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An Expected Loss Analysis of the ISEQ 20 Stock Index

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Abstract

Ireland is considered to have been one of the worst affected economies during the latest financial crisis. As a result, there is continuing uncertainty as to the potential losses that one could incur on Ireland's ISEQ 20 stock index. This thesis aims to quantify the expected loss of the index by using Value at Risk and Expected shortfall models, comparing their performance and explain the origin of the continuing high volatility on the market. Other indices are used as a benchmark to set the ISEQ 20 in context. The thesis finds no model passed the stress tests, however, the GARCH-filtered Age-weighted Historical Simulation is selected on other merits as the preferred estimation model out of those compared. The thesis highlights the limits of the application of theory and the benefits of having a margin of error included on the expected loss estimate.

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Introduction

No country in Europe has managed to escape the stranglehold of the financial crisis. Among the worst affected has been Ireland, being the first Eurozone country to enter official recession and its stock market having lost 66.2% of its value in 2008, the worst performing year since 1793.¹ The recession has shown some signs of improvement, however, there is still continuing uncertainty which has manifested itself in considerable volatility. With this persisting uncertainty, banks and investors are eager to limit potential losses and calculate a reliable estimate of expected loss.

¹ Dow has worst year since 1931; Ireland's ISEQ has worst performance since 1793

The aim of this thesis is to estimate the expected loss of the Irish stock market and attempt to explain the market's continuing volatility. This is done by comparing Ireland to various mature European stock markets and the US stock market, which are used as a benchmark throughout the study. Such estimations will then be used as a means of comparison of the severity of the financial crisis in Ireland to various developed economies. The final part of the thesis also aims to explain some of the Irish financial crisis from a risk perspective by analysing the potential causes of the volatility.

In order to estimate expected loss, several variations of the Value at Risk model and Expected Shortfall were chosen, the aim being to test a combination of non-parametric and parametric methods of estimation. The specific VaR models chosen are: Historical Simulation, Age-weighted Historical Simulation, Volatility-weighted Historical Simulation, Parametric Normal, Student t-distributed VaR and Expected Shortfall. There are of course a myriad of other methods, from which VaR may be calculated. However, this selection gives a balanced representation of parametric and non-parametric methods as well as methods that cope better with volatility than others. Two out-of-sample sub-periods, one encompassing relative calmness after the bursting of the dot com bubble and the other including the current financial crisis are used to stress test the models in order to determine which estimate generated is the most reliable. All tests will then be repeated using a GARCH filter to control for conditional volatility.

As stated above, in order to put the expected loss of the Irish stock index in perspective, it shall be compared to a variety of other control indices. The US, Eurozone and UK markets have been chosen since Ireland is a small open economy with strong political and economic links to these markets and is thus greatly affected by their movements. Spain is included as it is an open economy that was also heavily affected by the financial crisis and provides an interesting comparison for this reason. Finally, Denmark is included as it is a small open economy, which was one of the EU countries least affected by the banking crisis.

Therefore, this thesis has two parts to it. Firstly, it compares different models to determine which delivers the most reliable estimate for expected loss. Having established this, it moves on to explain the reasons behind the severity of the expected loss on the Irish stock index. This is done by firstly attempting to quantify roughly the extent of international influence on

the ISEQ 20 using correlation analysis. It then discusses both internal and external causes and highlights one of the shortcomings of VaR, the difficulty of making it reflect reality. Its shortcomings with regards world events and human error are discussed here along with a possible solution to the problem.

The remainder of the paper is structured as follows. Section 2 presents a review of the literature on the topic. Section 3 presents the data used in the thesis as well as a motivation behind the choice of indices and subsamples. Section 4 introduces the theories to be used and discusses the pros and cons of each theory. Section 5 presents the methodology of the paper. Section 6 presents the findings of the paper and a discussion of these results follows. Section 7 presents an outlook for the future of the ISEQ 20, whilst Section 8 concludes. Finally, Section 9 discusses possibilities for future research.

Literature Review

This section shall now outline some of the previous research in relation to VaR modelling, backtesting and in particular to applying such models to the ISEQ 20 index.

Value at Risk was first developed in the early 1990s by analysts at JP Morgan, many variations have arisen and systematically categorising each would be an essay in itself. However suffice to say due to fierce criticism of this method², many variations have sprung up in an attempt to improve its accuracy, which has resulted in many banks developing their own model. Its convenience at providing a unified risk measure has ensured the model's continuing usage by many banks and financial institutions. Its use was further ensured after the Bank of International Settlements (BIS) published an amendment to the Capital Accord, which mandated the use of in-house models to predict risk and the model recommended by them was VaR.³ A concise compendium and starting point from which to begin one's research on VaR modelling is Kevin Dowd's *Measuring Market Risk*. It is a key text relied upon for this thesis and has been widely quoted in academic papers and theses alike. It makes reference to keynote papers by authors such as Hull & White, who developed volatility-weighted Value at Risk. Opponents of VaR have outlined their critiques in several

²² A more detailed discussion of the pros and cons of VaR is presented in the Theory section.

³ Frain and Meegan (1996), p.2

papers, among the best known are Beder (1995), Taleb (1997) as well as Grootveld and Hallerbach (2004).

With regards backtesting VaR procedures, the first seminal paper was published by Kupiec (1995), establishing a simple but effective method to evaluate models by looking at the number of empirical exceedances.⁴ This was soon built on by what is perhaps the most widely used VaR backtesting procedure, namely Christoffersen's (1998) two-part conditional coverage test. This built upon Kupiec's test by incorporating it in a maximum likelihood format and added a second test of independence to it. Other backtests focus more on the size of exceedances rather than their frequency using Rosenblatt and/ or Berkowitz transformations,⁵ however this thesis employs only the Christoffersen test.

There does not exist an extensive literature on the application of VaR to the Irish stock market. The bulk of papers discuss rather, the application of more specialised VaR models to the Irish market. Furthermore, many of these papers date back to the 1990s or have a focus on this time period.

In Bredin and Hyde's 2004 paper, Ireland is used as an example of a small open economy in order to compare different VaR models. They focus on pre EMU Ireland for their study comparing the Historical Simulation, orthogonal GARCH VaR, weighted average and a standard variance-covariance approach in their study.⁶ Guidolin and Hyde's 2008 paper uses a similar approach in comparing markets, albeit for different ends. They use the US and UK markets as a means of comparison due to Ireland's strong market correlation with these.⁷ This paper goes beyond Bredin and Hyde's by adding other European countries and the Eurozone as a whole as a means of comparison.

Patrick Honohan provides a more general overview of the role of risk management in causing the Irish financial crisis. He points the finger of blame directly at risk managers for having become over-reliant on "sophisticated but mechanical risk-management models."⁸

⁴ Kupiec (1995), pp. 73-84

⁵ Berkowitz (2001), p 468-9

⁶ Bredin & Hyde (2004), p. 1390

⁷ Guidolin and Hyde (2008), p.294

⁸ Honohan (2008), p.15

According to Honohan, these models failed to allocate sufficient capital to hedge against asset risks. His analysis, as we see later on, rings true in this thesis.

Therefore, this paper is unique in that it seeks to quantify the expected loss for the ISEQ 20 and compare it to other relevant indices using VaR and ES techniques. This is a topic not often written about with regards to the Irish market, let alone on the post-Celtic Tiger era. Honohan's paper is significant, yet it is more of a critique of the causes of the Irish recession rather than an empirical study. However, it should be noted that numerous studies have been carried out with regards predicting expected loss on other stock exchanges.

Data

This section sets about describing the sources, types of data used and how it was manipulated to get the data series required to obtain accurate expected loss estimates.

The data used for this thesis was collected from Thomson Datastream. It consists of daily stock market index returns from 02/01/1998 to 25/03/2010, a period of approximately twelve years. The raw data was then logged and transformed into daily percentage differences.

As stated above, the data comprises of six data series representing six different markets. The starting date represents the first date at which daily returns for the ISEQ 20 stock index became available. To represent the US market, returns from the S&P 500 were used, for the UK, the FTSE 100, for Spain the Ibex 50, to represent the Euro zone, the Eurostoxx 50 was used and for Denmark, the OMX C20 was used.

In order to facilitate backtesting of the chosen models, two subsamples representing out-of-sample sub-periods were created, one encompassing relative calmness (OS1) and the other the latest financial crisis (OS2). From this, it would be possible to choose the best-performing model in order to most accurately quantify expected loss on the respective index. Both OS1 and OS2 were set to approximately a year in length, encompassing 260 observations each (260 being approximately the number of trading days in a year). The exact dates used for each subsample are set out in Table 1.

Table 1 List of subsamples

Subsample	Start Date	End Date
<i>In Sample 2 (IS1)</i>	02/01/1998	25/03/2009
<i>Out-of-Sample 1 (OS1)</i>	05/01/2005	03/01/2006
<i>Out-of-Sample 2 (OS2)</i>	27/03/2009	25/03/2010

Data for Irish trade levels with other countries was obtained from the Central Statistics Office.

Theory

The paper shall now set about presenting and discussing the models that shall be tested in order to find the optimal expected loss model for the ISEQ 20. There will follow a discussion on the merits and drawbacks of VaR followed by a description of the models, filters and backtests that will be used.

Value-at-Risk: its Strengths and its Weaknesses

Strengths

Developed in the early 1990s by JP Morgan, VaR is a popular method for calculating expected loss, given its simplicity and ability to present risk as an aggregate variable. The model was a great improvement on preceding portfolio theory as it gave more accurate estimates of market risk, prior to which arbitrary trading limits were often imposed by banks. JP Morgan's decision to releasing a version of its Riskmetrics database led to the adoption by many credit institutions of the VaR method.⁹

VaR can be summarized as the threshold value that the expected loss of a portfolio exceeds over a given time horizon. Mathematically, this can be seen in the following way. Supposing there is a given confidence level, α . Furthermore, $p=1-\alpha$ and q_p is defined as the p -quantile of the portfolio's profit/ loss distribution over a given horizon, then the portfolio's VaR over that horizon at that confidence level may be described as:¹⁰

$$\text{VaR} = -q_p \tag{1}$$

⁹ Dowd (2005),P.11

¹⁰ Ibid., p.27

According to Dowd, there are several advantages of VaR over other risk measures. Firstly, it is a consistent, common measure, which is easily comparable across different risk factors and positions. It is universally applicable to any kind of portfolio, thus allowing us to have a universal risk measurement for all investments. Furthermore, as opposed to older measurements, it takes account of all mitigating risk factors, as opposed to focusing on one or several of these, thus accounting for always in which risk factors interact with each other. It is also a probabilistic function, and can give information on the probability of a predicted loss occurring, something which older models could not.¹¹ Finally, losses incurred beyond the VaR are in accordance with a specified small probability decided by the individual.¹²

Weaknesses

However, VaR has not escaped significant criticism. Researchers such as Taleb criticised the transfer of scientific models to the real world, claiming it failed to account for social systems (By which we mean the factoring in of intelligent agents, which evolve to better adapt to their situation, non-stationarity and interdependence of market processes).¹³ This leads to models being imprecise, Beder argues that this can even lead to a huge difference in the results between VaR models.¹⁴ Another major drawback of VaR is that it is not subadditive, i.e. if ρ is a risk measure, then it is deemed to be subadditive when the following relationship is satisfied:

$$\rho(X + Y) \leq \rho(X) + \rho(Y) \quad (2)$$

That is the risk of a portfolio, which is constructed of subportfolios will add up to more (and sometimes less) than the combined risk of the subportfolios. Misjudging risk using an inaccurate model can of course lead to disastrous consequences for investors by indicating that diversification might be a poor tactic to follow.¹⁵ Another shortcoming of the model is that it only indicates the maximum possible loss if a tail event does not occur, however fails to indicate the extent to which it may actually be exceeded should a tail event occur.¹⁶

However, it should be remembered that although the above criticisms are valid for VaR, they may also be valid for other risk measurement models. Grootveld and Hallerbach note that

¹¹ Ibid., p.12

¹² Linsmeier and Pearson (1996), p. 5

¹³ Taleb, (1997)

¹⁴ Beder (1995), p.12

¹⁵ Dowd (2005), P. 33

¹⁶ Ibid., p. 31

none of the below models operate under the assumption that the agent is risk-averse,¹⁷ something which given today's financial crisis may need to be reassessed. The paper shall now turn to describe the specific models used. Despite these criticisms, Linsmeier and Pearson raise a valid point that VaR is rarely the sole criterion in determining risk, it is often used in conjunction with stress tests and scenario analyses among other things.¹⁸

Historical Simulation

The historical VaR is the simplest model to calculate, it can be obtained by plotting the returns series on a histogram, to find VaR at the 95% level, one must simply look at the number for the upper 5% of the distribution. Hence, it can be summarised it as the negative quantile of the profit/ loss distribution.¹⁹ This method is the simplest to demonstrate that as the confidence level falls, the more conservative the VaR estimate will be. VaR is also affected by the number of returns included. The higher the number of return included in the calculation, the less VaR will react to more recent returns, thus running the risk of less accurate daily VaRs. Too few returns will see the VaR overreacting to any jumps in volatility, bearing in mind this phenomenon is generally observed in clusters. However, ultimately this is an arbitrary parameter, which is best chosen according to the situation. Dowd notes (and as is proven later), a shorter period is the better-performing choice in backtests.²⁰ However, in order to obtain a normal distribution, using a larger sample size would be preferable, therefore, it is necessary to make a trade-off between responsiveness to recent returns and the normality of the distribution.

This method uses the observed distribution of data as opposed to an assumed theoretical distribution as employed by parametric models. This leads to the assumption that future returns will behave in a similar fashion to past returns.²¹

Age-weighted Historical Simulation

This method incorporates a decay element into the standard historical simulation described above. The aim of adding the decay factor is to give more recent observations a heavier weighting and a steady declining weight to older observations in the series. In this paper, the

¹⁷ Grootveld & Hallerbach (2004), pp. 34-5

¹⁸ Linsmeier and Pearson (1996), p. 5

¹⁹ Dowd (2005), p. 28

²⁰ Ibid., p 29

²¹ Ibid., p. 83

rate of decay, λ , was set to a value of $\lambda=0.999$. We calculated the first weight using formula (2).

$$w(1) = \frac{1-\lambda}{1-\lambda^N} \quad (3)$$

This was then plugged into equation (3) in order to rescale the original returns.

$$r(i) = \frac{w(i)}{\frac{1}{N}} \quad (4)$$

VaR could then be calculated using the rescaled returns. To gain the greatest accuracy, a Microsoft VBA programme was written for this, thus allowing returns to be updated on a daily basis (the VBA script may be found in the Appendix).

The advantage of this method is that recent observations influence VaR more than older ones, thus enabling the VaR to better reflect current market trends. The decay element also helps to absorb shocks caused by one-off events. Finally, the decay element allows for the sample size to grow over time so that each new estimate is made with all available observed.²²

However, there are of course some drawbacks, the effective sample size is essentially reduced by the decay element and may provide inaccurate VaR estimates during periods of prolonged volatility.²³

Volatility-weighted VaR

It was decided to include this method as it is particularly suited to estimating VaR during periods of high volatility by producing more conservative estimates that can encompass the maximum loss in a sample. The key element of volatility weighting is the rescaling of returns, after which, VaR tests may be carried out on the data. The rescaling of the returns takes the following form:

$$r_{t,i}^* = \left(\frac{\sigma_{T,i}}{\sigma_{t,i}} \right) r_{t,i} \quad (5)$$

The formula states that in order to rescale the returns, one must multiply the daily returns by the ratio of the standard deviations for the day VaR is being calculated (T) and the

²² Ibid., p. 94

²³ Ibid., p. 94

historical return at time t in the sample.²⁴ Thus providing us with a neat formula for VaR, which accounts for changes in volatility in the returns. Its simplicity also allows it to be incorporated with other models, as demonstrated later in the paper.

Hull and White note however, that this method excels more for certain kinds of data than others. Notably, more accurate results were observed using exchange rate data whilst for stock index data, the results were more ambiguous.²⁵

Parametric Normal VaR

This method entails using two parameters, namely the mean ($\mu_{P/L}$) and standard deviation ($\sigma_{P/L}$). The critical value at a given confidence level is calculated using a normal distribution curve. Therefore, the assumption of normality must be made when applying this method to a particular data series. The formula is defined as follows:

$$VaR = -\mu_{P/L} + \sigma_{P/L}Z_{\alpha} \quad (6)$$

Where z_{α} is the critical value at a given confidence interval. A downside of this method is that it does not heed maximum possible losses and as a result may over-estimate the risk level.²⁶

This VaR uses two assumptions, which if both correct, lead to an easy and accurate expected loss estimate (which can result in being more accurate than the non-parametric methods). The first is the assumption of normality, that is, the observations are normally distributed, thus allowing the use of well-known critical values to calculate expected loss. The second assumption of serial independence states that the size of a price move on one day will not affect a price move on another day.²⁷ However, a notable drawback of this method is that distributions are rarely exactly normal and should thus be limited to well-behaved data series.

Student t-Distribution VaR

This method is particularly useful when dealing with a series that has a distribution with excess kurtosis. Instead of using a normal distribution, a t-distribution is used. However, it

²⁴ Ibid., P.90

²⁵ Hull & White (1998), p. 10

²⁶ Dowd (2005), p.160

²⁷ Hendricks (1996), p.42

should be noted that as the degrees of freedom, ν , increases, the t-distribution converges towards the normal distribution.²⁸ Furthermore, the t-distribution is not stable, that is when two t-distributed variables are added, the result itself may not be t-distributed.²⁹

The model is stated in equation (5), where VaR is a function of the mean, μ , the number of degrees of freedom, ν and the t-distribution for a specified quantile, $t_{\alpha,\nu}$.

$$t - VaR = \mu + \sqrt{(v - 2)/v} t_{\alpha,v} \quad (7)$$

In order to calculate the degrees of freedom, the following formula was used:

$$v = \frac{4k-6}{k-3} \quad (8)$$

In equation (6), k stands for kurtosis.

This method, like the parametric model, makes the assumption of a given distribution (albeit that in this case it is the Student t-distribution) and of serial independence as outlined in the above section.

Expected Shortfall

Dowd describes the Expected Shortfall (ES) as the weighted average of tail losses, which allows one to calculate the ES as the average of tail VARs.³⁰ Furthermore, ES is subadditive, this makes it a coherent risk measure, something which VaR is not. As it calculates the conditional expectation of loss given that loss is beyond the VaR level, Yamai et al. note that ES will always provide a more conservative estimate of the expected loss.³¹

ES can be summarised mathematically in the following way:

$$ES = -\mu_{P/L} + \sigma_{P/L} \frac{\phi(z_\alpha)}{1-\alpha} \quad (9)$$

Again, the key parameters are the mean ($\mu_{P/L}$) and standard deviation ($\sigma_{P/L}$). z_α is the critical value and $\phi(\cdot)$ is the corresponding value of the standard normal density function.

²⁸ Ibid., p.160

²⁹ Ibid., p.160

³⁰ Ibid., p. 64

³¹ Yamai et al. (2001), p.4

GARCH Filtering

In order to filter out volatility clusters, which by looking at the volatility graphs in the Appendix may be seen to be numerous and significant, General Autoregressive Conditional Heteroskedastic (GARCH) filters were used. The method used was developed by Tim Bollerslev and builds upon a model presented in a previous paper by Robert Engle. He expands Engle's model by allowing for past conditional variances when calculating the current figure. For the purposes of this thesis, the GARCH (1,1) process was used:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (10)$$

This was updated using parameters calculated at six month intervals. Ideally, these would be updated on a daily basis in order to have the most accuracy, however, further VBA programming would be required for this.

However, there are also disadvantages to using this method for filtering volatility, most notably, the leverage effect. This effect states that the "amplitude of relative price fluctuations of a stock tends to increase when its price drops, an effect first noted in an article by Black.³² Reinhard and Hansen performed tests on the GARCH (1,1), comparing it to a large number of variations of the GARCH model. They found that many other models outperformed the GARCH (1, 1), such as the A-PARCH (2, 2), V-GARCH and the GARCH-in-mean models³³

Cross-Correlation

The cross-correlation formula is used to analyse the correlation between two separate time series in order to investigate the degree to which the two series move in unison. It may be used as a sign of interdependence between series and is summarised by the following formula.

$$F(x, y) = \frac{1}{n-1} \sum_{x,y} \frac{(x-\bar{x})(y-\bar{y})}{\sigma_x \sigma_y} \quad (11)$$

If returns of the two series are independent of each other, the top line will be zero (i.e. zero covariance).³⁴

³² Bouchaud et al. (2001) referencing Black, (1976), p. 228701-1

³³ Hansen & Lunde (2003), p. 305

³⁴ Copeland et al. (2005), p.115

Backtesting

The models discussed all present different estimates of expected loss. Thus the question arises, which is the most accurate? This section discusses the various backtesting methods used to find the most reliable models. All tests were performed on the out of sample periods OS1 and OS2. The methods with the most consistent backtesting results were taken to be the most reliable as they were shown to perform consistently over both calm and volatile periods. Two tests were performed on the respective models, the Kupiec basic frequency test and the Christoffersen conditional testing backtest. This section shall now proceed to outline the respective tests.

The study begins with a basic frequency test generally referred to as the Kupiec basic frequency test. A critical value, e , representing the number of times observations in a tested series should surpass the VaR estimate is calculated using equation (11) where n is the number of observations in the series and c is the confidence interval at which the VaR should perform at.

$$e = n * c \tag{11}$$

Thus for example, to get the expected number of tail losses exceeding VaR to perform reliably at the 1% confidence level on a series containing 260 observed daily returns, the critical value would be 2.6. A model with significantly more than 2.6 observations exceeding VaR would be deemed to be underestimating the risk. If there are too few exceptions, the model is deemed to be too conservative in its risk estimation. In both cases, the model would need to be re-specified in order to calculate risk correctly.³⁵

The Christoffersen conditional testing backtest comprises of two key parts. the first part, like Kupiec's method, tests for basic frequency (correct unconditional coverage), however, the calculation is performed as a likelihood ratio. The second part tests for independence between observations, i.e. whether they are identically and independently distributed (i.i.d.).

The first part is essentially a repetition of Kupiec's test, whereby the number of times the VaR is exceeded during a given sample. Equation (12) sets out the null hypothesis for this test, where r is the continuously compounded daily returns.

³⁵ Kupiec (1995), pp.73-84

$$I_{t+1} = \begin{cases} 1, & \text{if } r_{t+1} < VaR_{t+1} \\ 0, & \text{if } r_{t+1} \geq VaR_{t+1} \end{cases} \quad (12)$$

Having established this, the likelihood ratio equation for this part of the test may be set up. This takes the form of equation (13), where x is the number of exceedances in the sample, p is the expected probability of exceedances and n is the number of observations.³⁶

$$LR_{uc} = -2\ln [(1 - p)^{n-x} p^x] + 2\ln [(1 - \frac{x}{n})^{n-x} (\frac{x}{n})^x] \quad (13)$$

In order to determine whether an expected loss model is reliable the backtesting result must be compared to the backtest's critical value, which takes the form of a $\chi^2(1)$ distribution. This test looks at the coverage of the interval, I_{t+1} , but cannot detect whether the exceedances are clustered together, therefore, it is necessary to look at the second half of the test, the test for i.i.d..

This calculation is somewhat lengthier. To start with, one must calculate the various combinations of n_{ij} , the number of observations with value i followed by value j . From this, we can calculate the ratios of the counts of the appropriate cells. Three were calculated for the purposes of this thesis:

$$\hat{\pi}_{01} = \frac{n_{01}}{n_{00} + n_{01}}, \hat{\pi}_{11} = \frac{n_{11}}{n_{10} + n_{11}}, \hat{\pi}_2 = \frac{n_{01} + n_{11}}{n_{00} + n_{01} + n_{10} + n_{11}}$$

These probabilities can be interpreted as follows: $\hat{\pi}_{01}$ is the probability of observing a return not exceeding VaR before a return that exceeds VaR. $\hat{\pi}_{11}$ is the probability that a return exceeding VaR will be observed before a return that also exceeds VaR. Finally, $\hat{\pi}_2$ is the absolute probability that an observation exceeding or not exceeding VaR will be followed by an observation that exceeds it. These probabilities act as parameters to the following likelihood ratio equation:³⁷

$$LR_{ind} = -2\ln [(1 - \hat{\pi}_2)^{n_{00}+n_{10}} \hat{\pi}_2^{n_{01}+n_{11}}] + 2\ln [(1 - \hat{\pi}_{01})^{n_{00}} \hat{\pi}_{01}^{n_{01}} (1 - \hat{\pi}_{11})^{n_{10}} \hat{\pi}_{11}^{n_{11}}] \quad (14)$$

The results of this test are also compared against a critical value distributed as $\chi^2(1)$.

³⁶ Dowd (2005), p. 329

³⁷ Please note that the model presented in Dowd (2005) in fact contains a misprint and the correct version is in fact that which is presented in Christoffersen (1998).

The final part of the Christoffersen test ties both stages of the test together, it seeks to provide a single number, with which to evaluate a VaR test and is simply given by equation (15):

$$LR_{cc} = LR_{uc} + LR_{ind} \quad (15)$$

The reliability of these test results are compared against a critical value distributed as a $\chi^2(2)$ distribution. The advantages, according to Christoffersen, are that two joint tests of reliability may be performed whilst still retaining the individual hypotheses for each test.³⁸

Confidence intervals were employed in order to determine the validity of results generated. They work on the principle that H_0 is accepted on a particular significance $p=1-\alpha$ given:

$$x^2\left(1 - \frac{p}{2}, i\right) \leq LR_{cc} \leq x^2\left(\frac{p}{2}, i\right) \quad (16)$$

Where i is the order of the particular chi distribution.

Methodology

Having outlined the different models as well as the data used, this section shall now explain how they are to be used in practice and what information shall be gleaned from each part. The thesis is divided essentially into two parts, quantifying the expected loss on the ISEQ 20 and looking at additional factors not necessarily picked up by the expected loss calculations as well as their sources.

Expected Loss Analysis

With the correlations kept in mind, the thesis now proceeds to estimate expected loss in order to gain an understanding of the overall risk in the Irish market. Once estimated, each expected loss model is backtested in order to determine the validity and accuracy of each model tested.

