916
BA	0.03	0.002346	0.03762	0.02488	0.04556	0.04747	0.04263	0.0525	0.05316	0.05383	0.039
BAC	0.04128	0.04128	0.04263	0.04319	0.05	0.05122	0.05306	0.06826	0.07475	0.09169	0.05574
CAT	0.04263	0.07642	0.04128	0.02797	0.02846	0.04063	0.03878	0.04128	0.04	0.065	0.04425
CSCO	0.06547	0.03839	0.04263	0.009231	0.006949	0.007544	0.008519	0.007544	0.007544	-0.01	0.01838
CVX	0.03	0.01899	0.02704	0.02704	0.0275	0.02896	0.02846	0.02704	0.0275	0.01469	0.02572
DD	0.003514	0.03	0.05024	0.0311	0.02614	0.03878	0.04882	0.05818	0.07046	0.1024	0.04596
DIS	0.01564	0.04195	0.02488	0.02571	0.02529	0.03598	0.05024	0.04952	0.04882	0.04814	0.03662
GE	0.004085	0.03938	0.0541	0.05667	0.08677	0.05522	0.07511	0.07511	0.07421	0.06547	0.05861
HD	0.03286	0.003889	0.015	0.004286	0.004493	0.004286	0.004925	0.05757	0.06895	0.08211	0.02784
HPQ	0.01703	0.04263	0.05329	0.0775	0.06595	0.07861	0.0714	0.08639	0.08756	0.07889	0.06592
IBM	0.04063	0.07974	0.06143	0.05977	0.06229	0.06865	0.07046	0.06955	0.07046	0.06368	0.06467
INTC	-0.01	0.003514	0.01817	0.003699	0.01703	0.04128	0.04405	0.03	0.03054	0.04	0.02183
JNJ	0.02947	0.05494	0.07219	0.08722	0.08091	0.0939	0.1116	0.1233	0.1233	0.1233	0.09002
JPM	0.01597	0.02846	0.02896	0.04747	0.05452	0.06609	0.04435	0.07333	0.06071	0.05731	0.04772
KO	0.03286	0.09127	0.09	0.1105	0.08756	0.07889	0.07602	0.09	0.1076	0.09843	0.08632
MCD	0.0203	0.01778	0.03	0.03167	0.07108	0.05667	0.04405	0.04263	0.04263	0.06407	0.04209
MMM	0.04634	0.01985	0.02077	0.06692	0.07824	0.03167	0.05849	0.06407	0.06059	0.06059	0.05075
MRK	0.0311	0.005385	0.01985	0.01667	0.01597	0.01564	0.015	0.01597	0.01564	0.02846	0.01797
MSFT	0.04172	0.05452	0.05349	0.03918	0.005873	0.03615	0.03348	0.04479	0.04714	0.04714	0.04035
PFE	0.004706	0.03412	0.02947	0.02896	0.0275	0.01817	0.02704	0.02947	0.04128	0.04263	0.02834
PG	0.005625	0.02279	0.01632	0.02797	0.03762	0.05579	0.08412	0.08302	0.09227	0.09465	0.05202
T	0.05849	0.05944	0.0525	0.06407	0.06407	0.07974	0.05024	0.06955	0.07235	0.06407	0.06345
TRV	0.02896	0.03	0.03651	0.03545	0.04435	0.06955	0.06059	0.04952	0.05977	0.07989	0.04946
UNH	0.02509	0.03412	0.05452	0.05349	0.07333	0.07333	0.07772	0.04882	0.08804	0.08804	0.06165
UTX	0.01985	0.01469	0.04479	0.05667	0.03762	0.06059	0.05522	0.09526	0.1058	0.06368	0.05542
VZ	0.01597	0.03054	0.06143	0.07	0.05173	0.06595	0.06317	0.07537	0.07333	0.0775	0.0585
WMT	0.004085	0.08231	0.04556	0.07	0.06792	0.06692	0.08091	0.1133	0.11	0.0939	0.07349
XOM	0.002987	0.05329	0.03	0.02896	0.03167	0.02614	0.02571	0.03762	0.04952	0.04682	0.03327
Mean	0.02528	0.03807	0.04184	0.04412	0.04669	0.05121	0.05282	0.0608	0.06544	0.06661	0.04929

Table 9: Table of the abnormal probability to have a VaR-break after another VaR-break for 99% VaR with the parametric normal method

	100	200	300	400	500	600	700	800	900	1000	Mean
AA	0.02086	0.04031	0.03403	0.05098	0.05061	0.06018	0.04389	0.04488	0.04844	0.04806	0.04422