Estimating Expected Loss

The next step involves obtaining VaR and Expected Shortfall estimates from the models outlined above. All VaR models were estimated over the entire sample period, OS1 and OS2. Each VaR was tested at the 5% and 1% value and again tested using a window of 1000 returns and 260 returns. These estimations were then repeated with the GARCH filter to

³⁸ Christoffersen (1998), pp. 845-6

control for volatility clustering. Combinations of the most suitable methods will also be tried in order to find an optimal model for each index. Of course, like with VaR models, there are many other filters which could have been tested. As stated in the theory section, there are several variants of the GARCH model which outperformed the GARCH (1, 1) model (used here). However, due to its simplicity and widespread use it was decided to continue with the GARCH (1, 1) model. Other types of filters such as the exponentially-weighted moving average (EWMA) have been shown to be inferior to GARCH models as it is unable to correctly predict future volatility. Therefore, it was decided to omit them from this study.³⁹ For this thesis the GARCH filter used parameters, which were maximised at six month intervals (as maximisations were performed manually). The accuracy of these filters could be improved by maximising parameters on a daily basis, however six month intervals is sufficient to give accurate estimates.

In order to further improve the accuracy of the models, it was decided to then add a volatility weighting to the best performing models. Again, when calculating the volatility weighting it was decided to use a six month gap between the predicted and historical returns used for reasons of consistency and again, because when looking at the volatility graphs in the Appendix, this could be deemed a reasonable time period as volatility would not have changed too significantly over this period.

Backtesting and Stress Testing

Having run estimates for all models, the paper proceeds to test the reliability of the results generated. Having so many estimates to choose from, it is necessary to choose the best-performing model or rather, eliminate the worst-performing ones. Here, the Christoffersen and Kupiec tests come into play. Since the test for correct unconditional coverage is in essence the Kupiec test rephrased as a likelihood ratio, only the version used to calculate correct conditional coverage will be presented, as using both versions will add no significant additional information. Furthermore, an element of stress-testing is introduced by comparing results between OS1 and OS2, looking for the most reliable method in both subsamples. This is done by simply comparing backtesting results and choosing the most reliable models from each subsample. The aim here, being to find a model that passes backtesting in both subsamples thus indicating a model which can remain consistent during

³⁹ Dowd (2005), p.131

periods of both low and high volatility. This part of the analysis will focus on analysing the test statistic for conditional coverage rather than the individual components of the test. Having done so it becomes possible to conclude which model performs best overall for each stock index. The aim is not to find one general model to fit all markets. This is neither possible nor prudent, given that each market chosen has its own unique characteristics and therefore VaR models that take particular aspects into account will tend to perform better on some markets than others. Therefore, the aim is to identify the optimal model for the ISEQ 20 using the other control indices as a contextual frame used to highlight the differences between the ISEQ20 and other indices and the differing performance of certain models on certain markets, using them ultimately as benchmarks with which the ISEQ 20 may be compared from a volatility and expected loss perspective.

Correlation

The aim of performing a test for correlation was to gain some insight into just how much the ISEQ 20 was influenced by international market activity and how much of the movement is derived from home-country activity. This would then give an indication of how much the expected loss was dictated by foreign influences. This test for correlation between data series was performed once for the entire data series. However, the results generated should be taken with a pinch of salt since when looking at the raw data graphs in the Appendix, significant changes in the direction of the data series may be observed and further looking at the volatility graphs also in the Appendix, one may suspect that there may be a break in the data. For these reasons, it was decided to repeat these tests on the subsamples OS1 and OS2. Furthermore, the use of log-differenced data greatly reduces the possibility of non-stationarity. This gives us an understanding of the extent to which other indices affect the ISEQ 20's volatility and provides a contextual frame for the ISEQ 20's expected loss.

Beyond the analysis: additional factors and explanations to be considered

Having considered the results generated, the thesis turns to look at real-world explanations behind the continuing high volatility on the ISEQ 20. This section aims to highlight the limitations of expected loss analysis and recommends that additional consideration be given to events, which may not be necessarily picked up by historical time series.

Results and Discussion of Empirical findings

The paper now moves on to present the empirical findings calculated. Again, this chapter is divided into two parts: the first focuses on the expected loss analysis and backtests performed, the second turns to look at the factors driving the current high levels of expected loss; both those incorporated in the calculation of expected loss, and those not considered when performing the calculation.

Analysis of Backtests

As outlined in the methodology section of this thesis, the best-performing VaR for each market index will be chosen by ranking their performance using backtests. Having done so, they will then be stress tested by assessing the consistency of results between OS1 and OS2. Tables 4 and 5 present the models that passed the backtest at a five percent confidence level for the particular market on which they were tested for each model in OS1 and OS2 whilst Tables 6 and 7 present the backtest results for VaR models using GARCH filtered data. Each table presents the results for the LR_{UC} , LR_{ind} and LR_{cc} backtests, x's indicate backtesting results, which are deemed acceptable as they are within the confidence interval brackets for the associated with the respective test. For the purposes of this thesis, the confidence interval for the backtest results has been set to 5%. X's highlighted in turquoise have not only passed the test for conditional coverage but have also passed one of the sub-tests composing this result. X's highlighted in green have not only passed the test of correct conditional coverage but have also passed both subtests which make up the Christoffersen test. These tables have been compiled using Tables 8 to 11, which may be found in the appendix (these may also be interpreted using the same system as described above for interpreting the backtest results).

Backtest Results of unfiltered Models

Turning to Table 4, we see that the best-performing models are the Historical Simulation (for the Euro Stoxx, IBEX 35 and OMX C20) and the Volatility-weighted Student-t (S&P 500, Euro Stoxx and IBEX 35) and the Volatility-weighted Expected shortfall models (S&P 500, FTSE 100, Euro Stoxx and IBEX 35). It was found that adding a volatility weighting dramatically improved results. Expected shortfall was the most notable, passing zero tests at first but upon having the weighting added to it, passed the unconditional coverage test for 260 observations at the 5% level. It should be noted that this combination was the most

frequently passed during this out-of-sample period. Therefore, as expected, we see the majority of tests passed are at the 5% level.

A recurring pattern in the following tables with the Age-weighted Historical Simulation is that the VaR's shape is dictated more by the confidence level rather than the number of observations used (however, this varies in significance depending on the decay rate selected). In fact, looking at the graphs in the Appendix, one notes that the difference between using 1000 observations or 260 observations is extremely small. The difference is usually of a size between 0% and 0.1%, with the estimates generated using 1,000 observations always being the more conservative. This may be explained by the fact that the VaR at 1,000 observations includes the first 260 observations as well as an additional 740 observations, which due to the rate of decay renders the older observations largely insignificant. This becomes evident when comparing the lines for VaR at a given confidence level. Both at the 5% and 1% confidence level, the lines generated using 260 observations and 1,000 observations are almost identical in both cases. However, it would be imprudent to go in the other direction and reduce the number of observations used as undoubtedly the accuracy of the estimate would decrease with every past observation that is excluded and lead to a less conservative estimate, exposing the investor to a greater number of potential losses. The question then arises, if the VaRs are the same, why does the backtesting on these models appear to favour those with a window of 260 observations? A possible explanation is that the actual number of observed exceedances are the same for both 1,000 and 260 observations. Therefore, if the required number of exceedances to pass the test varies, yet the empirically observed number of exceedances does not, then it may lead to a biased result in the backtest, leading one to believe a smaller observation window is more effective, whilst in reality, the difference is negligible.

Table 2 OS1

	Test	S&P 500 COMP OSITE - PRICE INDEX	ISEQ 20 - PRICE INDEX	FTSE 100 - PRICE INDEX	EURO STOXX (Euro Average) - PRICE INDEX	IBEX 35 (Spain) - PRICE INDEX	OMX COPEN HAGEN (OMXC20) - PRICE INDEX
HS	LRuc 1000 Obs @ 1%		x				
HS	LRuc 260 Obs @ 5%	x	x	x	x	x	x

HS	Lrind 260 Obs @ 1%						x
HS	Lrind 260 Obs @ 5%						x
HS	Lrcc 1000 Obs @ 1%	x		x	x	x	x
HS	Lrcc 260 Obs @ 1%						x
HS	Lrcc 260 Obs @ 5%				x	x	x
<u>AWHS</u>	LRuc 1000 Obs @ 1%		x				
<u>AWHS</u>	Lrcc 1000 Obs @ 1%	x		x	x	x	x
<u>Para norm</u>	LRuc 1000 Obs @ 1%		x				
<u>Para norm</u>	LRuc 1000 Obs @ 5%	x	x	x	x	x	x
<u>Para norm</u>	Lrind 260 Obs @ 1%			x	x	x	x
<u>Para norm</u>	Lrind 260 Obs @ 5%	x			x	x	x
<u>Para norm</u>	Lrcc 1000 Obs @ 1%	x		x	x	x	
<u>Para norm</u>	Lrcc 1000 Obs @ 5%				x	x	
<u>Stu T</u>	LRuc 260 Obs @ 5%			x	x		
<u>Stu T</u>	Lrcc 260 Obs @ 5%			x	x	x	
<u>ES</u>	LRuc 1000 Obs @ 1%		x				
<u>ES</u>	Lrcc 260 Obs @ 5%			x	x	x	
<u>VW Para norm</u>	LRuc 1000 Obs @ 1%		x				x
<u>VW Para norm</u>	LRuc 1000 Obs @ 5%	x	x	x			x
<u>VW Para norm</u>	LRuc 260 Obs @ 5%		x				
<u>VW Para norm</u>	Lrcc 1000 Obs @ 1%						x
<u>VW Para norm</u>	Lrcc 260 Obs @ 5%				x	x	
<u>VW Stu t</u>	LRuc 1000 Obs @ 1%		x				
<u>VW Stu t</u>	LRuc 1000 Obs @ 5%		x				x
<u>VW Stu t</u>	LRuc 260 Obs @ 5%	x	x		x	x	x
<u>VW Stu t</u>	Lrcc 260 Obs @ 1%	x		x	x	x	
<u>VW ES</u>	LRuc 1000 Obs @ 1%		x				

<u>VW ES</u>	LRuc 1000 Obs @ 5%		x				x
<u>VW ES</u>	Lrcc 260 Obs @ 5%	x		x	x	x	

Turning to Table 5, what becomes immediately apparent is that non-parametric models perform significantly better than parametric models. Out of the models tested, the Age-weighted Historical Simulation model clearly outperforms all other models passing both tests at the 1% level using 260 observations. It should be noted that using volatility weighting on the parametric methods did not significantly improve their performance during periods of high volatility. Of course infinite combinations of VaR models might have been tested to find the optimal model. However, another logical possibility in this case would be to add volatility weighting to the non-parametric models, to see whether performance would be further improved. From looking at the table, it can be seen that the problem with increased volatility was that it weakened conditional coverage. A pattern visible throughout Table 5 is that the test of independence is passed in the vast majority of cases whilst the test of conditional coverage is not. This says that the observed frequency of exceedances is far beyond the predicted frequency, indicating the volatility clusters were not properly captured by the models tested.

Table 3 OS2

	<u>Test</u>	S&P 500 COMP OSITE - PRICE INDEX	ISEQ 20 - PRICE INDEX	FTSE 100 - PRICE INDEX	EURO STOXX (Euro Average) - PRICE INDEX	IBEX 35 (Spain) - PRICE INDEX	OMX COPEN HAGEN (OMXC20) - PRICE INDEX
HS	LRuc 1000 Obs @ 1%		x			x	
HS	LRuc 1000 Obs @ 5%	x		x	x	x	
HS	Lrcc 1000 Obs @ 1%	x		x	x		x
HS	Lrcc 1000 Obs @ 5%	x		x	x		x
<u>AWHS</u>	LRuc 260 Obs @ 1%	x		x	x	x	x
<u>AWHS</u>	Lrind 1000 Obs @ 1%		x	x	x	x	
<u>AWHS</u>	Lrind 1000 Obs @ 5%		x	x	x	x	
<u>AWHS</u>	Lrind 260 Obs @ 1%	x	x	x	x	x	x

<u>AWHS</u>	Lrind 260 Obs @ 5%	x	x	x	x	x	x
<u>AWHS</u>	Lrcc 260 Obs @ 1%	x		x	x	x	x
<u>Para norm</u>	Lrind 1000 Obs @ 1%	x	x	x	x	x	x
<u>Para norm</u>	Lrind 1000 Obs @ 5%	x	x	x	x	x	x
<u>Para norm</u>	Lrind 260 Obs @ 1%	x	x	x	x	x	x
<u>Para norm</u>	Lrind 260 Obs @ 5%	x	x	x	x	x	
<u>Stu T</u>	Lrind 1000 Obs @ 1%	x		x	x	x	x
<u>Stu T</u>	Lrind 1000 Obs @ 5%	x	x	x	x	x	x
<u>Stu T</u>	Lrind 260 Obs @ 1%	x	x	x	x	x	x
<u>Stu T</u>	Lrind 260 Obs @ 5%	x	x	x	x	x	x
<u>ES</u>	Lrind 1000 Obs @ 1%	x	x	x	x	x	x
<u>ES</u>	Lrind 1000 Obs @ 5%	x	x	x	x	x	x
<u>ES</u>	Lrind 260 Obs @ 1%	x	x	x	x	x	x
<u>ES</u>	Lrind 260 Obs @ 5%	x	x	x	x	x	x
<u>VW Para norm</u>	Lrind 1000 Obs @ 1%	x		x	x	x	x
<u>VW Para norm</u>	Lrind 1000 Obs @ 5%	x	x	x	x	x	x
<u>VW Para norm</u>	Lrind 260 Obs @ 1%	x	x	x	x	x	x
<u>VW Para norm</u>	Lrind 260 Obs @ 5%	x	x	x	x	x	x
<u>VW Stu t</u>	Lrind 1000 Obs @ 1%	x	x	x	x	x	x
<u>VW Stu t</u>	Lrind 1000 Obs @ 5%	x	x	x	x	x	x
<u>VW Stu t</u>	Lrcc 1000 Obs @ 5%	x	x				
<u>VW ES</u>	Lrind 1000 Obs @ 1%	x	x	x	x	x	x
<u>VW ES</u>	Lrind 1000 Obs @ 5%	x	x	x	x	x	x
<u>VW ES</u>	Lrind 260 Obs @ 1%	x	x	x	x	x	x
<u>VW ES</u>	Lrind 260 Obs @ 5%	x	x	x	x	x	x

Backtest Results of GARCH (1, 1) filtered Models

The paper now looks at the same tests performed again, but this time with a GARCH (1, 1) filter applied to the data.

The first thing to be noted is that adding a GARCH filter significantly improves the parametric models' effectiveness, with most parametric models passing the test (or one of the subtests) for conditional coverage on the S&P 500 and OMX Copenhagen indices. The general improvement, when comparing the graphs in the Appendix, seems to indicate that adding a GARCH filter to account for volatility clustering leads to more conservative expected loss estimates. It may be observed that the models tested are best suited to stable, mature indices with shorter periods of volatility clustering. This is evident given the number of models that passed the Christoffersen test on the S&P 500 and OMX Copenhagen, two of the most stable indices included (this can be deduced by comparing volatility graphs included in the Appendix). The ISEQ 20 index on the other hand appears to pass many tests for unconditional coverage but fails the tests for independence, thus indicating that the problem lies with prolonged high volatility on the market. However, it should be noted that the IBEX 35, another index deemed to have been heavily hit by the recession, was more successful and passed the final Christoffersen test and at least one of the subtests using both parametric and non-parametric models.

Table 4 OS1 (GARCH Filtered)

	Test	S&P 500 COMPO SITE – PRICE INDEX	ISEQ 20 – PRICE INDEX	FTSE 100 – PRICE INDEX	EURO STOXX (Euro Average) – PRICE INDEX	IBEX 35 (Spain) – PRICE INDEX	OMX COPEN HAGEN (OMXC2 0) – PRICEIN DEX
<u>HS</u>	Lruc 1000 Obs @ 1%		x				
<u>HS</u>	Lruc 260 Obs @ 1%	x					x
<u>HS</u>	Lruc 260 Obs @ 5%		x	x		x	x
<u>HS</u>	Lrind 1000 Obs @ 1%	x					
<u>HS</u>	Lrind 1000 Obs @ 5%	x					x
<u>HS</u>	Lrind 260 Obs @ 1%	x					
<u>HS</u>	Lrind 260 Obs @ 5%	x					

<u>HS</u>	Lrcc 260 Obs @ 1%	x					x
<u>HS</u>	Lrcc 260 Obs @ 5%			x		x	
<u>AWHS</u>	Lruc 1000 Obs @ 1%	x					
<u>AWHS</u>	Lrind 260 Obs @ 1%	x					
<u>AWHS</u>	Lrind 260 Obs @ 5%	x					
<u>AWHS</u>	Lrcc 1000 Obs @ 1%		x	x	x	x	x
<u>AWHS</u>	Lrcc 260 Obs @ 1%	x					
<u>Para norm</u>	Lruc 1000 Obs @ 1%		x				x
<u>Para norm</u>	Lruc 260 Obs @ 1%	x					x
<u>Para norm</u>	Lruc 260 Obs @ 5%		x			x	x
<u>Para norm</u>	Lrind 1000 Obs @ 1%	x					
<u>Para norm</u>	Lrind 1000 Obs @ 5%	x					x
<u>Para norm</u>	Lrind 260 Obs @ 1%	x					x
<u>Para norm</u>	Lrind 260 Obs @ 5%	x					
<u>Para norm</u>	Lrcc 1000 Obs @ 1%			x	x	x	
<u>Para norm</u>	Lrcc 260 Obs @ 1%	x					x
<u>Para norm</u>	Lrcc 260 Obs @ 5%			x	x	x	
<u>Stu T</u>	Lruc 1000 Obs @ 1%		x				
<u>Stu T</u>	Lruc 260 Obs @ 1%	x					
<u>Stu T</u>	Lruc 260 Obs @ 5%	x					x
<u>Stu T</u>	Lrind 1000 Obs @ 1%	x					
<u>Stu T</u>	Lrind 1000 Obs @ 5%	x					
<u>Stu T</u>	Lrind 260 Obs @ 1%	x					x
<u>Stu T</u>	Lrind 260 Obs @ 5%	x					
<u>Stu T</u>	Lrcc 1000 Obs @ 1%			x	x	x	x
<u>Stu T</u>	Lrcc 260 Obs @ 1%	x					
<u>Stu T</u>	Lrcc 260 Obs @ 5%	x			x	x	

<u>ES</u>	LRuc 1000 Obs @ 1%		x				x
<u>ES</u>	LRuc 260 Obs @ 1%	x					
<u>ES</u>	LRuc 260 Obs @ 5%	x				x	x
<u>ES</u>	Lrind 1000 Obs @ 1%	x					
<u>ES</u>	Lrind 1000 Obs @ 5%	x					x
<u>ES</u>	Lrind 260 Obs @ 1%	x					x
<u>ES</u>	Lrind 260 Obs @ 5%	x					
<u>ES</u>	Lrcc 1000 Obs @ 1%			x	x	x	
<u>ES</u>	Lrcc 260 Obs @ 1%	x					
<u>ES</u>	Lrcc 260 Obs @ 5%	x			x	x	
<u>VW Para norm</u>	LRuc 1000 Obs @ 1%		x				x
<u>VW Para norm</u>	LRuc 260 Obs @ 1%		x		x	x	
<u>VW Para norm</u>	LRuc 260 Obs @ 5%		x				
<u>VW Para norm</u>	Lrind 1000 Obs @ 1%	x					
<u>VW Para norm</u>	Lrind 1000 Obs @ 5%	x					x
<u>VW Para norm</u>	Lrind 260 Obs @ 1%	x					x
<u>VW Para norm</u>	Lrind 260 Obs @ 5%	x					
<u>VW Para norm</u>	Lrcc 1000 Obs @ 1%			x	x	x	
<u>VW Stu t</u>	LRuc 1000 Obs @ 1%		x				
<u>VW Stu t</u>	LRuc 260 Obs @ 1%				x	x	x
<u>VW Stu t</u>	LRuc 260 Obs @ 5%		x				
<u>VW Stu t</u>	Lrind 1000 Obs @ 1%	x					
<u>VW Stu t</u>	Lrind 1000 Obs @ 5%	x					
<u>VW Stu t</u>	Lrind 260 Obs @ 1%	x					
<u>VW Stu t</u>	Lrcc 260 Obs @ 1%	x					x
<u>VW Stu t</u>	Lrcc 260 Obs @ 5%				x		
<u>VW ES</u>	LRuc 1000 Obs @ 1%		x				

<u>VW ES</u>	LRuc 260 Obs @ 1%		x	x	x	x	x
<u>VW ES</u>	LRuc 260 Obs @ 5%		x				
<u>VW ES</u>	Lrind 1000 Obs @ 1%	x					
<u>VW ES</u>	Lrind 1000 Obs @ 5%	x					
<u>VW ES</u>	Lrind 260 Obs @ 1%	x					x
<u>VW ES</u>	Lrcc 1000 Obs @ 1%			x	x	x	x
<u>VW ES</u>	Lrcc 260 Obs @ 1%	x					x
<u>VW ES</u>	Lrcc 260 Obs @ 5%				x		

During the second out-of-sample period, a decrease in the reliability of all models was noted, but especially with the parametric models, which scored especially badly on both parts of the conditional coverage test. Surprisingly, the models did not perform as well during OS2 when including a volatility weighting on the already filtered data. A possible reason for this is that the GARCH filter already corrects for conditional volatility. However, some improvement had been expected.

The best-performing model here is without a doubt the Age-weighted Historical Simulation, which also passed the test for conditional coverage for the ISEQ 20 using 260 observations on both the 5% and 1% level. The S&P 500 index also passed the test for conditional coverage with 1000 observations at the 5% level using this model and passed it using 260 observations at the 5% level using the Parametric Normal model. The parametric models seem to fail on both tests of conditional coverage and independence.

Table 5 OS2 (GARCH Filtered)

	<u>Test</u>	S&P 500 COMPOSITE - PRICE INDEX	ISEQ 20 - PRICE INDEX	FTSE 100 - PRICE INDEX	EURO STOXX (Euro Average) - PRICE INDEX	IBEX 35 (Spain) - PRICE INDEX	OMX COPEN HAGEN (OMXC20) - PRICE INDEX
<u>HS</u>	LRuc 1000 Obs @ 1%	x					
<u>HS</u>	LRuc 1000 Obs @ 5%		x		x	x	
<u>HS</u>	LRuc 260 Obs @ 5%	x					

<u>HS</u>	Lrind 260 Obs @ 1%	X					
<u>HS</u>	Lrind 260 Obs @ 5%	X			X	X	
<u>HS</u>	Lrcc 1000 Obs @ 1%		X	X	X	X	X
<u>HS</u>	Lrcc 1000 Obs @ 5%				X		X
<u>HS</u>	Lrcc 260 Obs @ 5%	X					
<u>AWHS</u>	LRuc 1000 Obs @ 1%		X	X	X	X	X
<u>AWHS</u>	LRuc 1000 Obs @ 5%	X	X	X			
<u>AWHS</u>	LRuc 260 Obs @ 1%	X	X				
<u>AWHS</u>	LRuc 260 Obs @ 5%	X	X				
<u>AWHS</u>	Lrind 1000 Obs @ 1%	X					X
<u>AWHS</u>	Lrind 1000 Obs @ 5%	X					X
<u>AWHS</u>	Lrind 260 Obs @ 1%	X	X				X
<u>AWHS</u>	Lrind 260 Obs @ 5%	X	X				X
<u>AWHS</u>	Lrcc 1000 Obs @ 1%				X		X
<u>AWHS</u>	Lrcc 1000 Obs @ 5%	X					
<u>AWHS</u>	Lrcc 260 Obs @ 1%	X	X				
<u>AWHS</u>	Lrcc 260 Obs @ 5%	X	X				
<u>Para norm</u>	LRuc 1000 Obs @ 1%		X			X	
<u>Para norm</u>	LRuc 1000 Obs @ 5%	X	X				
<u>Para norm</u>	LRuc 260 Obs @ 5%	X					
<u>Para norm</u>	Lrind 260 Obs @ 1%	X				X	
<u>Para norm</u>	Lrind 260 Obs @ 5%	X					
<u>Para norm</u>	Lrcc 1000 Obs @ 1%			X	X		X
<u>Para norm</u>	Lrcc 260 Obs @ 5%	X					
<u>Stu I</u>	LRuc 1000 Obs @ 1%	X				X	
<u>Stu I</u>	LRuc 1000 Obs @ 5%	X					
<u>Stu I</u>	Lrcc 1000 Obs @ 1%		X	X	X		X
<u>ES</u>	LRuc 1000 Obs @ 1%	X				X	

<u>ES</u>	LRuc 1000 Obs @ 5%	X					
<u>ES</u>	Lrcc 1000 Obs @ 1%		X	X	X		X
<u>VW Para norm</u>	Lrcc 1000 Obs @ 1%	X	X	X	X	X	X
<u>VW Stu t</u>	Lrcc 1000 Obs @ 1%	X	X	X	X	X	X
<u>VW ES</u>	Lrcc 1000 Obs @ 1%	X	X	X	X	X	X

Interpreting the Results

Having compared the models' performance in each out of sample period, it can be concluded that none of these models passed the stress testing part of the analysis. A general trend appears that the models perform much better in calm periods with low volatility. During periods of high volatility, non-parametric models fail to catch volatility spikes whilst parametric models generate overly-conservative estimates (with ES estimates being even more conservative). This is reflected in the expected loss graphs included in the Appendix.

What may be seen is an overall trend of the classical VaR models performing significantly better on large, mature markets (such as the S&P 500) and not so well on smaller markets, where smaller shocks are more likely to have a significant impact. Therefore, it is evident that the classical expected loss models, when placed in extreme circumstances, fail to properly forecast expected loss. This is problematic as market risk capital requirements are directly linked to the validity of the VaR model used⁴⁰ and are the preferred method of market risk calculation proposed by the Basel II accords.⁴¹ Thus recognising the growing use of VaR models by financial institutions to calculate expected loss. Even if the models fail one of the sub-tests but pass the other, this can be problematic. If the test for correct unconditional coverage is not fulfilled, this implies that violations in excess of the confidence level are not predicted by the VaR model. On the other hand, if the test for independence is not fulfilled, the model fails to adjust fast enough to a change in volatility, thus leaving a firm exposed for a possibly dangerous level of time, from which it may be extremely difficult to recover.⁴²

⁴⁰ Campbell (2005), p. 1

⁴¹ Basel II, Part 2, p. 73

⁴² Ibid., p. 4

Looking at the individual tests passed, a general trend emerges that the vast majority were VaR estimates with a window of 260 observations. This indicates that there is no long-term memory in the indices. This is in line with findings from other studies, which used varying methods in order to test stock market memory. Crane et al. use various rescaled range methods to test for this on the various ISEQ indices.⁴³ Therefore using an increased number of observations could lead to the problem of underestimating volatility if it happens as a cluster (which it often does) as the VaR is still being calculated using observations from the preceding calm period and hence slow to adapt to the new jumps in volatility.

It becomes evident from looking at the VaR graphs in the Appendix collectively that the problem of short-term memory may be extended to a further issue. Given that the calculation of VaR is entirely reliant on past returns, the VaR lines in the graph are clearly lagged with respect to the actual observations, the extent of which is dependent on the VaR method used. Frey and Michaud came to a similar conclusion, arguing that smaller windows better captured structural changes due to altering trading patterns.⁴⁴ However, as noted by Angelidis, other studies have come to the contrary conclusion.⁴⁵ Thus indicating that the problem may be down to the nature of the VaR model and the market it is applied on.

Escanciano and Olmo, however, are of the opinion that the Christoffersen test is biased as it fails to encompass estimation risk and therefore may lead to incorrect critical values being used.⁴⁶ They fix this issue by correcting the variance in accordance with the “recursive, rolling and fixed out-of-sample forecasting scheme.” Significant differences between the Kupiec test used here and their test were found.⁴⁷ Incorporating their amendments into the model could be the subject of future research.

What Model best predicts Expected Loss for the ISEQ 20?

The discussion up until now has been of a more general nature and has not focused on the ISEQ 20 index. The paper now turns to find the best-performing expected loss model based on the above data. As seen thus far, no model is entirely satisfactory for the purpose of

⁴³ Crane et al.(2006), p.8

⁴⁴ Frey & Michaud (1997)

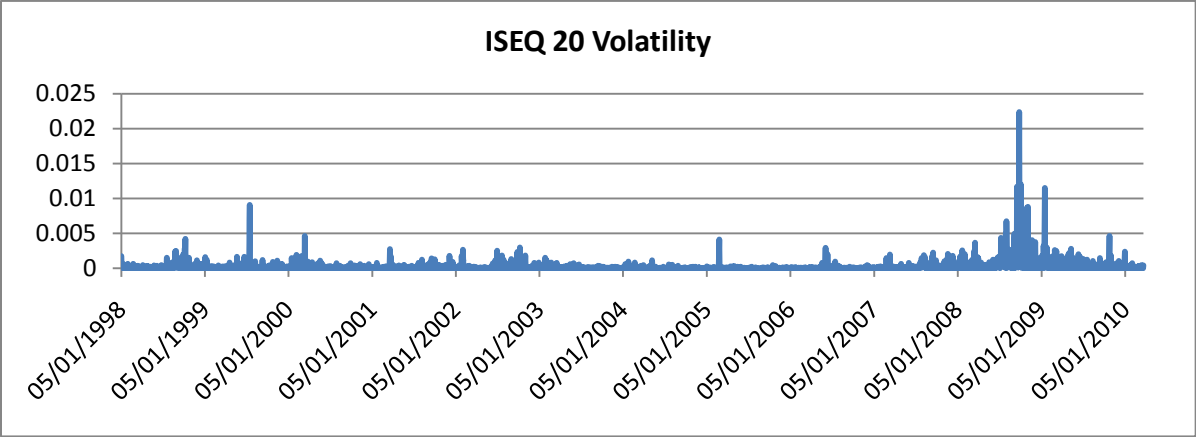
⁴⁵ Angelidis et al. (2004), p.106

⁴⁶ Escanciano & Olmo (2009), p.37

⁴⁷ Ibid., p. 48

estimating expected loss. When choosing a model most suited to the ISEQ 20 index, several things must be kept in mind.

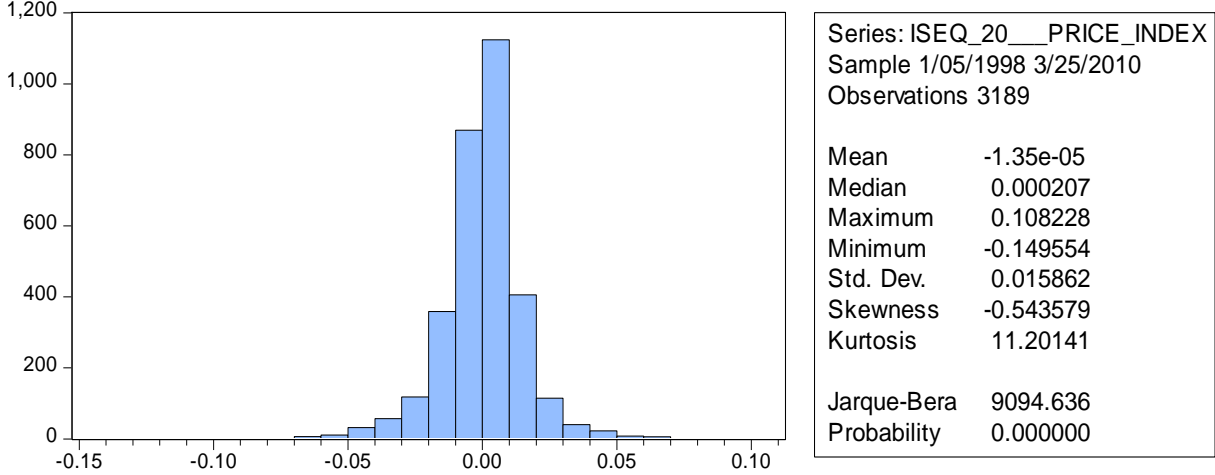
Figure 1 Volatility levels on the ISEQ 20



Firstly, comparing Figure 1 to the other volatility graphs in the Appendix, it is evident that there is significantly more volatility on the ISEQ 20 than on the other markets chosen. To place it in context, let us compare volatility on the 29th October 2008, the day observed on all six volatility graphs with the highest spike in volatility (bearing in mind no volatility is when the value hits zero). The S&P 500 recorded a value of 0.0064, the FTSE 100 0.0037 and the Euro Stoxx 0.0030 whilst the ISEQ 20 recorded a whopping 0.0224, a spike more than seven times larger than that observed on the FTSE 100 or Euro Stoxx. Turning to Figure 2 (please see the Appendix for other indices’ statistics), we observe an incredibly high kurtosis of 11.20141 over the entire sample period (a more normal figure being around 3), we conclude that the ISEQ 20 possesses fat tails. This indicates that the index’s volatility is due to infrequent, erratic deviations, rather than continuous, controlled deviations and extreme outcomes occur more frequently. Secondly, the ISEQ 20 has a skewness value of -0.5436, which also indicates the presence of a large amount of high values and a distribution that is far from normal. This affects expected loss estimates, which makes estimates overly-conservative for this market. However, what can also be seen is that despite the fact that the other markets also have considerably more volatility in OS2, the contrast is particularly notable in OS1. Therefore, indicating that a significant portion of this volatility may be generated at home. This is discussed further in the next section. Looking at the volatility graph for the ISEQ 20, it may be seen that Ireland’s volatility has not slowed down to the

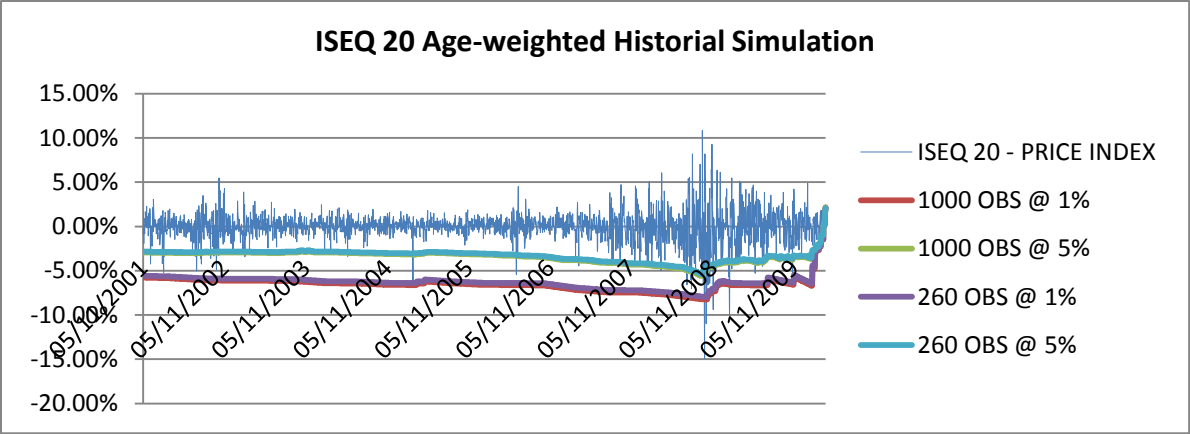
extent of the other markets and in fact looks set to remain significantly volatile for the foreseeable future.

Figure 2 Distribution graph and statistics for the ISEQ 20 market index



Bearing the above in mind, out of the models compared, it seems the GARCH-filtered Age-weighted Historical Simulation (depicted in Figure 3) using 260 observations would be the most appropriate model to use when calculating expected loss for the ISEQ 20. The reason behind this is two-fold. Firstly, it was the only model to satisfy both parts of the Christoffersen test on both the 5% and 1% level at 260 observations. Secondly, given that it achieved this during OS2, the period of high volatility, would imply it is better suited to predict the expected loss for the immediate future. The fact that this appears to be the best-performing model also serves to reinforce the claim that the ISEQ 20 index has a relatively short memory and models with heavier weights on recent returns seem to perform better.

Figure 3 Expected Loss for the ISEQ 20 stock index



Turning to the AWHs (GARCH-filtered) graph in the Appendix, the VaR can be seen to be providing rather conservative expected loss estimates during calm periods. This is adjusted to a relatively small extent during the volatile period. The jumps in volatility are mostly caught by the conservative estimates generated using returns from the tranquil period. However, VaR’s greatest weakness comes to light here as several spikes in volatility significantly exceed the VaR, which would have been problematic for banks had they been using this method. Therefore, on the whole, if this model were utilised for expected loss, banks would have overly conservative levels of bank reserves during calm periods, which during volatile periods would be insufficient on given days of excessive volatility.

Correlation Analysis

The thesis now moves on to dissect the expected loss figure. A question that arises is how much of the volatility (and by association, expected loss) is homegrown and how much should analysts be looking overseas in order to get indications of the future of the ISEQ 20? Table 2 presents the correlation results, whereby the ISEQ 20 was tested for correlation with each index.

Table 6 Correlation with the ISEQ 20

Market	Entire Sample	OS1	OS2
S & P 500	0.323731	0.339036	0.363823
FTSE 100	0.613753	0.600996	0.697478
Euro Stoxx	0.624952	0.61815	0.732434
Ibex 35	0.554955	0.55103	0.687179
OMX C20	0.551602	0.502399	0.637761

The reliability of these results are supported by Irish government statistics identifying Ireland’s largest trading partners in terms of imports and exports displayed in Table 3 (the exact figures may be found in the Appendix) where trade patterns tend to proportionally reflect the ranking of the ISEQ 20’s correlations with other indices. That is, in line with the above findings, the trade statistics confirm the UK, EU and USA as Ireland’s largest trading partners and hence changes in these markets would likely have a significant impact on the ISEQ 20.

Table 7 Ireland's percentage imports and exports

Trading Partner	% Imports	% Exports
Great Britain and Northern Ireland	30.4%	16.2%
Other EU Countries	28.7%	44.9%
USA	17.5%	21.1%
Rest of World	23.4%	17.9%

We see from Table 2 that the ISEQ 20 is most highly correlated with the Eurostoxx index with a coefficient of 0.62 over the entire sample, followed closely by the FTSE 100 with 0.61. The ISEQ 20 is least correlated with the S & P 500, having a correlation of 0.32. The reason that the OMX C20 and the Ibex 35 appear to be highly correlated is not so much because their respective countries trade to such a large extent with Ireland (which is of course part of the reason), but rather because they too are closely tied to Eurozone movements and hence would follow a similar pattern as the Eurozone. This in a way demonstrates the theory that with the removal of international barriers, as well as political and economic integration, the markets themselves become more integrated. This also goes some way to explaining the lower correlation with the US, for between the two markets, there are much greater capital controls than between EU member states, thus impeding market integration.

Another interpretation of the results may be taken from Longin and Solnik’s paper, where they show that correlations between markets increase during periods of high volatility, thus indicating that the ISEQ 20 reflects to a greater extent bad news in these foreign markets than good news, thus making Black’s theory⁴⁸ a possible economic reality. It may also be explained by international factors simply dominating domestic ones in all financial markets.⁴⁹

⁴⁸ Bouchaud et al. (2001) referencing Black, (1976), p. 228701-1

⁴⁹ Longin and Solnik (1995), p. 4

This is in line with Bertero and Meyer's findings that such behaviour is observable during an event such as a stock market crash.⁵⁰

Given that the ISEQ 20 is so highly correlated with the Ibex 35 and OMX C20, why is its volatility so much higher? The answer must be that there are many domestic factors driving the high volatility as well as influence from the FTSE 100, to which the ISEQ 20 has been historically linked.

Beyond the data analysed, what lies in store for the ISEQ 20?

As seen in the section devoted to correlation analysis, the ISEQ 20 is very susceptible to events abroad, given the high correlation with European, UK and US indices. However, comparing the ISEQ 20's volatility in Figure 1 to the other indices in the Appendix, we must conclude that the higher volatility on the ISEQ 20 must be due to significant domestic factors as well. This section aims to explain the continued volatility on the ISEQ 20, discussing the most significant events that triggered the latest recession on the ISEQ 20.

The relatively high volatility observed seems likely to persist at these levels, not solely because of the after-shock from a property market meltdown, banks loaded with toxic assets and overly zealous lending policies during the preceding ten years. 2010 has thrown many more challenges towards the Irish economy, foreign investors have grown increasingly jittery since Greece's downfall and fears that a similar scenario could take place in Ireland have done little to calm the market. Eyjafjallajökull's eruption caused periodic travel chaos across Europe. Ireland could claim to be especially hard-hit. Being an island, it is particularly dependent on air travel, therefore closing airspace adds a significant degree of international isolation to this small island economy and the fragility of the country's supply chain became evident during this time. Furthermore, the airline companies Ryanair and Aer Lingus, are among the largest companies listed on the ISEQ exchange (Ryanair for example, having lost approximately €50m due to the ash cloud disruption).⁵¹ Thus, continuing uncertainty regarding the volcanic eruptions are hardly likely to restore investor's confidence in these companies. The weakening euro will also cause problems for economic stability. We see a trend that with Ireland's continuing economic integration with the rest of Europe, the effect

⁵⁰ Bertero and Meyer (1990), p. 1179

⁵¹ Irish Times, 20th July 2010

of significant events in other EU states are being increasingly felt at home. Finally, something not picked up by a VaR analysis is the possibility of human error. During a recent speech by the *Taoiseach* (Prime Minister) Brian Cowen, he admitted that the domestic economic and banking crisis was worsened by internal factors, not excluding mistakes made by the Government.⁵² However, ultimately, the elephant in the room, which until now has not been much discussed, is the domestic property crisis. This happened to coincide with the above mentioned causes. The severity of this property meltdown was eloquently captured in an IMF report, which stated: “never has an increase in residential property prices occurred of a magnitude similar to that which has already occurred in Irish house prices over the past decade without a subsequent large correction in prices.”⁵³ To put this quotation in perspective, the Financial Services Regulator estimated price-rental ratios to be overvalued to the tune of between 55 and 63 per cent.⁵⁴ All this indicates that the period of prolonged volatility which is currently plaguing the ISEQ 20 and other markets is not entirely the product of poor business strategy by the companies comprising the stock index but is a complex menagerie of both domestic and international events.

What the above examples highlight is the number of different sources an economic shock may emanate from. Both domestic and international events have had a powerful effect on determining the direction of the ISEQ 20. It is therefore not enough to base future expected loss estimates based solely on a VaR estimate. The effect of news significantly impacts the results as does human error. Therefore, it is necessary to be able to anticipate future events, which analysing solely past returns will not necessarily pick up. Knowledge of future events may be factored in when adjusting expected loss estimates, either by including them as a parameter in the model being used or adding a larger margin of error on the expected loss result.

Conclusion

The credit crunch dealt a heavy blow to economies worldwide. In Europe, one of the worst hit was Ireland. The aim of this paper was to analyse the ISEQ 20 stock index and provide a prediction as to the future expected loss of the market. The ISEQ 20 could be considered an

⁵² Irish Times, 14th May 2010

⁵³ Honohan (2010), p.81

⁵⁴ Ibid., p.81

accurate portrayal of the Irish economy and hence predictions made about the index would give a good prediction as to what would happen on the island as a whole. An expected loss analysis highlighted in essence the expected performance based on the maximum amount that one could lose on the market on any given day. In order to do so, several VaR and ES models were tested in order to find the best performing and hence, most accurate model. Kupiec and Christoffersen backtests were used to quantify the performance of models and a stress test was performed, comparing models' performance in calm and volatile periods. Other indices were also tested to provide a benchmark for the ISEQ 20 and place it in context.

Correlations between the various indices and the ISEQ 20 were also performed for the same purpose. Between the earlier out of sample period OS1 and the later OS2, a significant increase in the correlation between European indices was noted. They were also the highest correlated, whilst the S&P 500 was the lowest correlated. This indicates that events in Europe and the UK would tend to have a greater effect on the ISEQ 20 than those emanating from the US. However, it was also noted that the ISEQ 20's volatility remained significantly higher than other European indices indicating that domestic issues played a significant role in dictating the course of the index.

Having run the backtests, the results indicated that the models failed the stress testing and were generally unable to cope with extreme levels of volatility. GARCH filtering did significantly improve forecasting, particularly for parametric models. What the analysis highlighted rather was the models' inability to cope with periods of high persistent volatility.

Out of the models tested, it was decided that for the ISEQ 20, the GARCH-filtered AWHs at 260 observations was the best-performing model. The motivation for this was twofold. Firstly, despite it failing the stress test, it was the only model to pass the Christoffersen test at the 5% and 1% level during the more volatile OS2 period. Secondly, given the ISEQ 20's persisting volatility, a model that performed well only in OS2 would be preferable to one that performed better only in OS1 (the period of low volatility).

The thesis also took note of VaR's critics, discussing the variety of outside factors, which could affect the VaR results in the real world. Thus demonstrating that in order to most accurately predict expected loss of the ISEQ 20 (or other indices for that matter), it is not

enough to base the prediction on past returns. The ability to predict future events may have an impact in predicting volatility and expected loss estimates may be adjusted accordingly. Analysing past returns exclusively will not always factor in such events (the eruption of Eyjafjallajökull being an example). Thus it would be prudent to adjust the margin of error on predictions, more often than not manifesting itself in a marginally more conservative estimate.

Future Research

There is a large scope for further research given that there has been little analysis of this sort on the ISEQ 20. Only a limited number of VaR and ES models have been tested here and as demonstrated, none passed the stress tests despite some performing better than others during different out-of-sample periods. A vast combination of models and filters could be tested to further improve the reliability of the results and backtesting procedures. The primary focus of downside risk analysis on the ISEQ 20 should centre around adequate controls for high levels of volatility. One possibility is testing extreme value theory as an alternative method of calculation, thus eliminating the issue of distribution assumptions. However, a possible drawback of this method is that it makes the assumption of independently and identically distributed variables, thus ignoring the possibility of volatility clustering.⁵⁵ Alternatively, the incorporation of other filters such as the Exponentially Weighted Moving Average (EWMA) may further help control for volatility (however, previous research has shown that this filter is less effective than GARCH and was for this reason excluded during this thesis). Dowd and Blake suggest the use of other more modern risk measurements such as spectral, coherent or distortionary risk measures and they argue that the VaR has been widely discredited and its continued use is down to its established status as a risk measure.⁵⁶

Given the fact that no models successfully passed the stress tests set out in this paper, further research could go into this field. Consideration might be given to applying elements of the stress test outlined by the Committee of European Banking Supervisors (albeit there being some criticisms it was too lenient).