AXP	0.01597	0.04128	0.02896	0.03321	0.03762	0.03217	0.04325	0.05707	0.06229	0.06879	0.04206
BA	0.03861	0.05294	0.05475	0.04755	0.0497	0.05107	0.05923	0.05154	0.05015	0.05202	0.05076
BAC	0.07485	0.07333	0.08412	0.08524	0.09857	0.0889	0.09811	0.09695	0.1046	0.1131	0.09177
CAT	0.03861	0.02974	0.04442	0.02731	0.05618	0.07333	0.06576	0.05923	0.05618	0.05993	0.05107
CSCO	0.02226	0.01105	0.000989	0.01198	0.02371	0.02297	0.02158	0.03167	0.03167	0.03082	0.02087
CVX	0.003889	-0.01	-0.001935	-0.002308	0.005748	0.0129	0.01273	0.02077	0.02731	0.02731	0.009642
DD	0.009481	0.002987	0.015	0.008519	0.008072	0.008519	0.01424	0.0141	0.02468	0.02509	0.01307
DIS	0.02974	0.03545	0.03487	0.0311	0.04674	0.04797	0.03895	0.04517	0.04333	0.03762	0.03909
GE	0.04422	0.05289	0.03487	0.04521	0.04294	0.04294	0.05857	0.0525	0.05897	0.04882	0.04819
HD	0.06429	0.04921	0.04128	0.03605	0.04556	0.05536	0.0496	0.03698	0.03636	0.05122	0.04659
HPQ	0.015	0.01273	0.02846	0.02101	0.02521	0.02676	0.02597	0.02817	0.0358	0.0358	0.02549
IBM	0.01381	0.02448	0.0254	0.03237	0.0497	0.05154	0.05716	0.0497	0.05475	0.05475	0.04137
INTC	0.04185	0.02759	0.0265	0.01256	0.01222	0.0129	0.0129	0.01273	0.01273	0.0129	0.01849
JNJ	0.03225	0.02876	0.02252	0.02937	0.02937	0.03651	0.03478	0.03511	0.04385	0.05299	0.03455
JPM	0.02593	0.04325	0.03706	0.05215	0.05417	0.07065	0.07939	0.07939	0.06865	0.0987	0.06093
KO	0.06429	0.05587	0.05061	0.06975	0.07982	0.09625	0.09559	0.09191	0.08494	0.07917	0.07682
MCD	0.0579	0.06237	0.07966	0.07276	0.06042	0.06586	0.06534	0.05849	0.05207	0.04405	0.06189
MMM	0.04422	0.03	0.02448	0.02356	0.02378	0.02378	0.03027	0.03545	0.03667	0.04161	0.03138
MRK	0.05081	0.05667	0.05294	0.06971	0.05522	0.05569	0.05522	0.06353	0.06407	0.06634	0.05902
MSFT	0.03444	0.02101	0.03098	0.0239	0.02306	0.04738	0.03839	0.02252	0.03762	0.03878	0.03181
PFE	0.02311	0.01581	0.01564	0.01614	0.01098	0.02448	0.03167	0.01759	0.02546	0.01857	0.01995
PG	0.02797	0.03459	0.04063	0.03459	0.03636	0.03054	0.03138	0.03	0.04229	0.04229	0.03506
T	0.04556	0.04926	0.06383	0.0504	0.05081	0.05122	0.05207	0.05667	0.05383	0.04072	0.05144
TRV	0.07228	0.05536	0.07333	0.06595	0.07805	0.08697	0.08756	0.09897	0.1054	0.1088	0.08326
UNH	0.02676	0.04085	0.01727	0.01778	0.02738	0.03854	0.04051	0.03255	0.03348	0.03301	0.03081
UTX	0.02448	0.04229	0.03196	0.04634	0.05122	0.05081	0.05536	0.05081	0.05536	0.065	0.04736
VZ	0.04479	0.0496	0.06051	0.06595	0.05329	0.06639	0.04634	0.04755	0.04882	0.03651	0.05198
WMT	0.02846	0.04442	0.04732	0.05	0.04405	0.0393	0.04	0.05122	0.04442	0.0504	0.04396
XOM	0.02846	0.02788	0.02937	0.02704	0.02846	0.03511	0.02788	0.03065	0.03032	0.02906	0.02942
Mean	0.03551	0.03673	0.03766	0.03854	0.04197	0.0469	0.04712	0.0468	0.04915	0.05041	0.04308

Table 10: Table of the abnormal probability to have a VaR-break after another VaR-break for 99% VaR with the historical simulation method

	100	200	300	400	500	600	700	800	900	1000	Mean