⁵⁵ Cotter (2004), pp. 709-10

⁵⁶ Dowd et al. (2006), p.220

Glossary

AWHS – Age-weighted Historical Simulation

HS – Historical simulation

OS1 – Out-of-Sample Period 1

OS2 – Out-of-Sample Period 2

Para Norm – Parametric Normal

Stu T – Student-t

ES – Expected Shortfall

VW Para Norm – Volatility-weighted Parametric Normal

VW Stu T – Volatility-weighted Student-t

VW ES – Volatility-weighted Expected Shortfall

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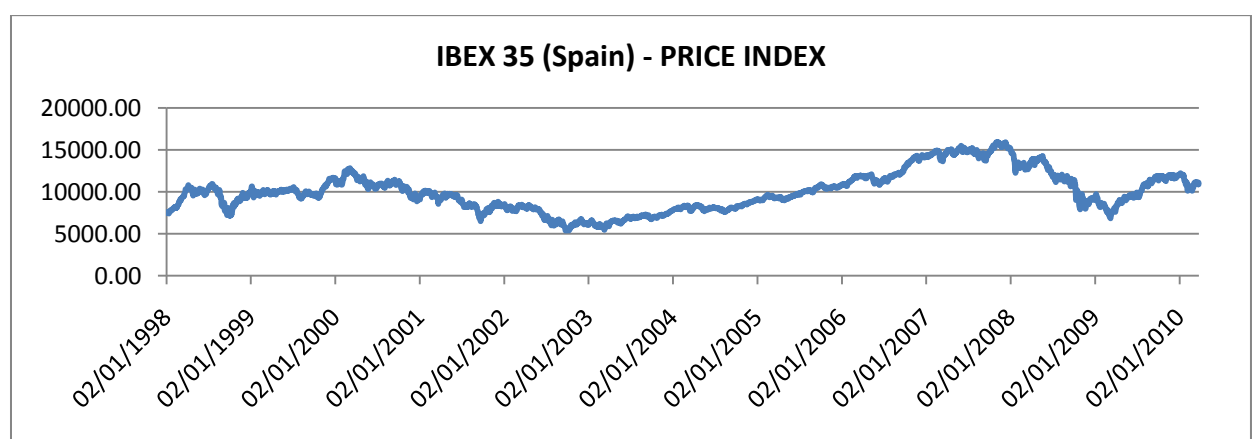
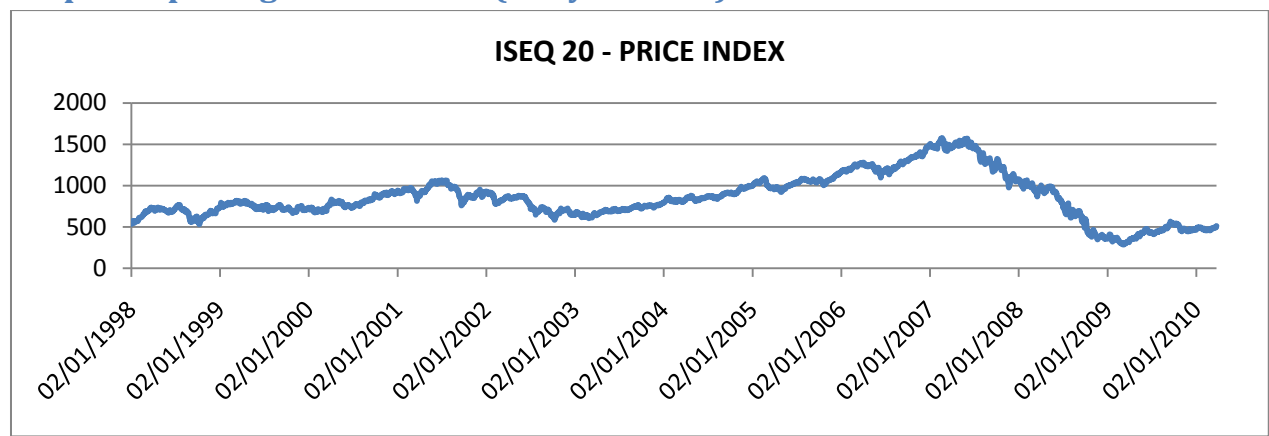
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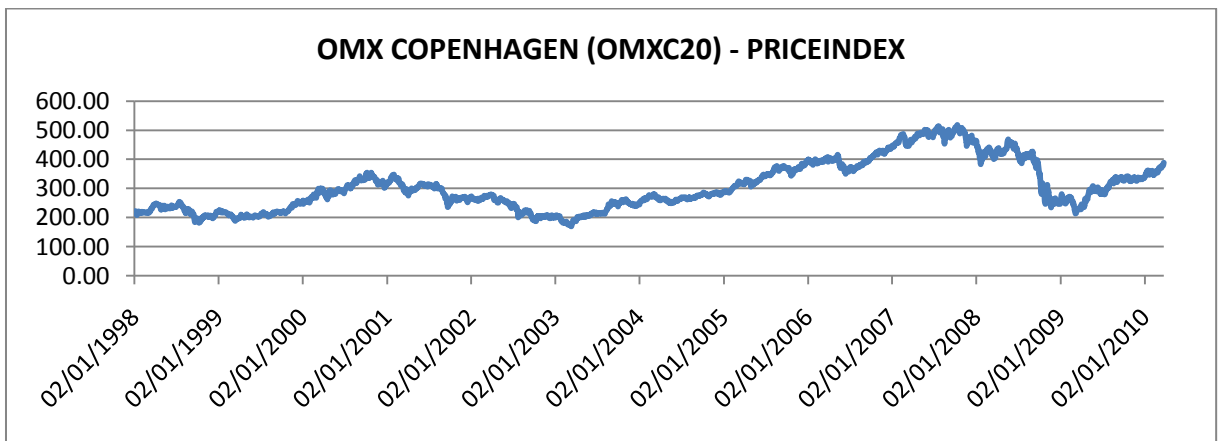
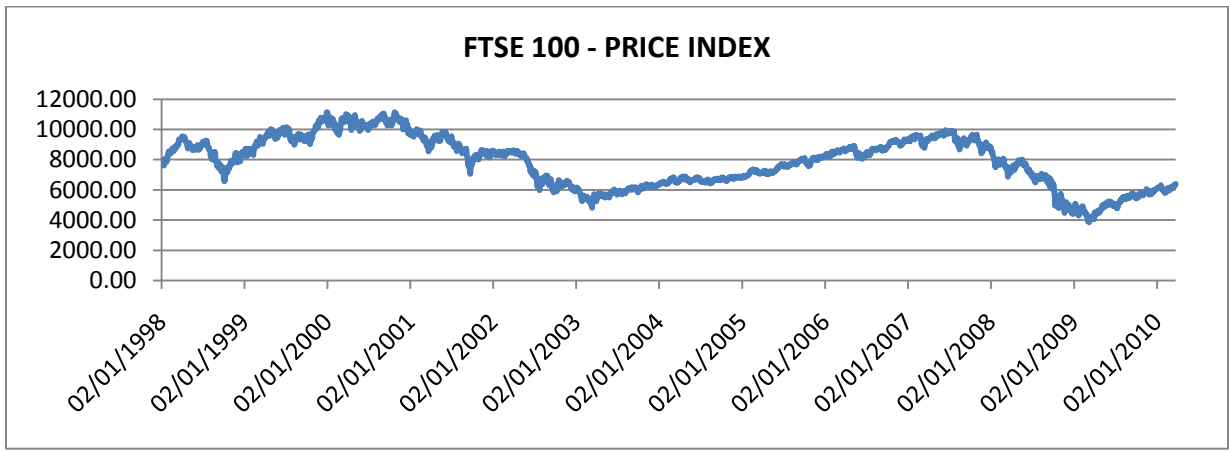
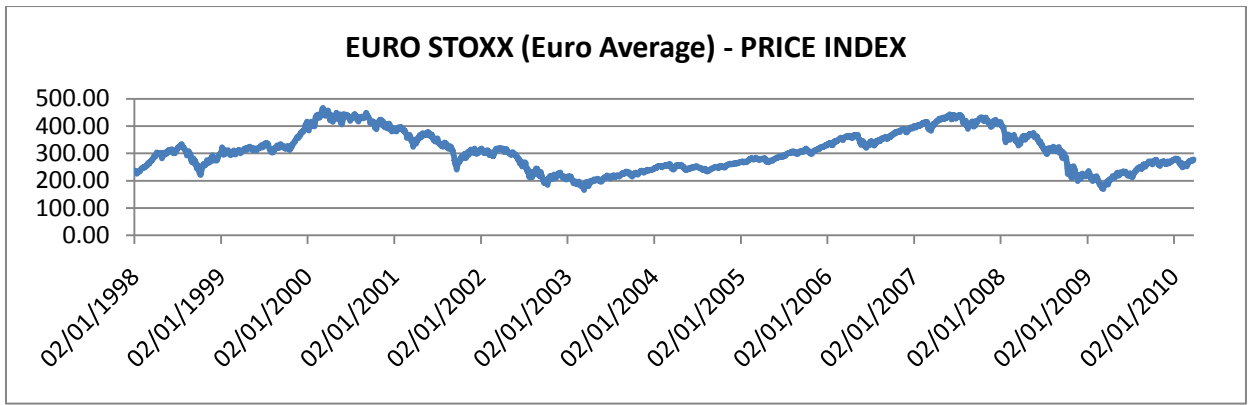
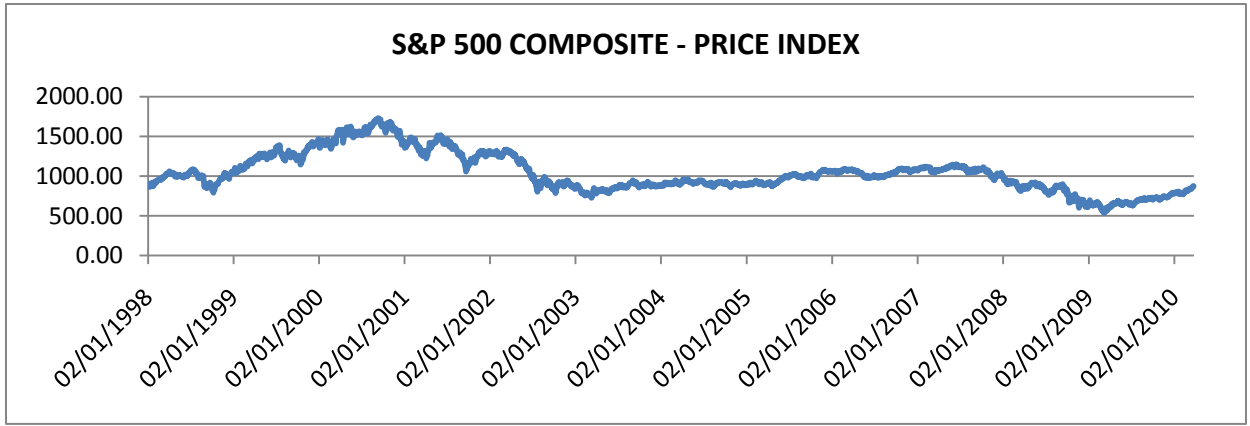
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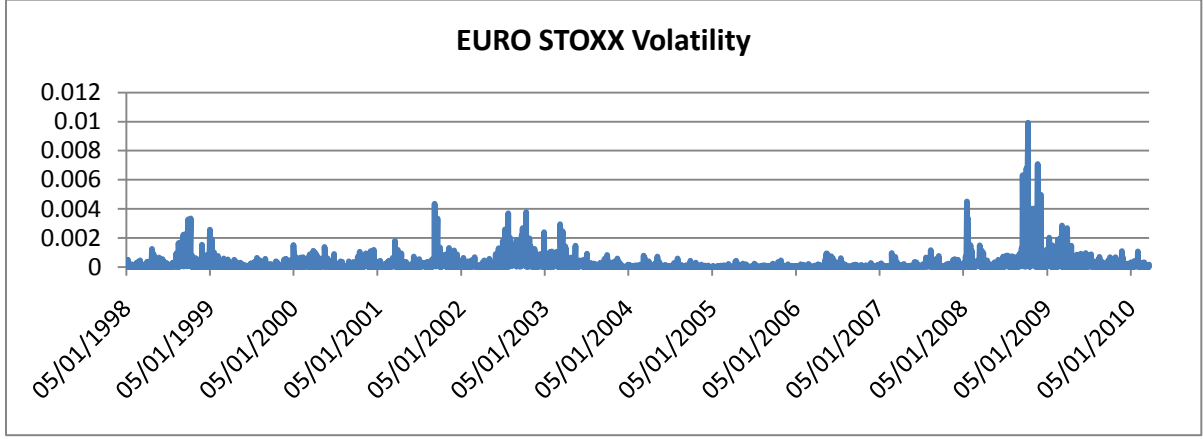
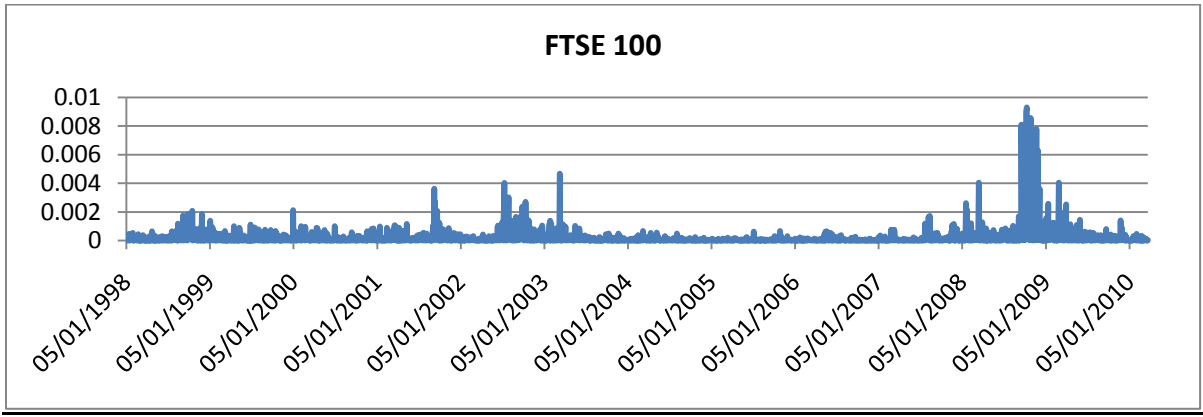
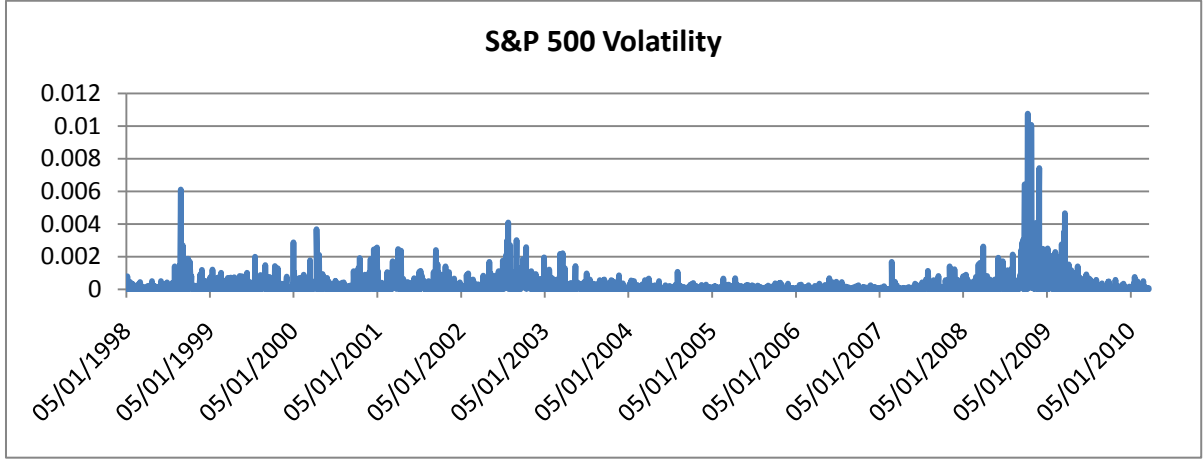
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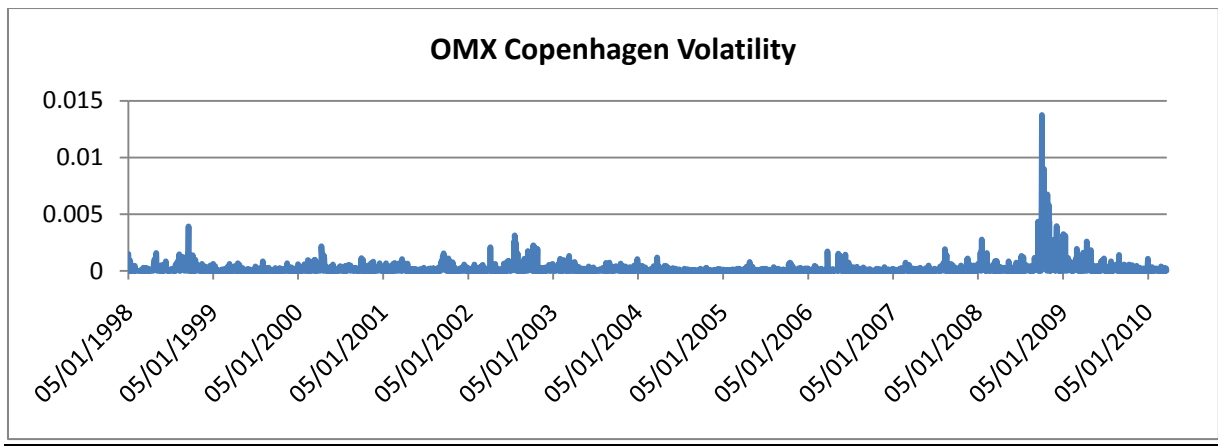
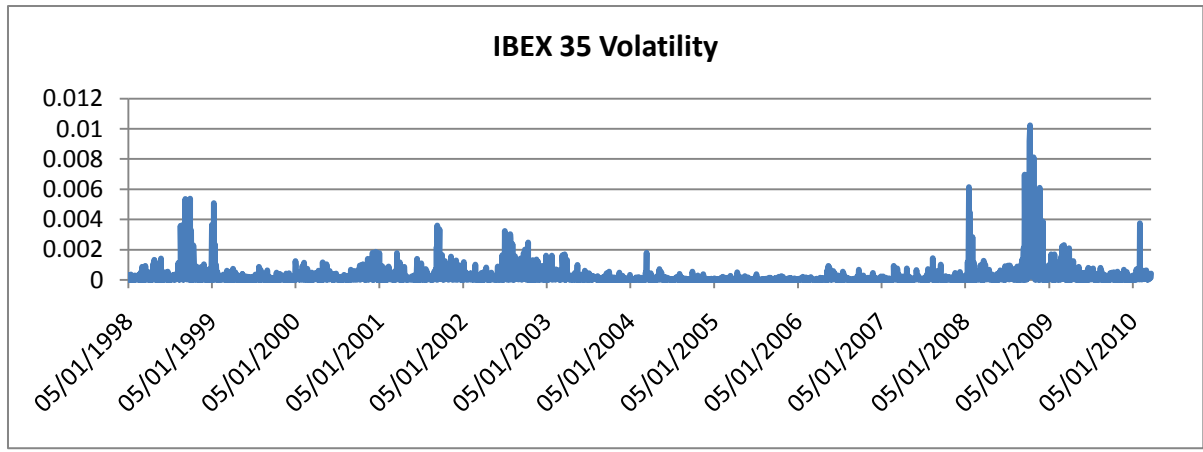
Graphs depicting the raw data (daily returns) for each stock market index.



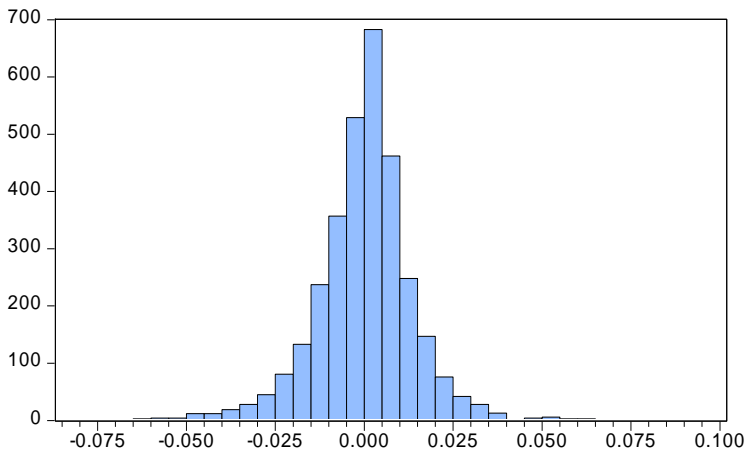


Volatility of each Return Series





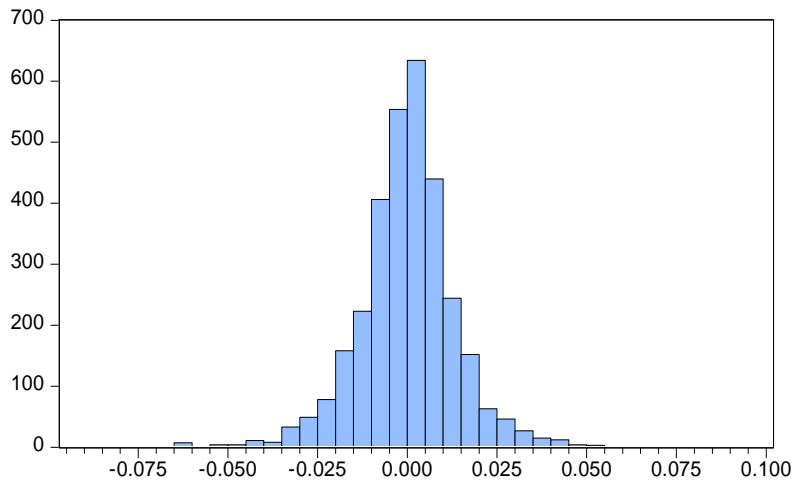
Correlogram and descriptive stats on each return series



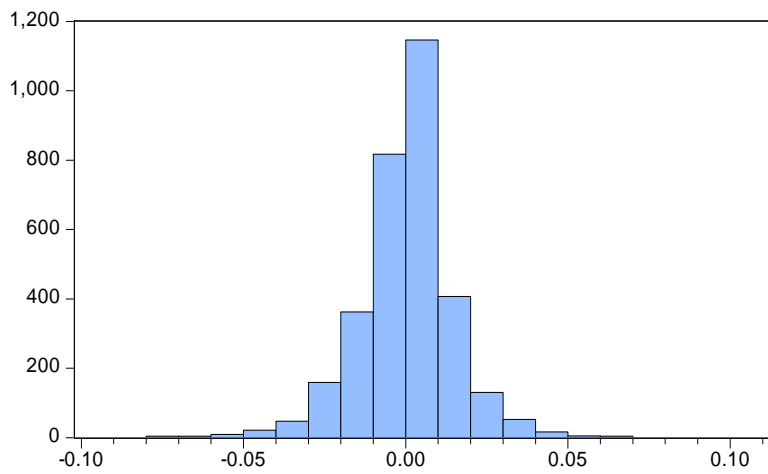
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 Sample 1/05/1998 3/25/2010
 Observations 3189

Mean	5.54e-05
Median	0.000487
Maximum	0.099621
Minimum	-0.082498
Std. Dev.	0.014219
Skewness	-0.127584
Kurtosis	7.323204

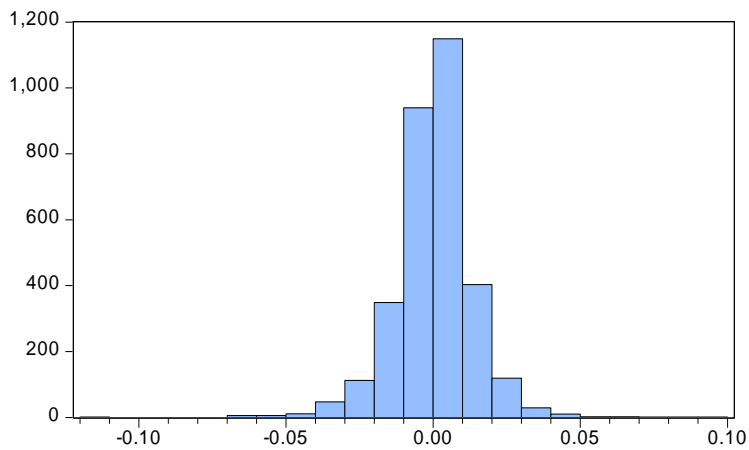
Jarque-Bera	2492.098
Probability	0.000000



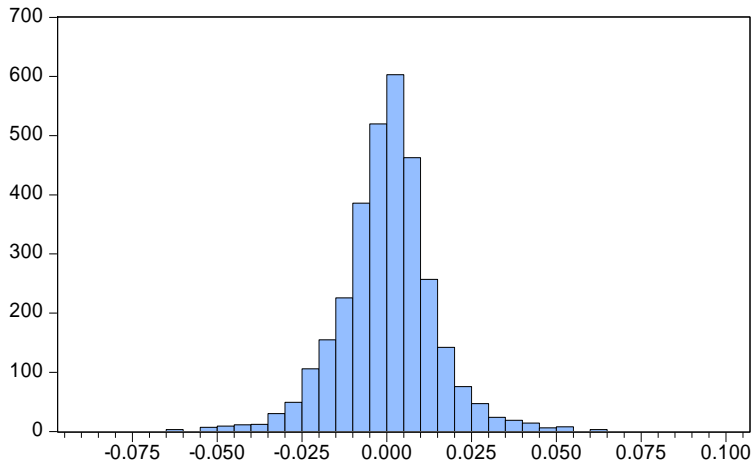
Series: FTSE_100__PRICE_INDEX	
Sample 1/05/1998 3/25/2010	
Observations 3189	
Mean	-6.40e-05
Median	0.000125
Maximum	0.096474
Minimum	-0.094801
Std. Dev.	0.014231
Skewness	-0.097875
Kurtosis	8.303139
Jarque-Bera	3741.973
Probability	0.000000



Series: IBEX_35__PRICE__	
Sample 1/05/1998 3/25/2010	
Observations 3189	
Mean	0.000125
Median	0.000475
Maximum	0.101176
Minimum	-0.095859
Std. Dev.	0.014982
Skewness	-0.149229
Kurtosis	7.488829
Jarque-Bera	2689.213
Probability	0.000000



Series: OMX_COPENHAGEN__OMXC20__	
Sample 1/05/1998 3/25/2010	
Observations 3189	
Mean	0.000187
Median	0.000000
Maximum	0.094964
Minimum	-0.117232
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Probability	0.000000

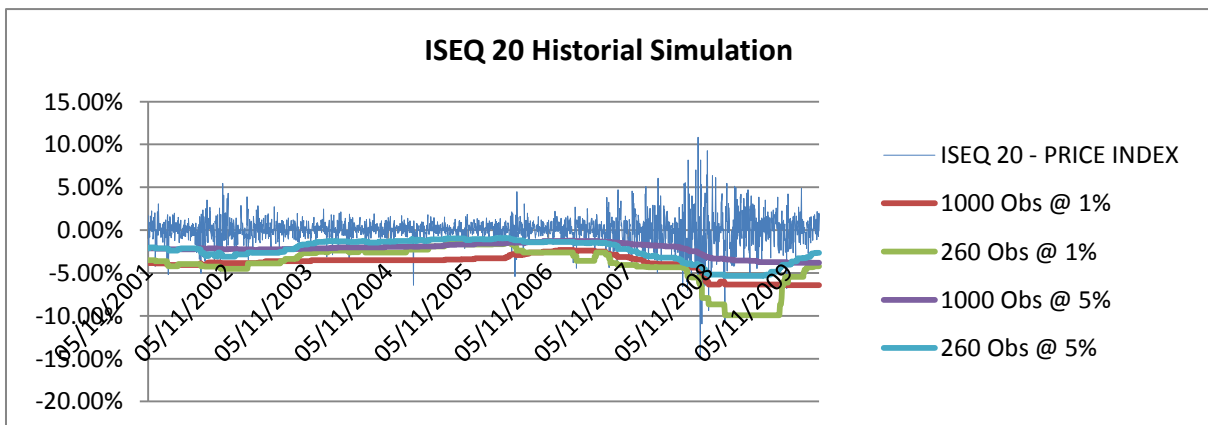
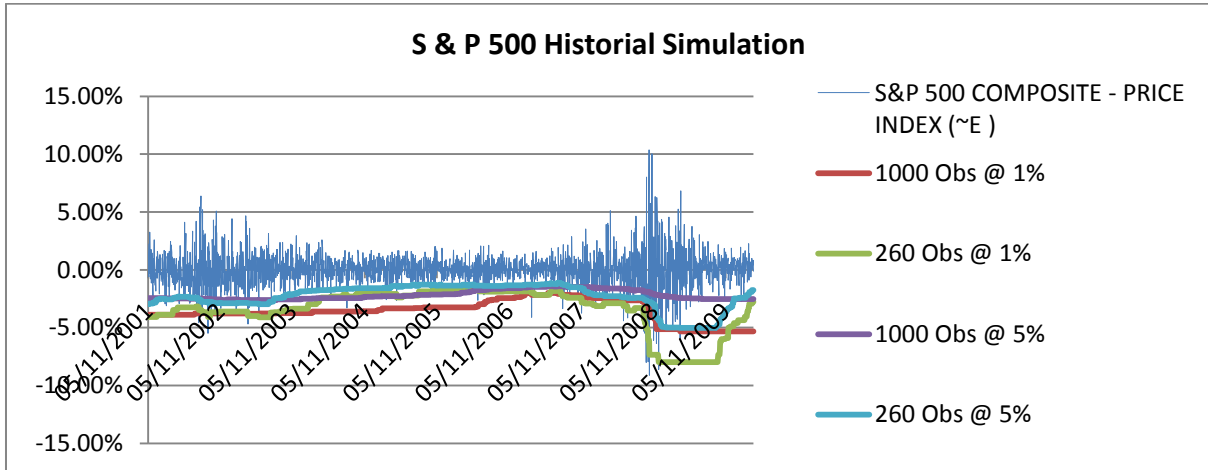


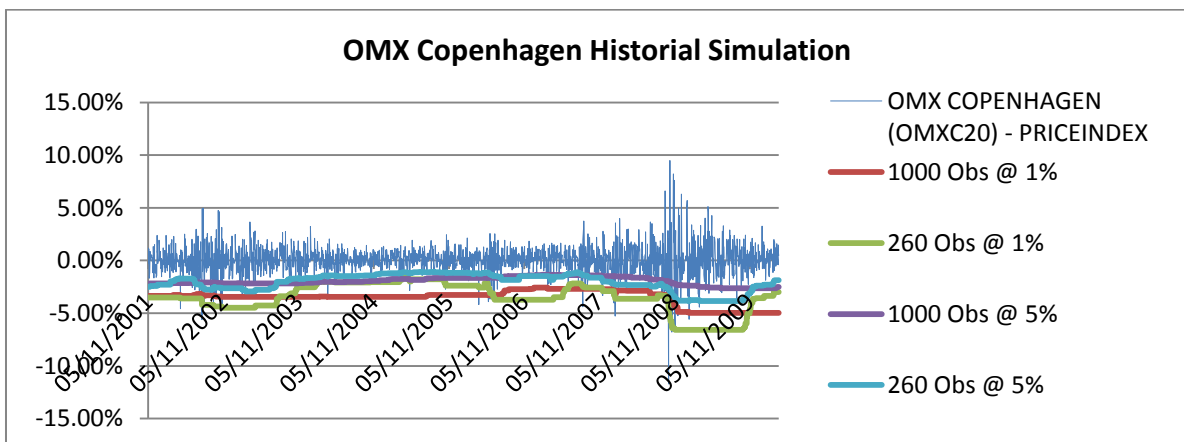
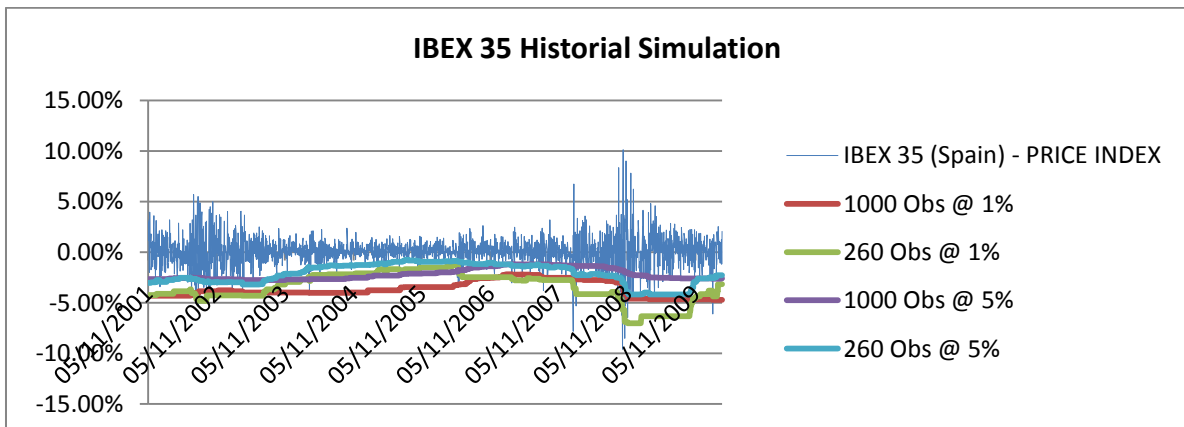
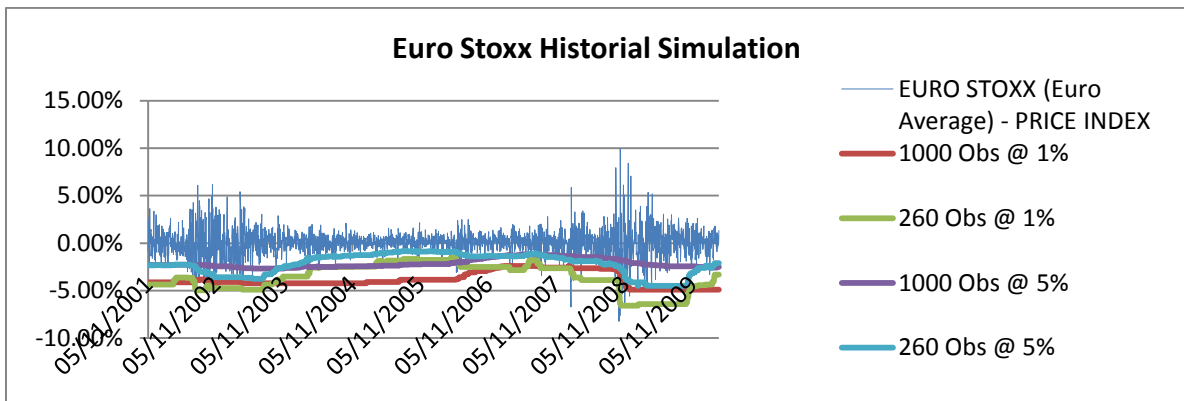
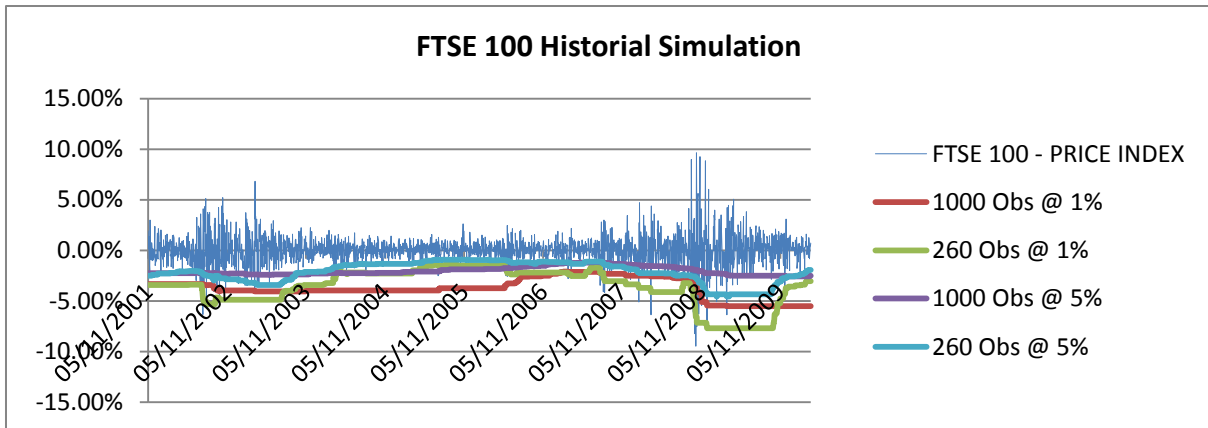
Series: S_P_500_COMPOSITE__PRIC
 Sample 1/05/1998 3/25/2010
 Observations 3189

Mean	-8.13e-06
Median	0.000304
Maximum	0.103675
Minimum	-0.091080
Std. Dev.	0.014910
Skewness	-0.065874
Kurtosis	7.684254
Jarque-Bera	2917.881
Probability	0.000000

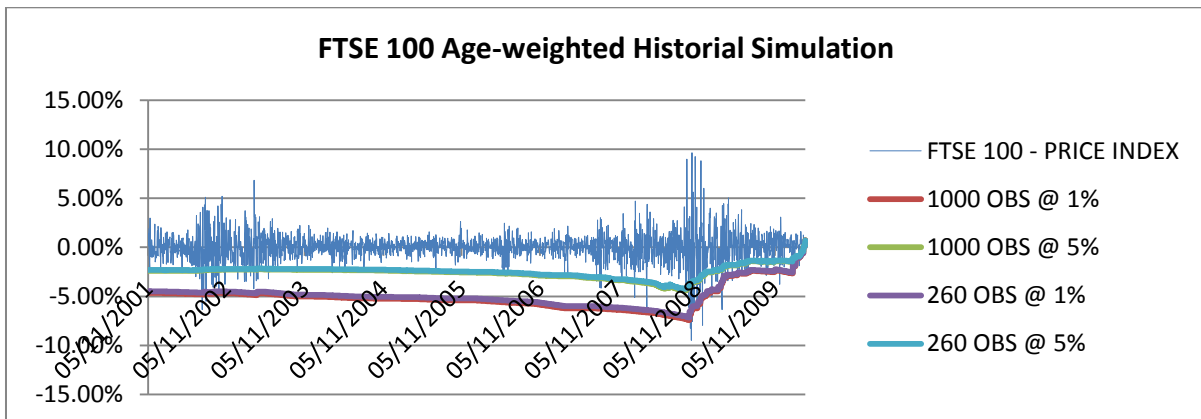
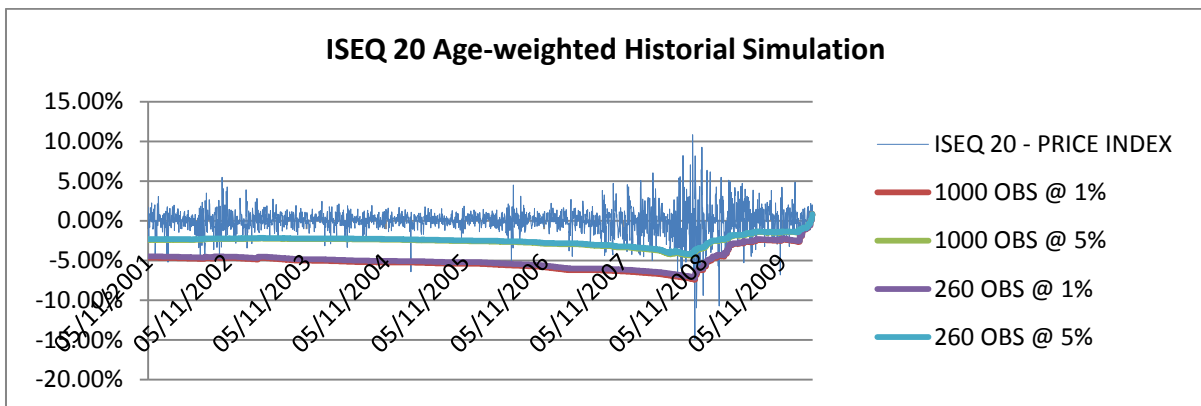
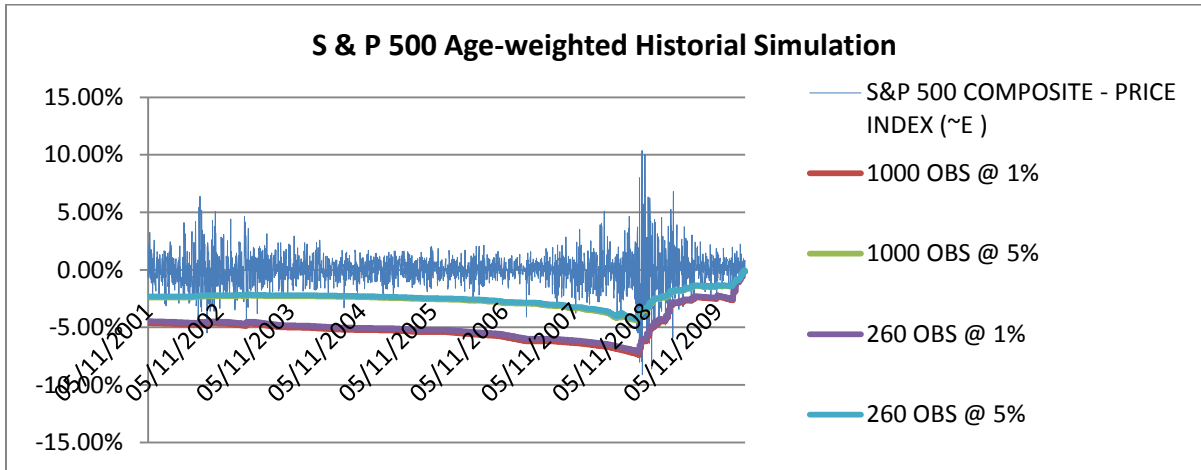
Graphs depicting VaR

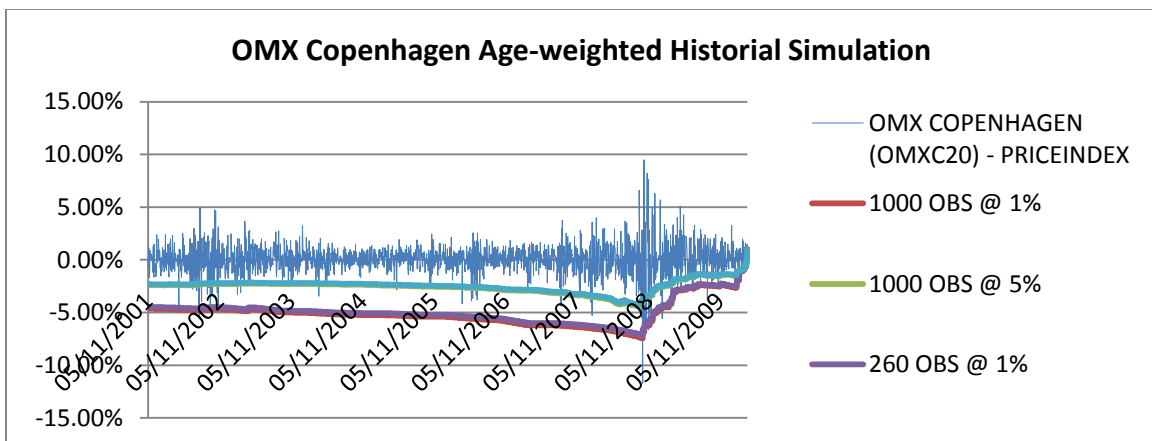
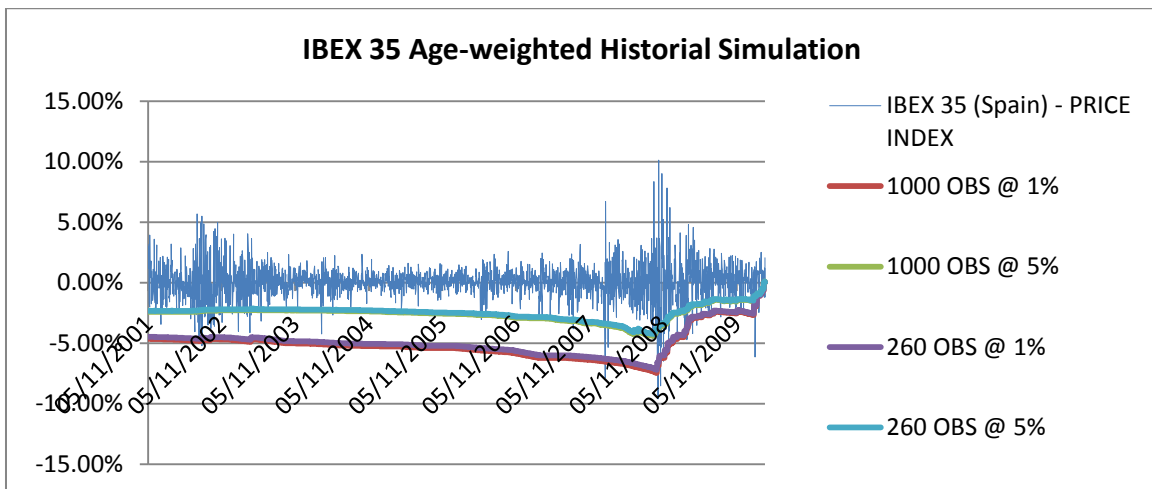
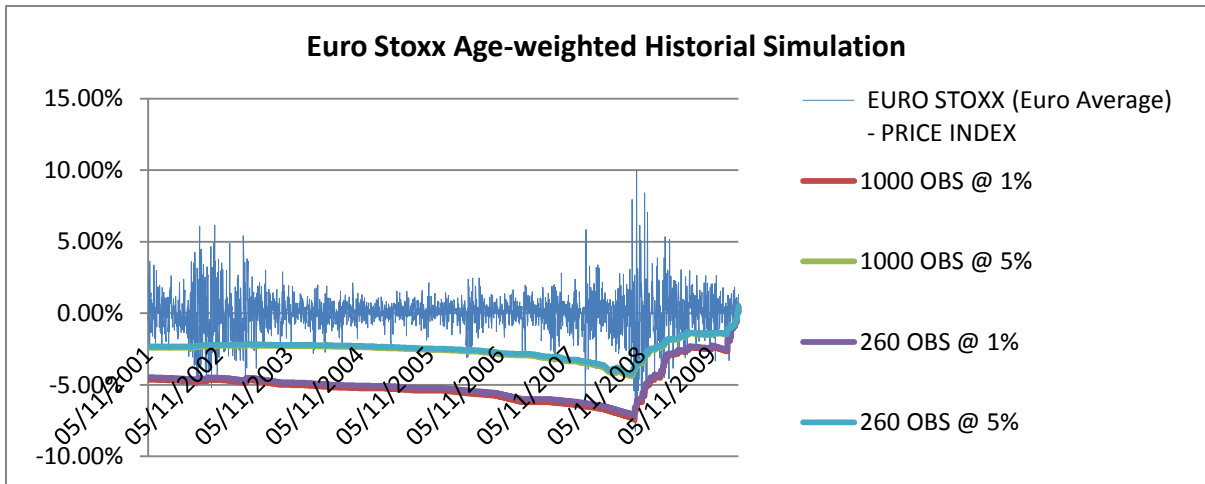
Historical Simulation (unfiltered)



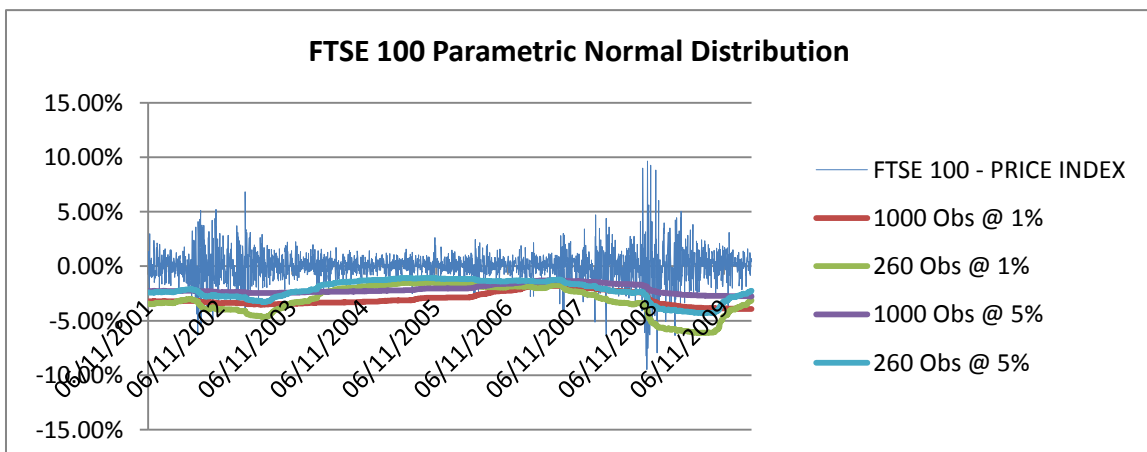
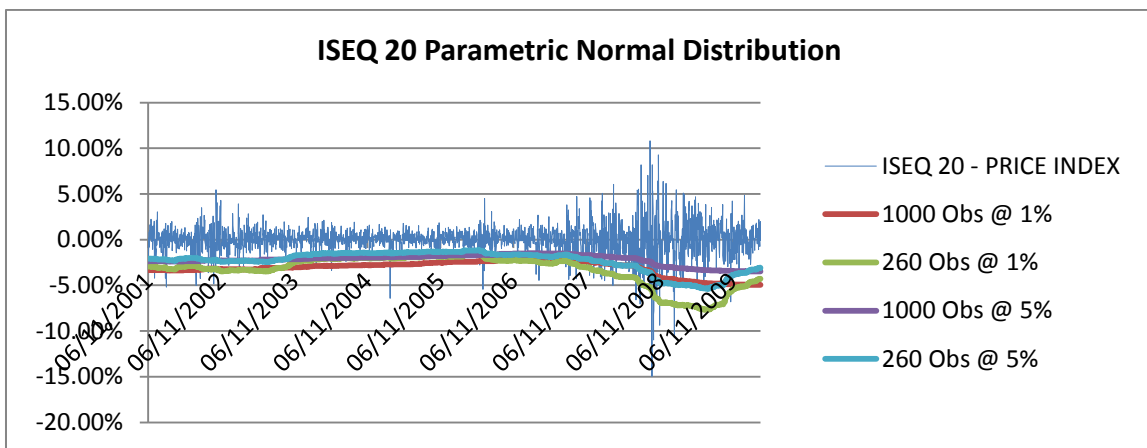
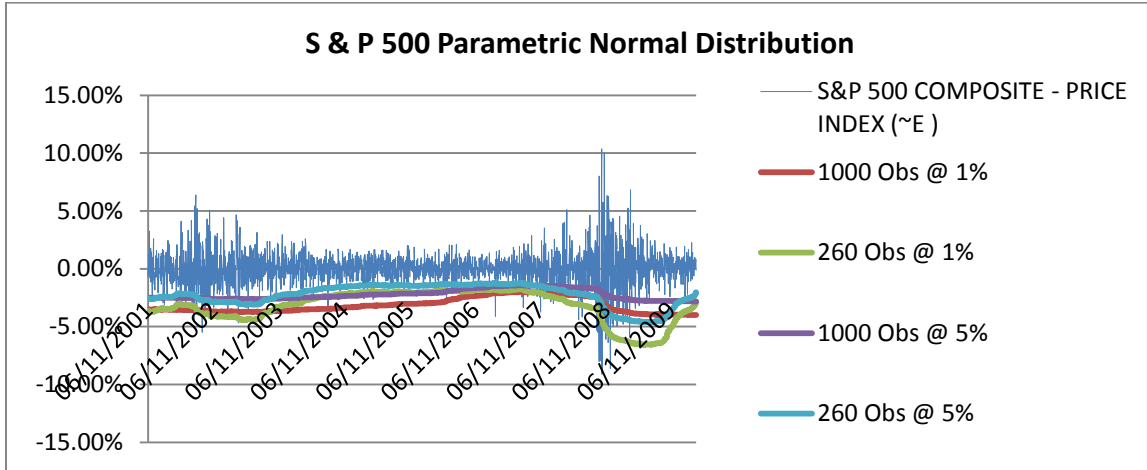


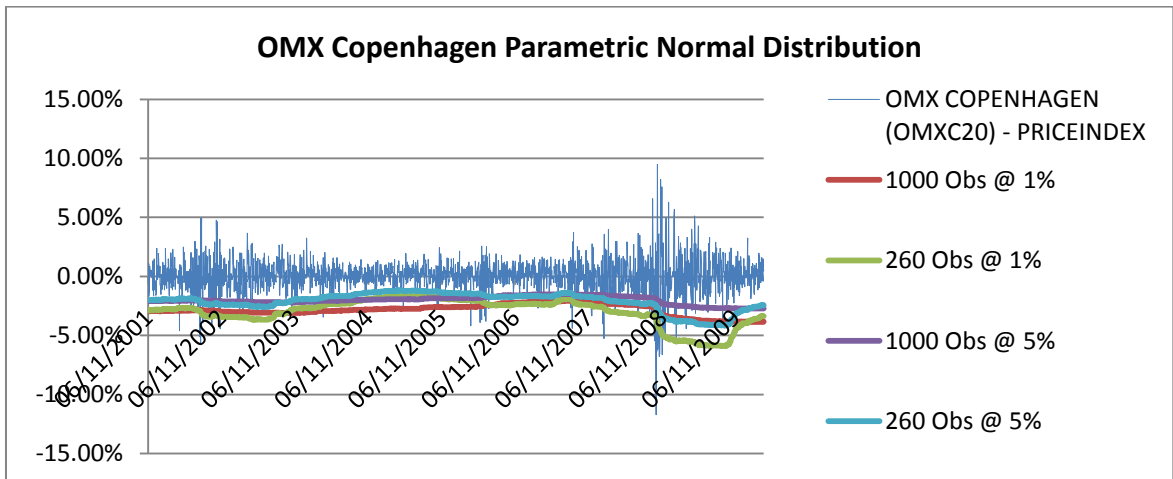
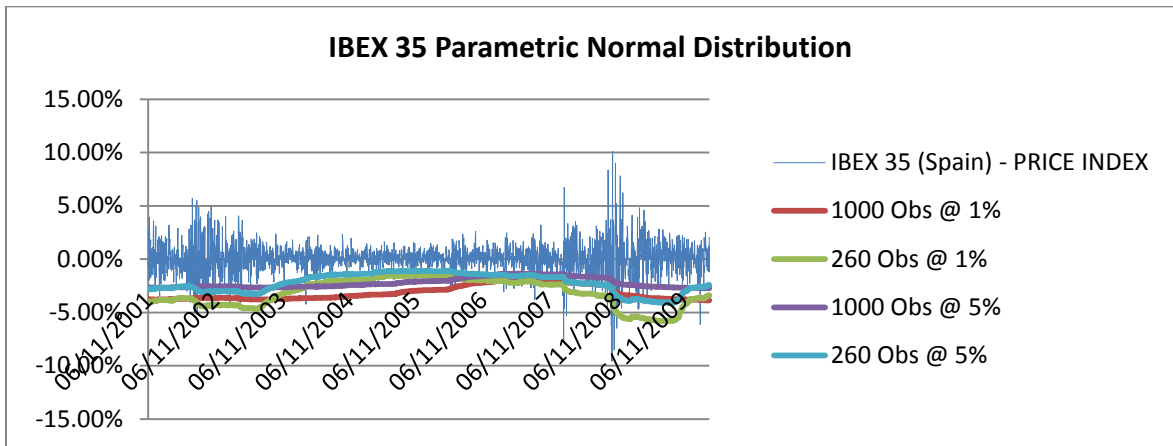
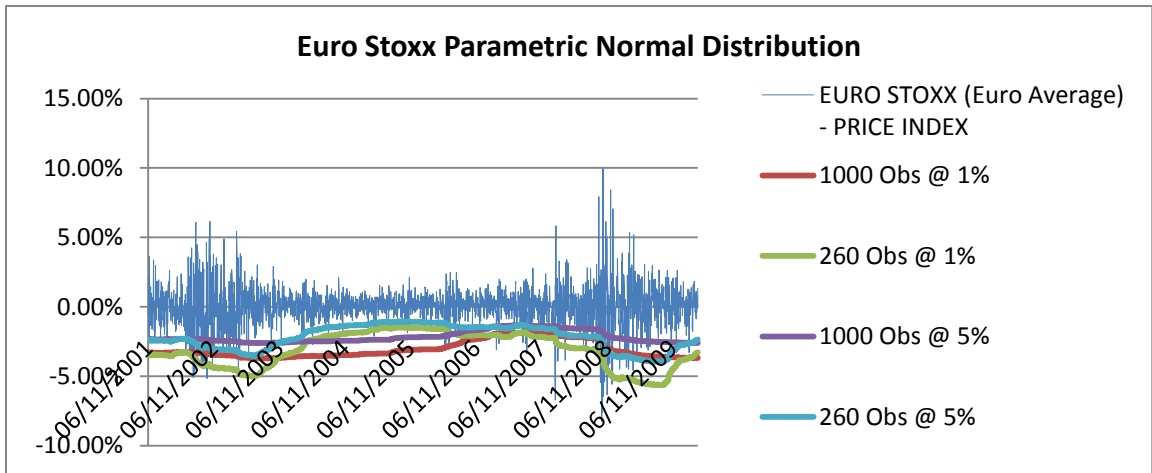
Age-weighted Historical Simulation (unfiltered)