AA	0.05	0.05582	0.05554	0.0539	0.04845	0.05667	0.05444	0.06257	0.06429	0.07276	0.05744
AXP	0.04249	0.05541	0.0776	0.07629	0.07661	0.08265	0.08811	0.0852	0.09323	0.09796	0.07756
BA	0.03982	0.05448	0.04064	0.04687	0.05145	0.05882	0.06813	0.06749	0.08092	0.08115	0.05898
BAC	0.03708	0.054	0.0629	0.07564	0.09436	0.1011	0.1021	0.1117	0.1127	0.1222	0.08738
CAT	0.04429	0.03986	0.05756	0.05364	0.06749	0.05894	0.06732	0.0764	0.07466	0.07188	0.0612
CSCO	0.0602	0.05331	0.05887	0.06673	0.07253	0.074	0.07941	0.07157	0.06508	0.06245	0.06642
CVX	0.03696	0.03092	0.03069	0.03782	0.03475	0.03696	0.0338	0.03023	0.03708	0.03914	0.03483
DD	0.03596	0.07162	0.07885	0.07903	0.08137	0.07973	0.07834	0.08351	0.08228	0.07533	0.0746
DIS	0.04065	0.06111	0.06264	0.06798	0.07216	0.07147	0.06272	0.06748	0.06798	0.06582	0.064
GE	0.04064	0.03964	0.06732	0.06781	0.08115	0.094	0.1022	0.09824	0.09861	0.1014	0.0791
HD	0.04632	0.06389	0.08068	0.09164	0.09167	0.07717	0.07464	0.07647	0.08411	0.09205	0.07786
HPQ	0.05986	0.07353	0.06976	0.07712	0.06681	0.06816	0.07256	0.07113	0.06732	0.07849	0.07047
IBM	0.05541	0.04695	0.04167	0.05298	0.05188	0.05484	0.05499	0.05638	0.05263	0.05263	0.05204
INTC	0.01916	0.01322	0.01389	0.003221	0.02353	0.02396	0.03012	0.0306	0.0358	0.04329	0.02368
JNJ	0.07877	0.08703	0.08772	0.0937	0.09203	0.08905	0.08253	0.08804	0.07883	0.07693	0.08546
JPM	0.075	0.06944	0.07064	0.06811	0.08452	0.09646	0.08466	0.08706	0.09573	0.09496	0.08266
KO	0.06798	0.07045	0.06396	0.08137	0.09096	0.08793	0.08838	0.08867	0.08838	0.08542	0.08135
MCD	0.05405	0.06953	0.075	0.07349	0.07647	0.075	0.07321	0.06304	0.06239	0.06662	0.06888
MMM	0.03284	0.02062	0.03192	0.04804	0.06019	0.05986	0.05959	0.0587	0.06022	0.06321	0.04952
MRK	0.06172	0.08239	0.08445	0.09127	0.08462	0.08056	0.06924	0.07228	0.06846	0.06749	0.07625
MSFT	0.0481	0.05204	0.0569	0.05884	0.05239	0.05811	0.06037	0.05997	0.05884	0.06186	0.05674
PFE	0.0258	0.0477	0.04943	0.05756	0.05375	0.05204	0.05632	0.06207	0.06561	0.06748	0.05378
PG	0.04036	0.03876	0.05571	0.05756	0.0608	0.07281	0.07	0.08105	0.07931	0.08636	0.06427
T	0.06562	0.06854	0.07216	0.06421	0.06421	0.05795	0.05306	0.05924	0.05145	0.04639	0.06028
TRV	0.05345	0.06602	0.07	0.06699	0.06202	0.0626	0.05243	0.04917	0.05165	0.04537	0.05797
UNH	0.08272	0.07258	0.08029	0.09058	0.09865	0.1017	0.09983	0.1	0.1013	0.09943	0.09271
UTX	0.03564	0.03743	0.03046	0.04706	0.05756	0.05787	0.06299	0.06429	0.06714	0.05924	0.05197
VZ	0.04568	0.04552	0.06594	0.05811	0.06748	0.06782	0.06207	0.07644	0.07166	0.07012	0.06308
WMT	0.04972	0.05526	0.04855	0.04668	0.0503	0.05526	0.05769	0.05976	0.06515	0.06782	0.05562
XOM	0.01358	0.01215	0.01286	0.03169	0.0354	0.04244	0.03883	0.04302	0.0451	0.04483	0.03199
Mean	0.048	0.05364	0.05849	0.06286	0.06685	0.06853	0.068	0.07006	0.07093	0.072	0.06394

Table 11: Table of the abnormal probability to have a VaR-break after another VaR-break for 99% VaR with the parametric normal method