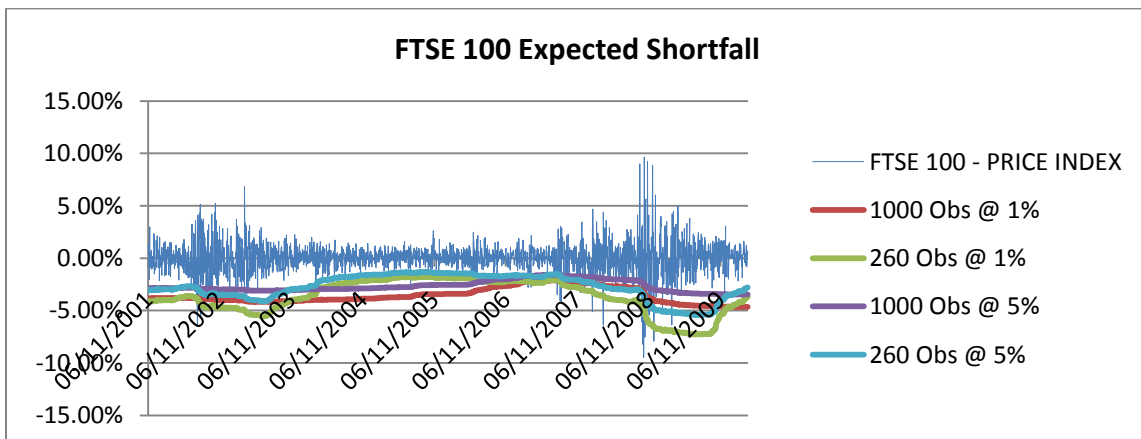
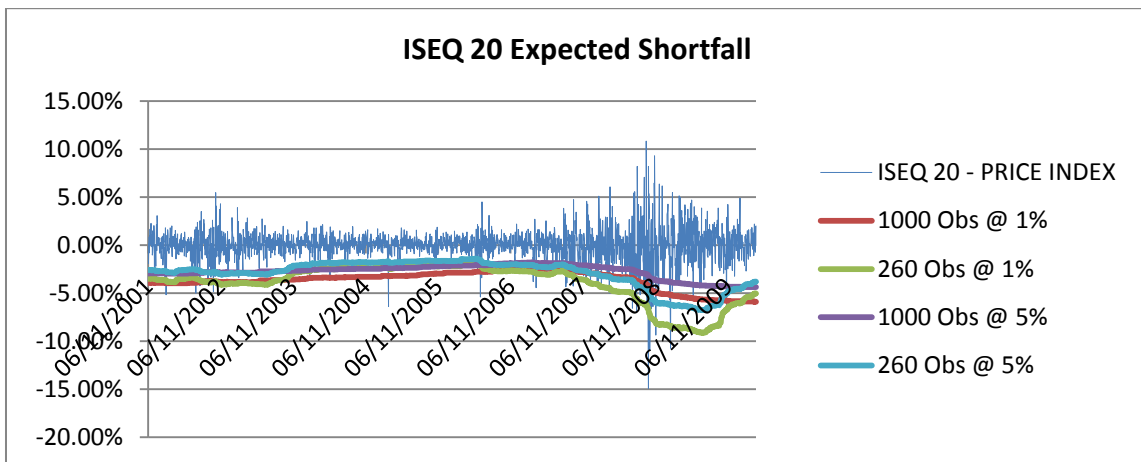
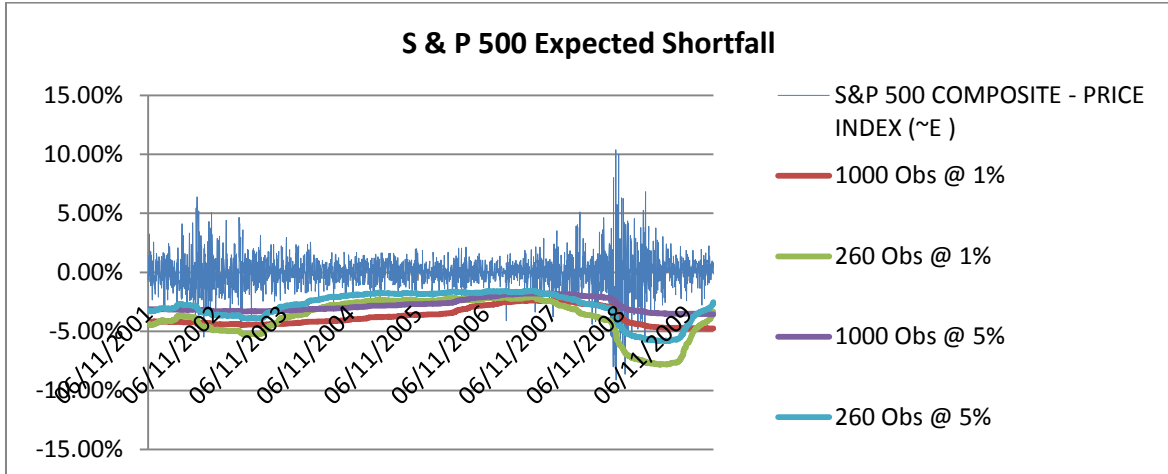


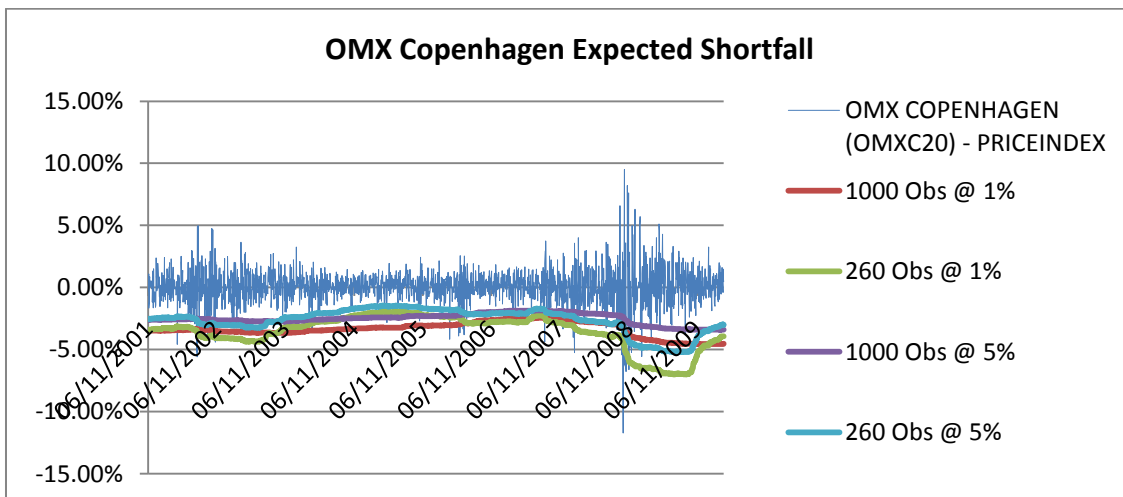
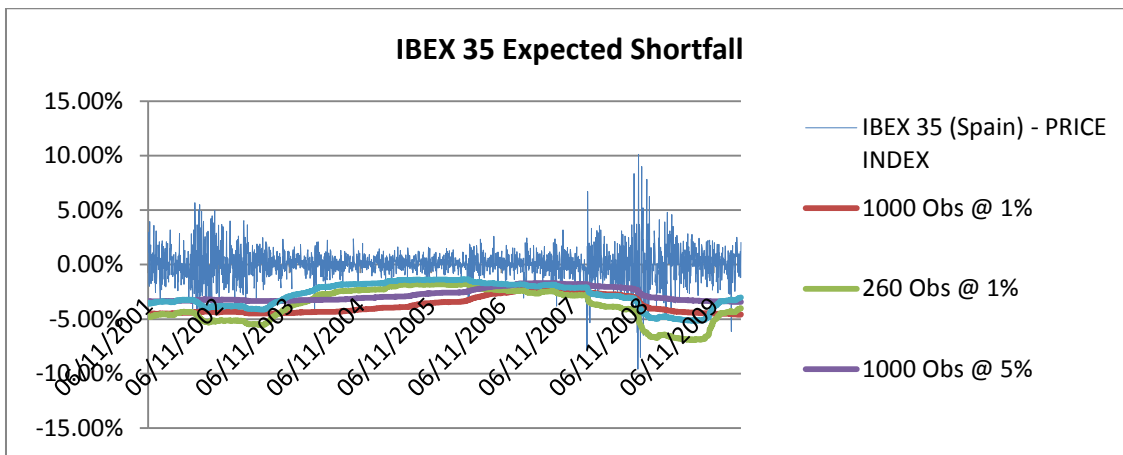
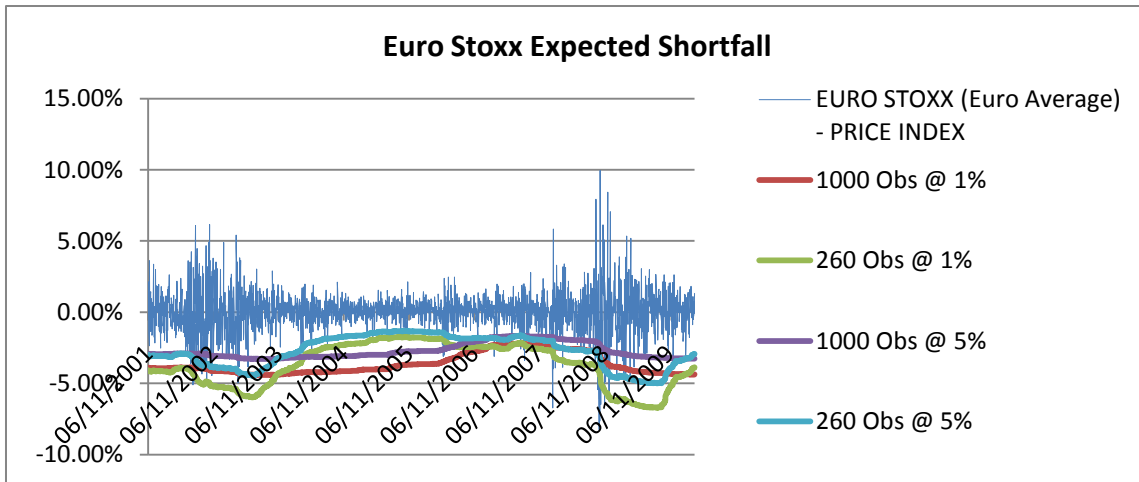
Parametric Normal Distribution (unfiltered)



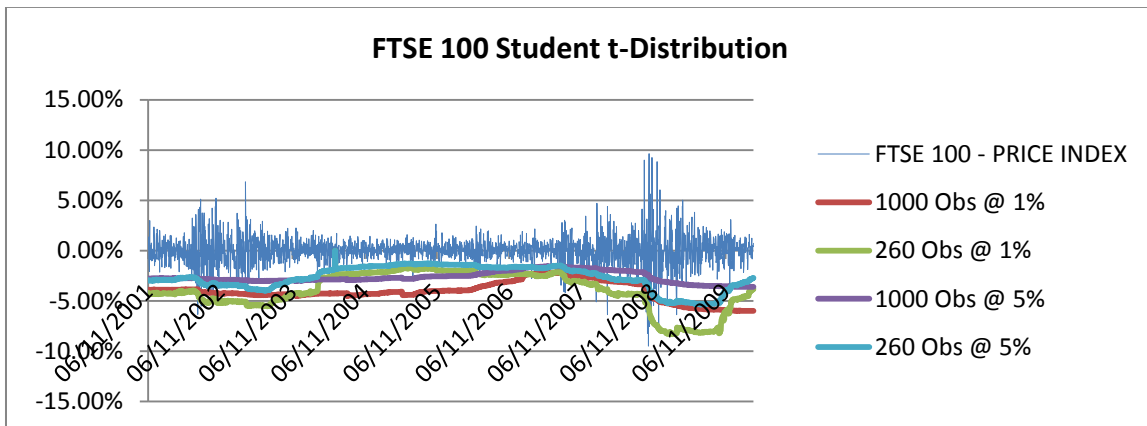
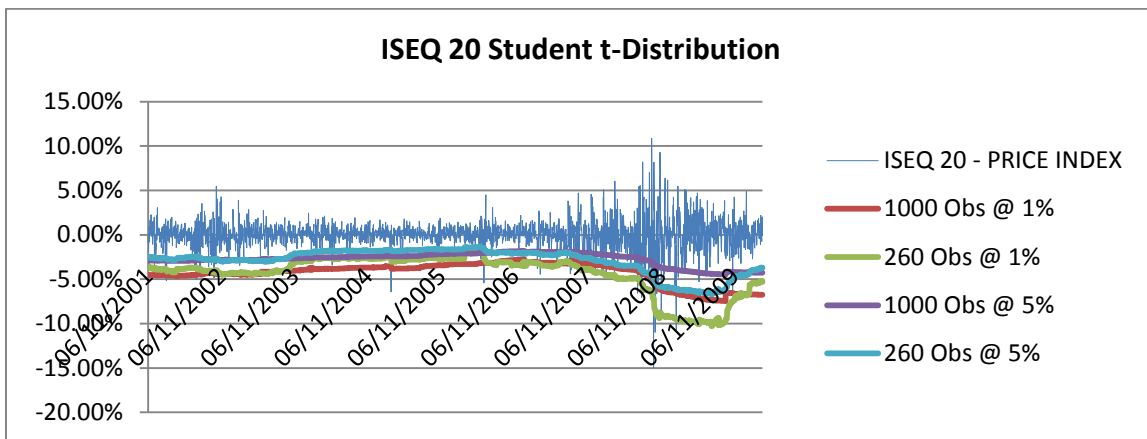
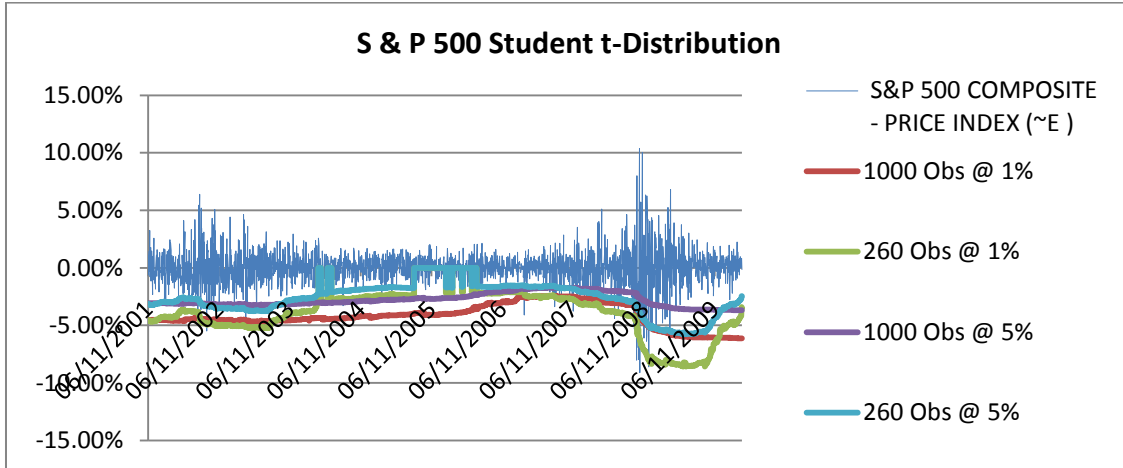


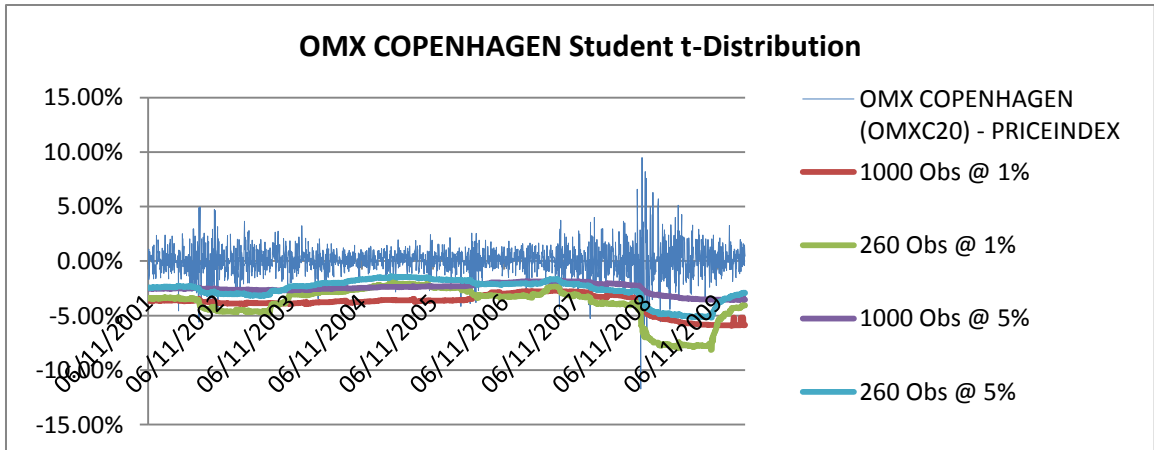
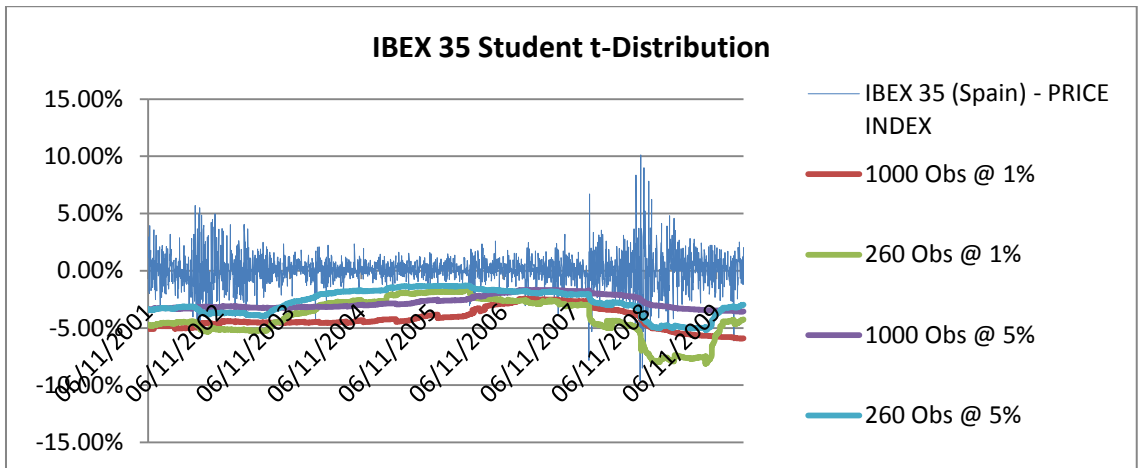
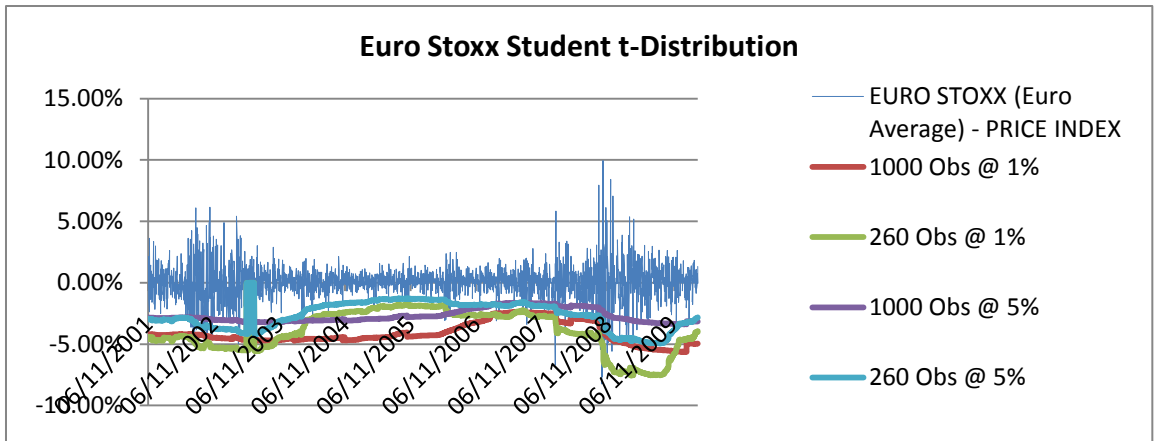
Expected Shortfall (unfiltered)



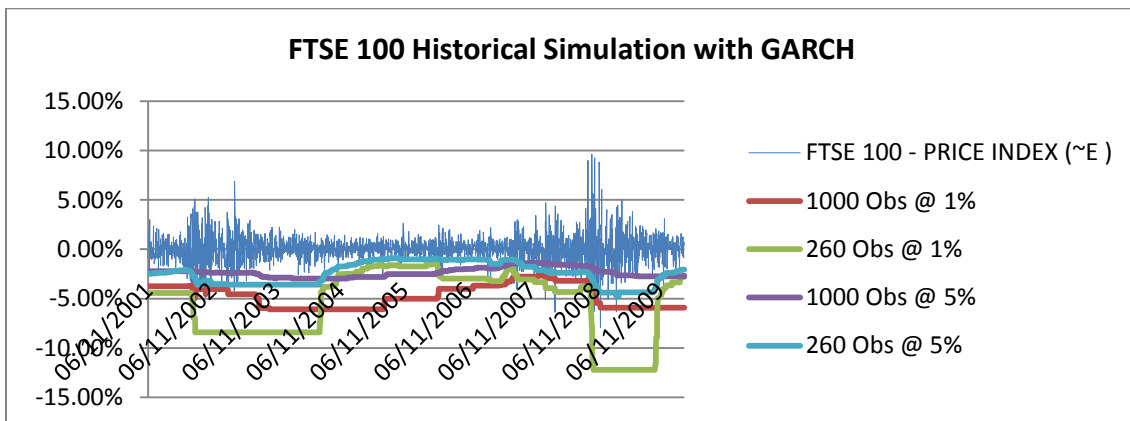
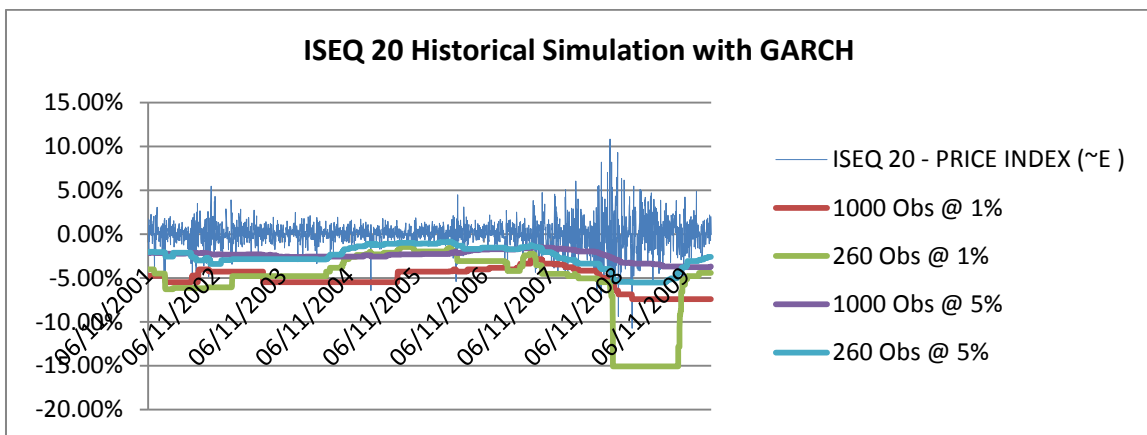
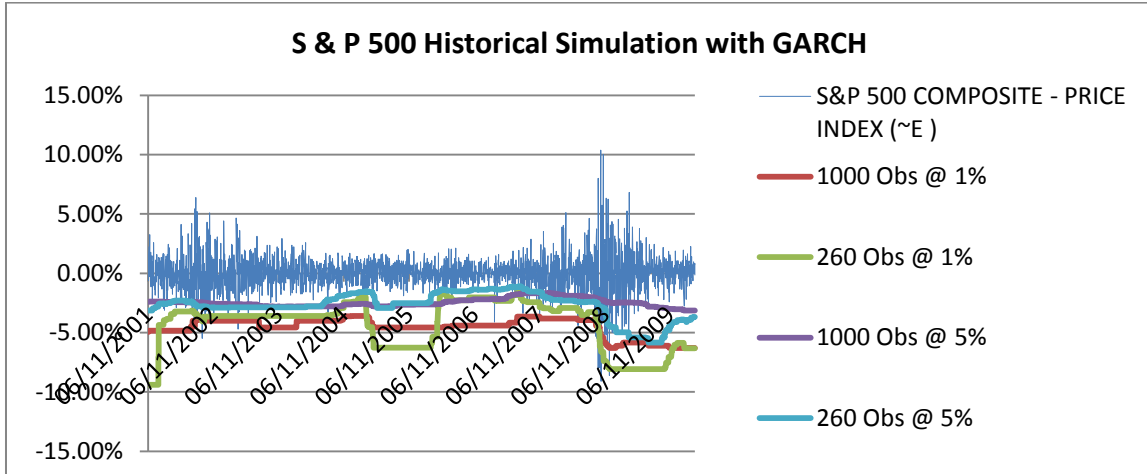


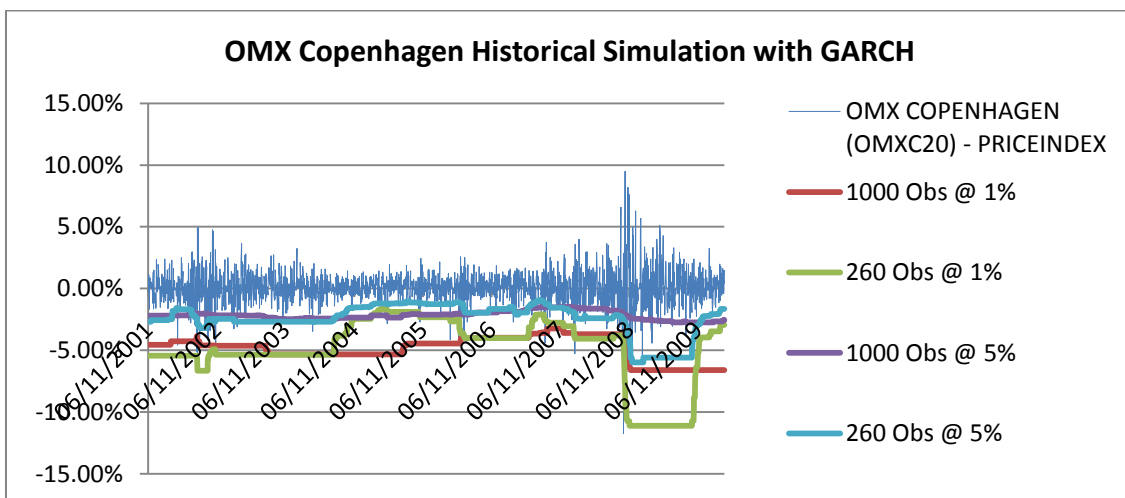
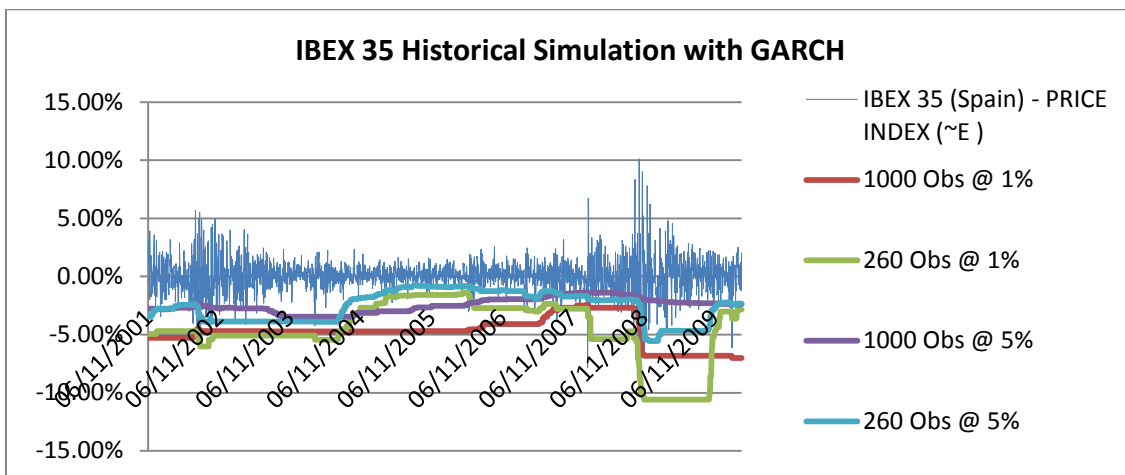
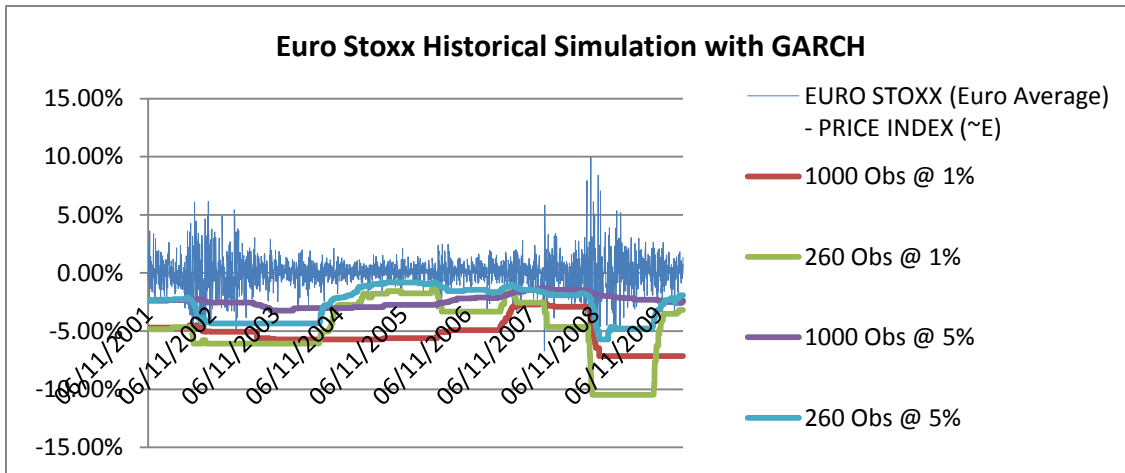
Student t-Distribution (unfiltered)



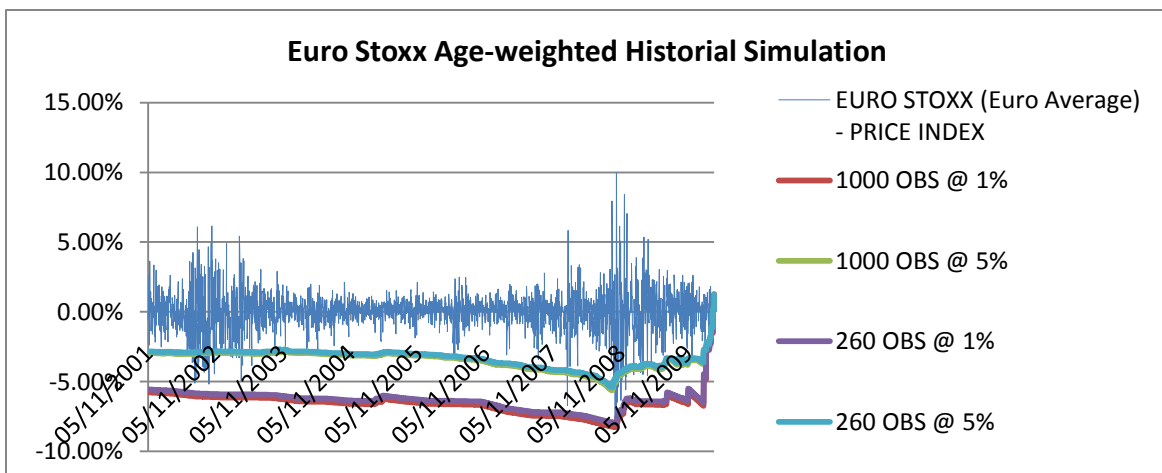
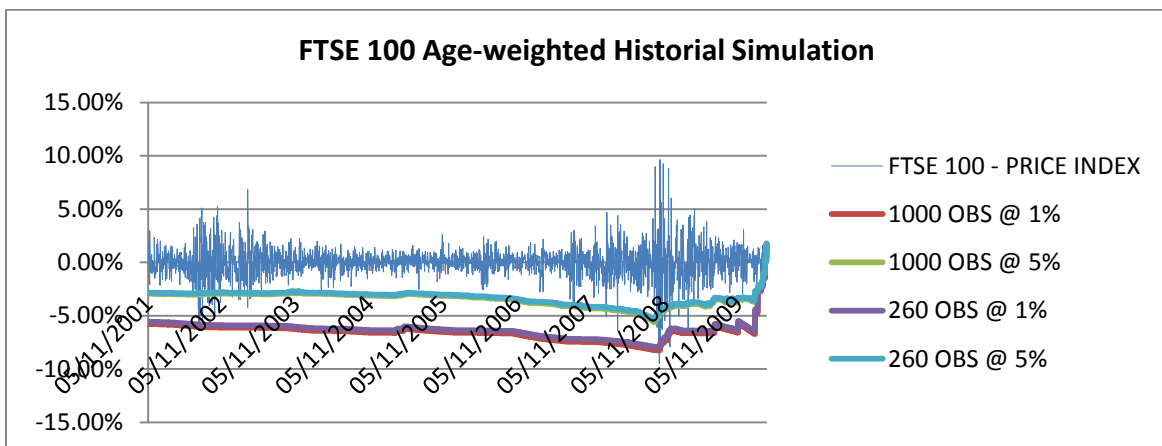
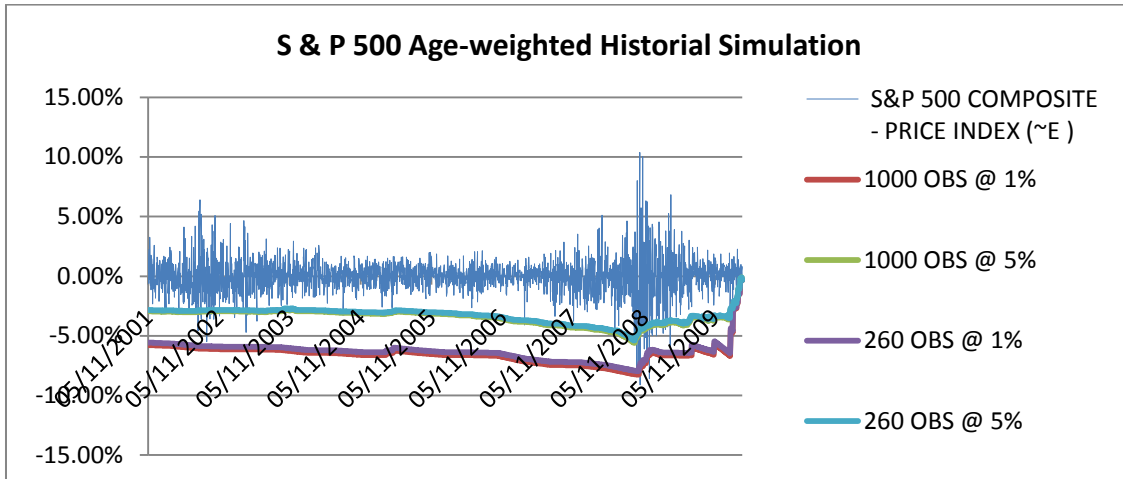


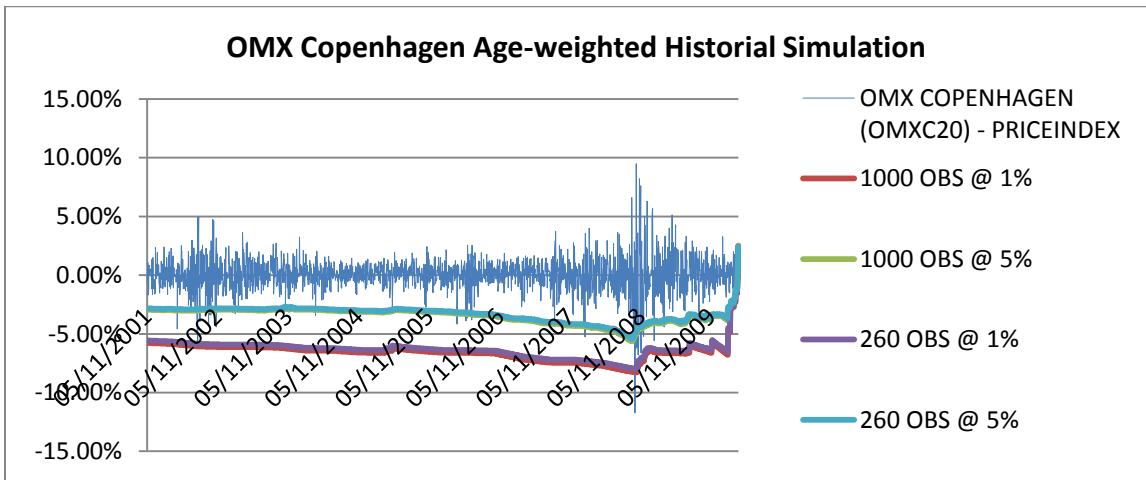
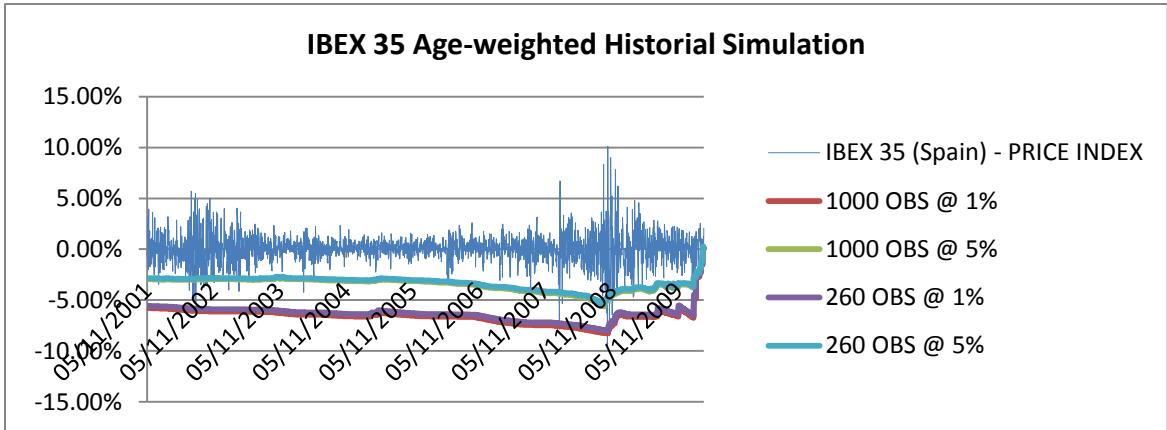
Historical Simulation (GARCH Filtered)



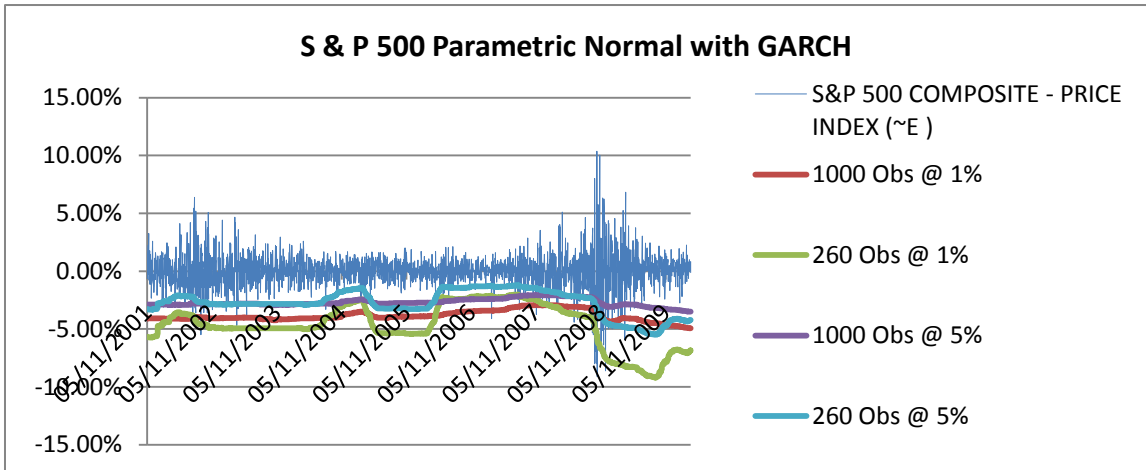


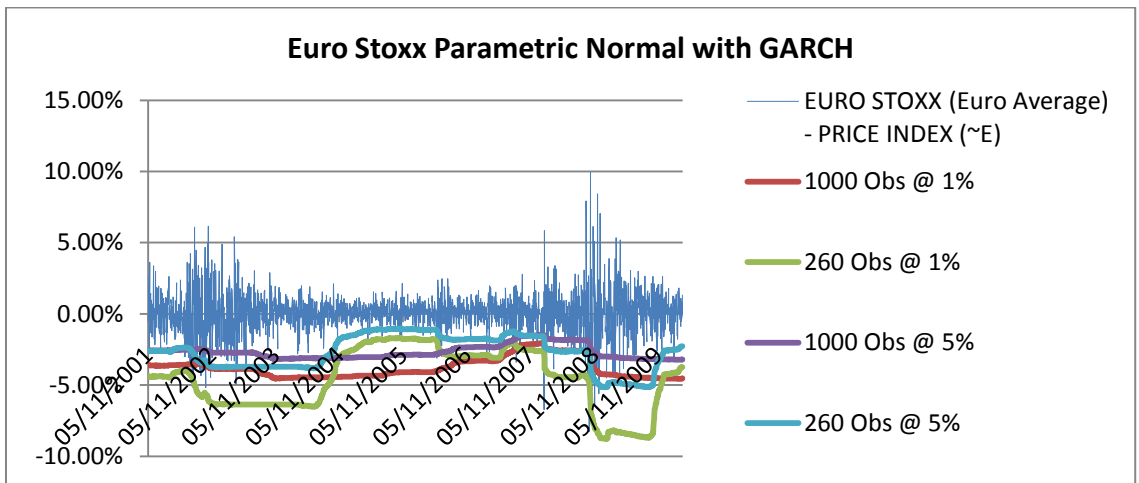
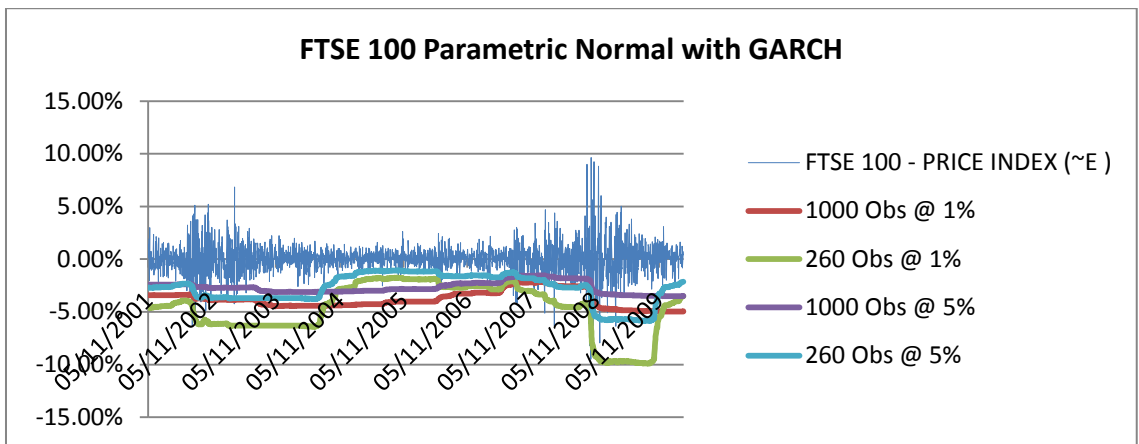
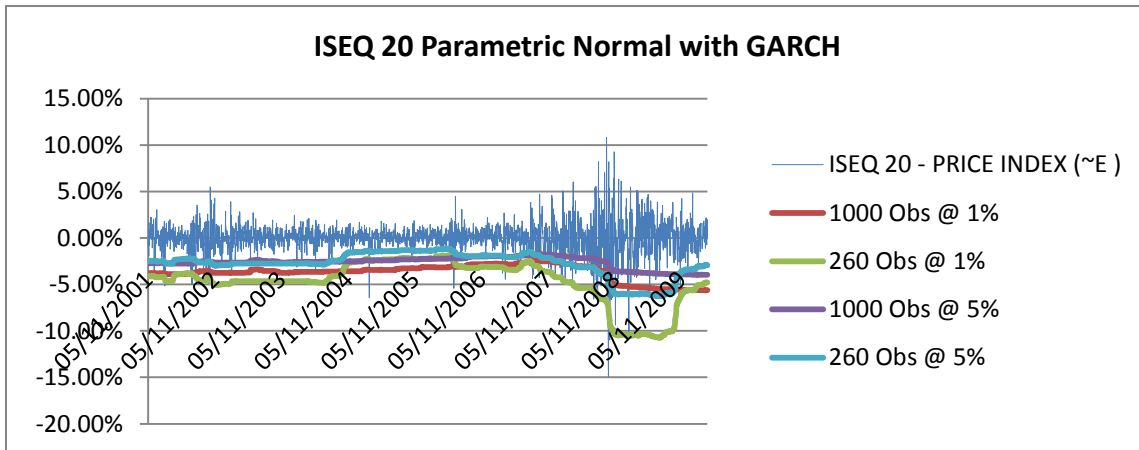
Age-Weighted Historical Simulation (GARCH filtered)

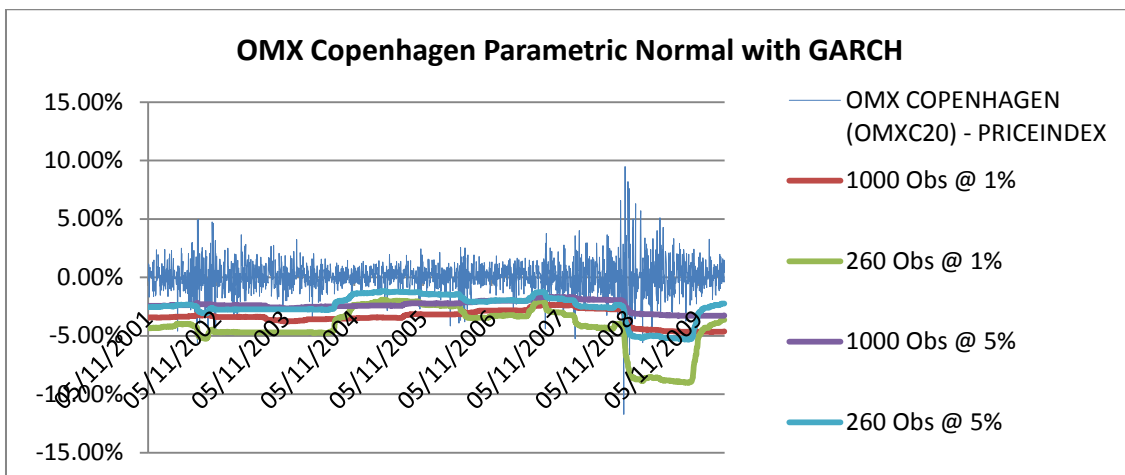
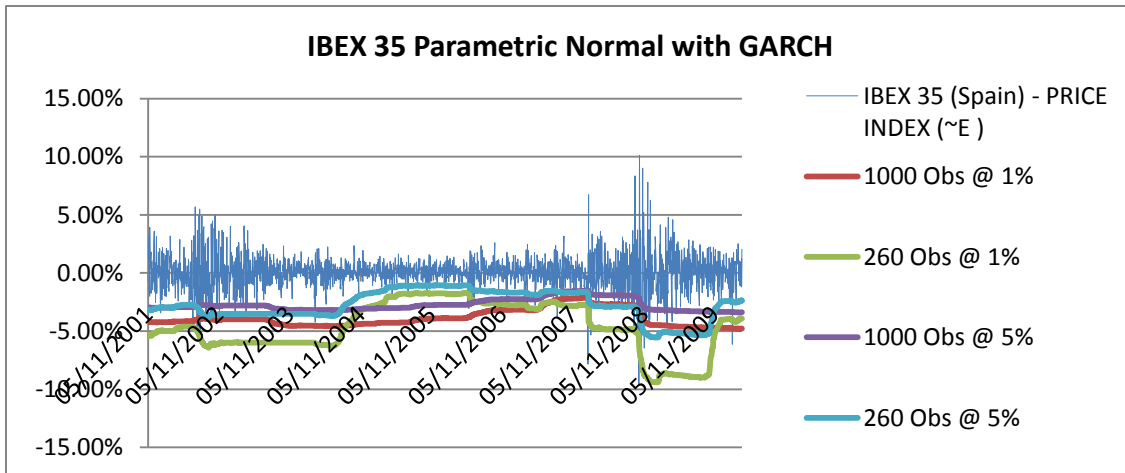




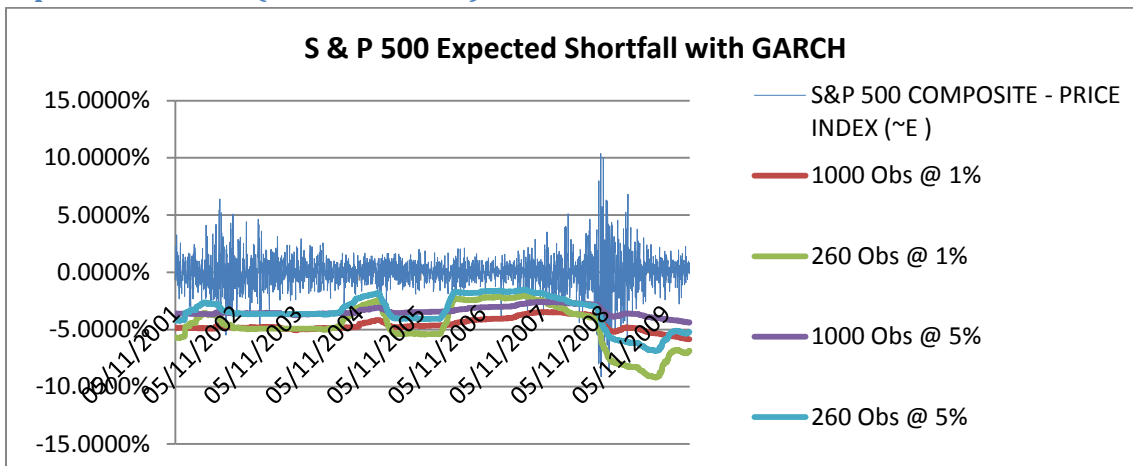
Parametric Normal Distribution (GARCH filtered)