	100	200	300	400	500	600	700	800	900	1000	Mean
AA	0.03858	0.0416	0.05742	0.0614	0.06364	0.06881	0.06911	0.06779	0.08648	0.08	0.06348
AXP	0.02692	0.01357	0.03101	0.03163	0.03229	0.0416	0.04661	0.04409	0.04763	0.05667	0.0372
BA	0.03941	0.04375	0.06307	0.06026	0.0678	0.06924	0.06233	0.06357	0.06175	0.05756	0.05887
BAC	0.07583	0.07357	0.07381	0.07077	0.08171	0.1033	0.1011	0.09458	0.09914	0.1105	0.08843
CAT	0.04929	0.05149	0.03947	0.04186	0.05	0.05753	0.05428	0.05109	0.04659	0.05141	0.0493
CSCO	0.03725	0.03451	0.04057	0.03333	0.03468	0.03	0.03032	0.04055	0.03333	0.03439	0.03489
CVX	0.01763	0.005138	0.01313	0.01753	0.01299	0.0125	0.002925	0.005556	0.01011	0.01216	0.01097
DD	0.05829	0.04456	0.04512	0.0436	0.04653	0.05831	0.0537	0.05539	0.05945	0.06707	0.0532
DIS	0.02907	0.03226	0.04383	0.05219	0.04296	0.04763	0.04867	0.04563	0.05243	0.05383	0.04485
GE	0.0319	0.03909	0.04375	0.03186	0.03241	0.05	0.04417	0.05115	0.05706	0.05251	0.04339
HD	0.07254	0.05817	0.06028	0.06735	0.07403	0.07827	0.07272	0.06609	0.05904	0.05456	0.0663
HPQ	0.0484	0.01647	0.0178	0.0267	0.03046	0.03746	0.04169	0.03504	0.03187	0.02485	0.03108
IBM	0.02507	0.02027	0.0114	0.02283	0.02649	0.03571	0.03914	0.03555	0.03876	0.03596	0.02912
INTC	0.03431	0.03521	0.03718	0.02671	0.02418	0.02843	0.02082	0.02143	0.02714	0.0267	0.02821
JNJ	0.04005	0.0575	0.07219	0.07245	0.0678	0.06765	0.06828	0.07748	0.06798	0.07	0.06614
JPM	0.04091	0.0294	0.04569	0.05194	0.05791	0.07315	0.07871	0.0799	0.08086	0.08568	0.06242
KO	0.04956	0.04647	0.05402	0.05689	0.0574	0.05074	0.05579	0.06082	0.05456	0.05326	0.05395
MCD	0.05514	0.05049	0.05973	0.06869	0.07304	0.07596	0.06811	0.07534	0.07737	0.08151	0.06854
MMM	0.02907	0.02692	0.02481	0.01941	0.0233	0.02507	0.02124	0.02124	0.02388	0.0288	0.02437
MRK	0.0549	0.05256	0.05219	0.05049	0.04804	0.05565	0.04391	0.04184	0.04924	0.05183	0.05006
MSFT	0.05579	0.0544	0.05029	0.05089	0.05876	0.05843	0.06079	0.07059	0.07048	0.0694	0.05998
PFE	0.04977	0.03962	0.03937	0.05843	0.0698	0.0702	0.06579	0.06559	0.06382	0.06475	0.05872
PG	0.02812	0.02601	0.03029	0.03088	0.04474	0.04284	0.046	0.04756	0.03939	0.03621	0.0372
T	0.07471	0.05451	0.05238	0.0568	0.05706	0.06194	0.05918	0.06399	0.06717	0.0608	0.06085
TRV	0.0747	0.07057	0.0694	0.07281	0.07958	0.07808	0.0703	0.05818	0.06765	0.06497	0.07062
UNH	0.05278	0.05494	0.05356	0.05458	0.06565	0.06744	0.05791	0.05687	0.05359	0.062	0.05793
UTX	0.04375	0.05072	0.04804	0.04924	0.04044	0.04391	0.04367	0.04351	0.04596	0.05433	0.04636
VZ	0.04548	0.05553	0.06358	0.0652	0.05997	0.06749	0.07169	0.08228	0.07064	0.06978	0.06516
WMT	0.02778	0.03134	0.02178	0.02538	0.0329	0.0329	0.02572	0.03511	0.03401	0.03564	0.03026
XOM	0.03726	0.036	0.04732	0.05448	0.05891	0.05732	0.055	0.05104	0.04867	0.03992	0.04859
Mean	0.04481	0.04155	0.04542	0.04755	0.05052	0.05492	0.05265	0.05363	0.0542	0.0549	0.05002