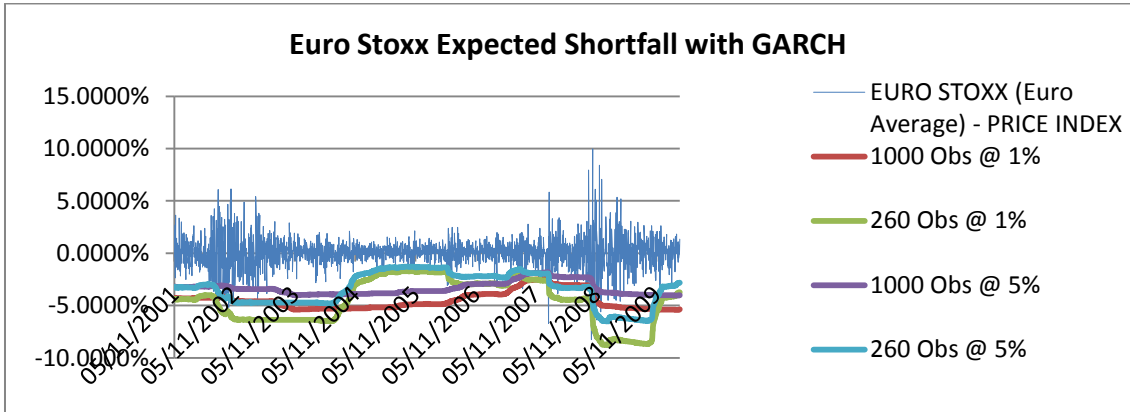
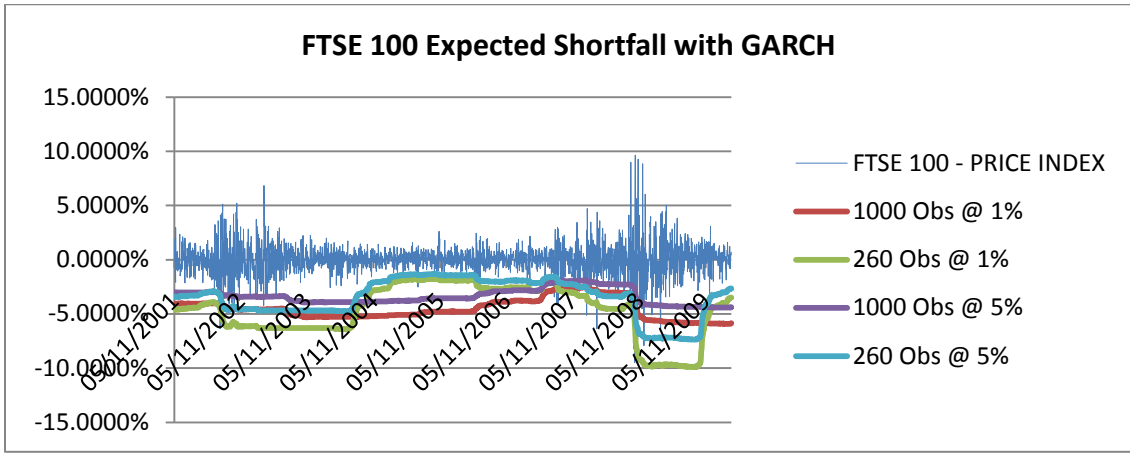
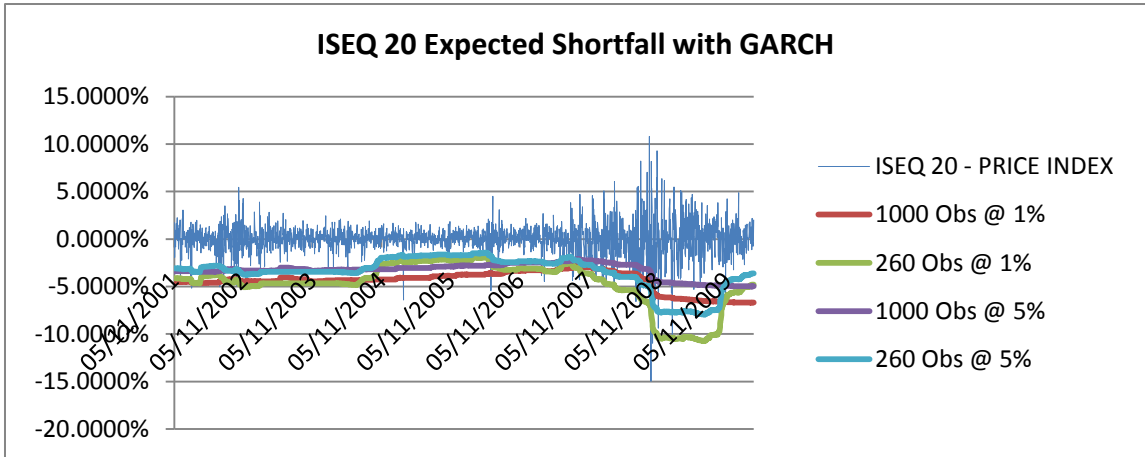


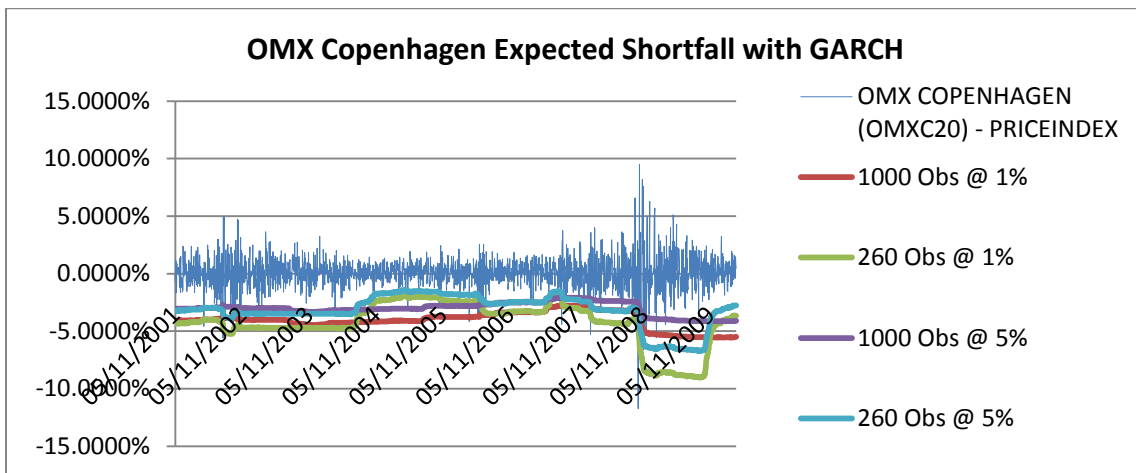
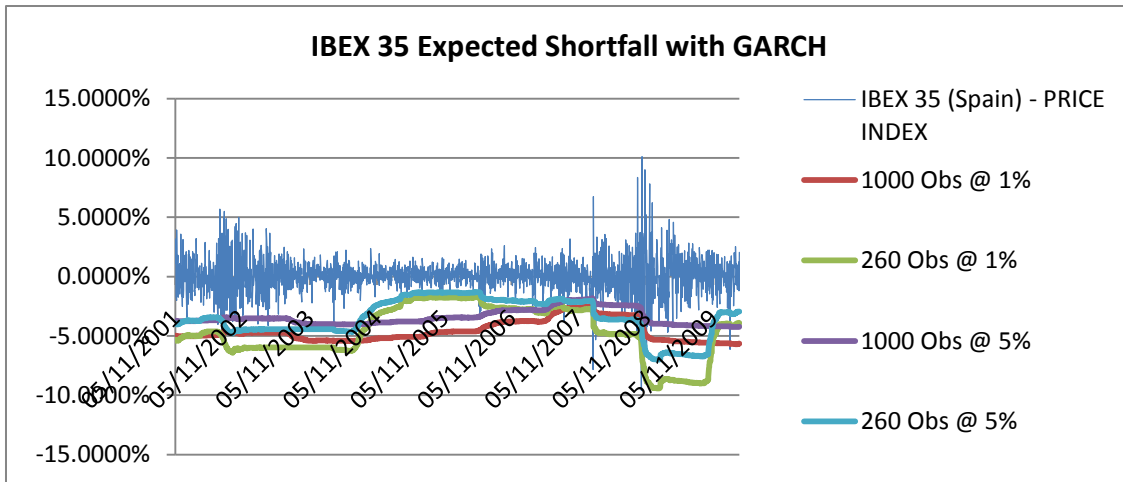




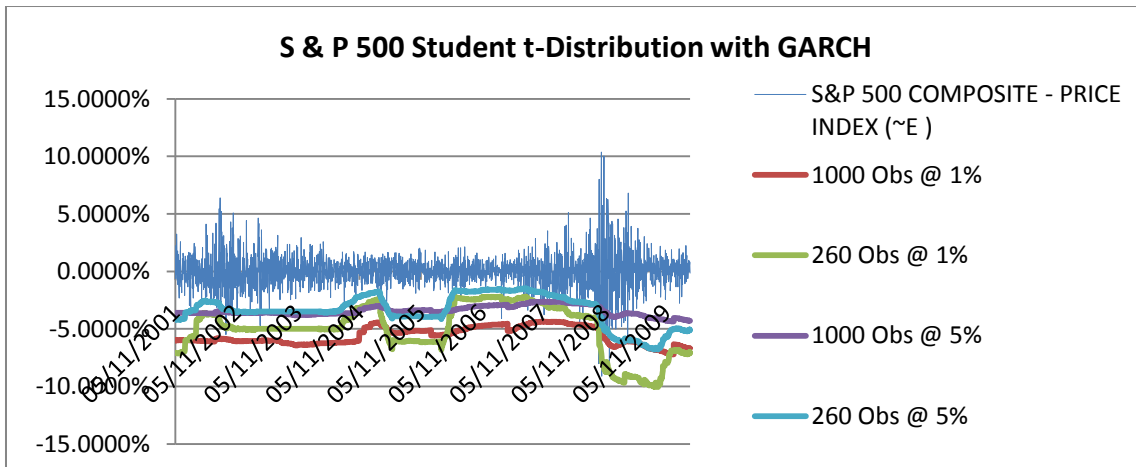
Expected Shortfall (GARCH filtered)

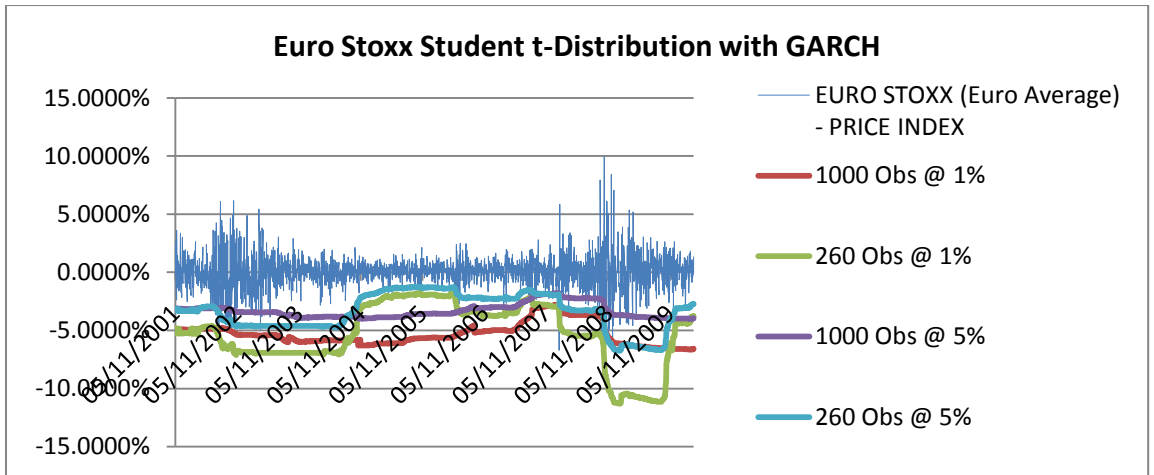
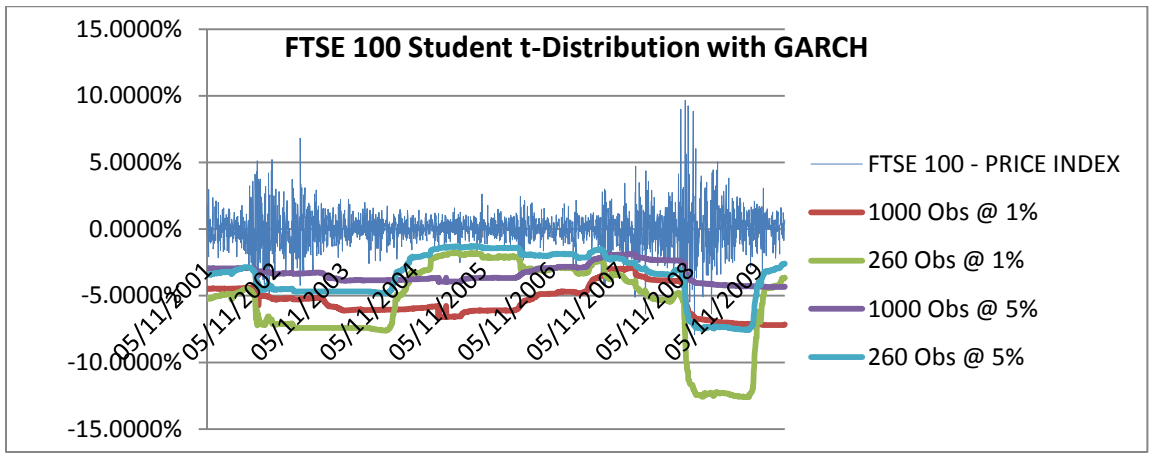
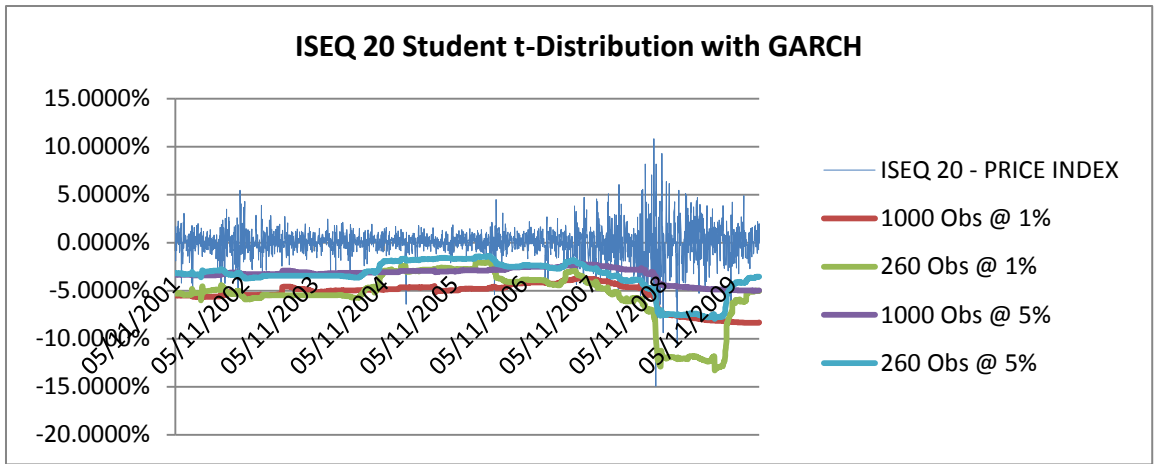


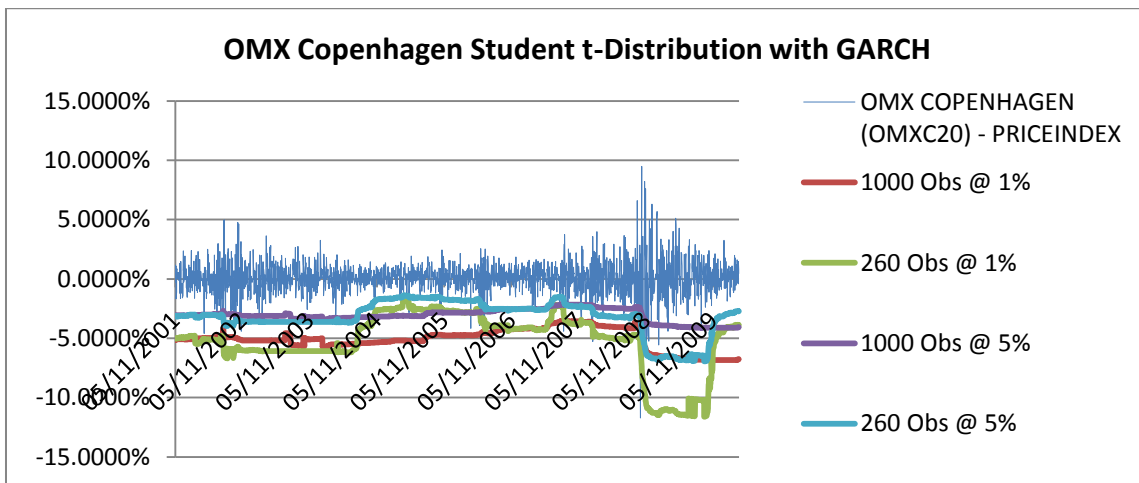
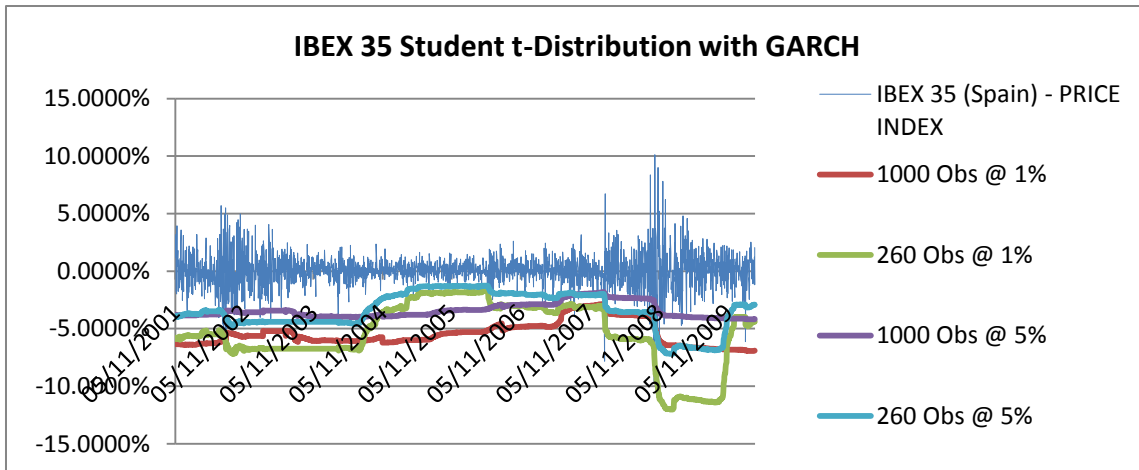




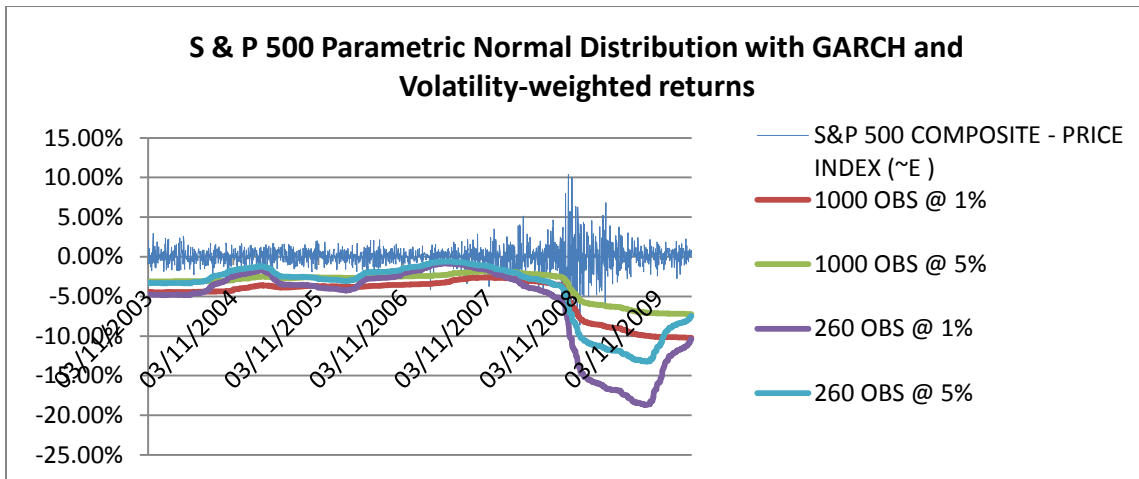
Student t-Distribution (GARCH filtered)



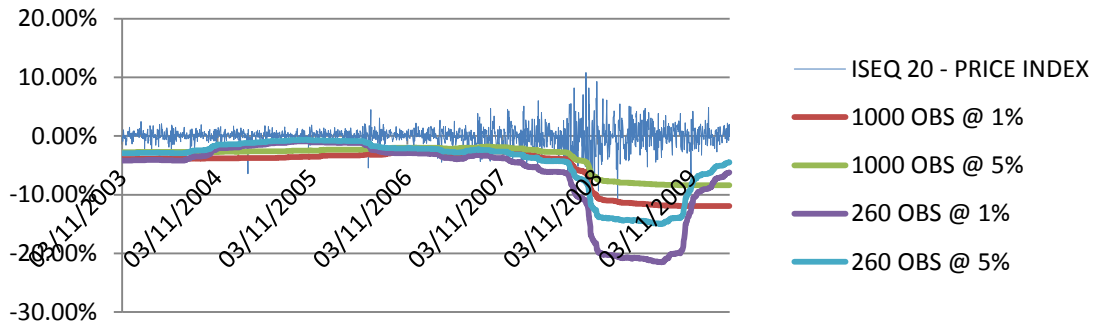




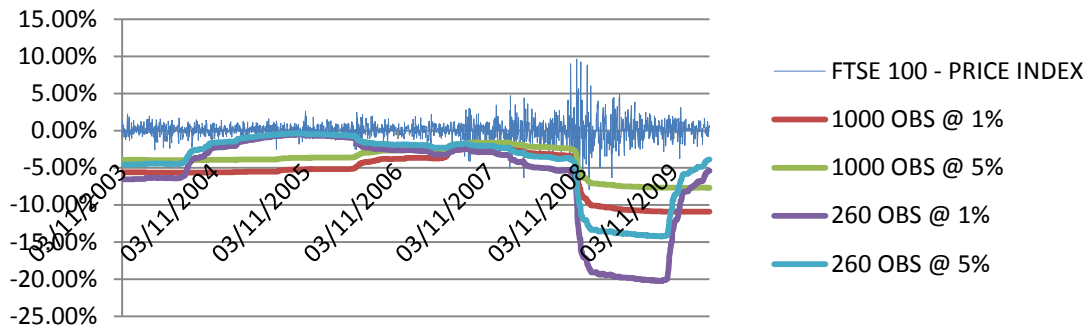
Parametric Normal Distribution with Volatility-weighted Returns (GARCH filtered)



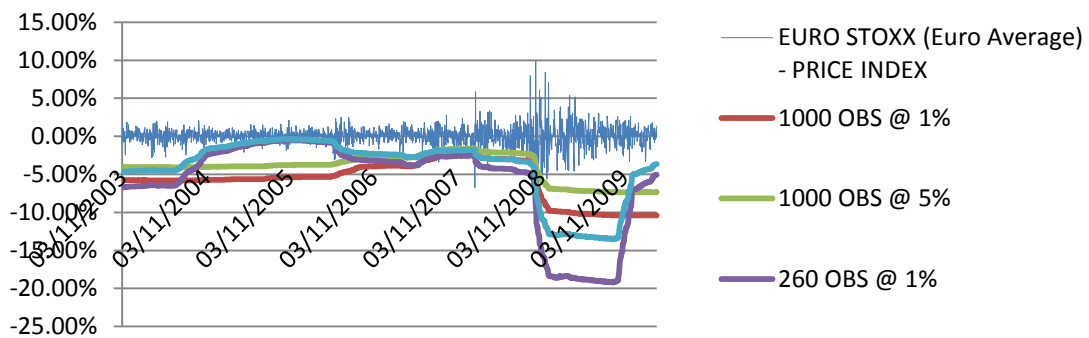
ISEQ 20 Parametric Normal Distribution with GARCH and Volatility-weighted returns

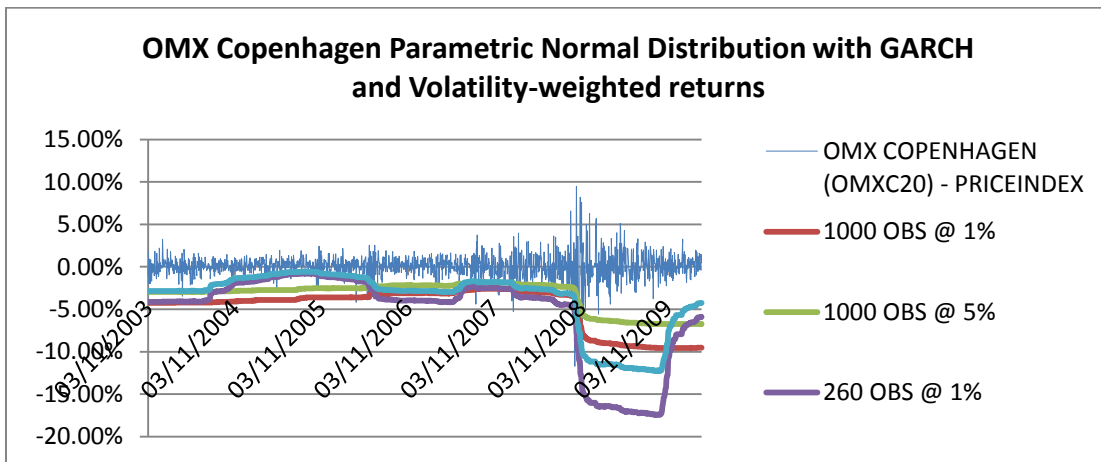
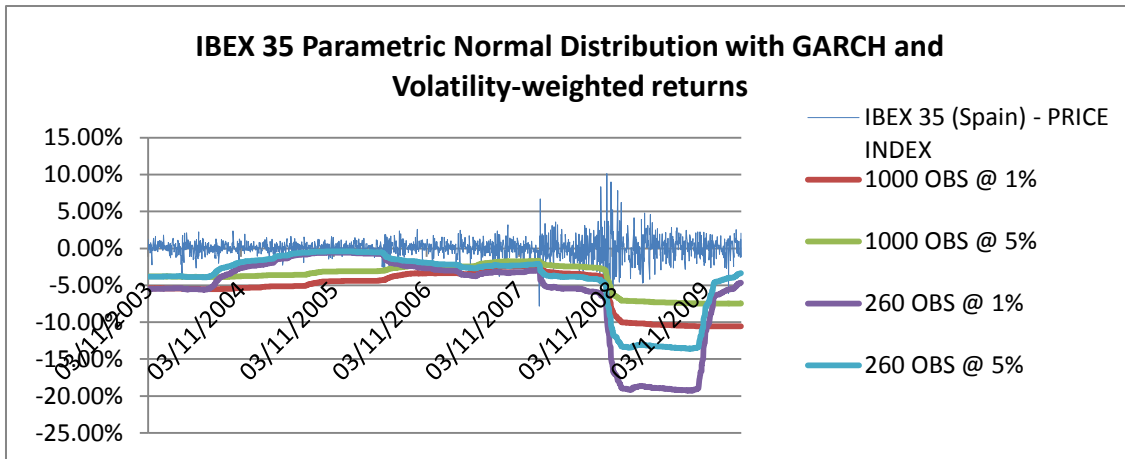


FTSE 100 Parametric Normal Distribution with GARCH and Volatility-weighted returns

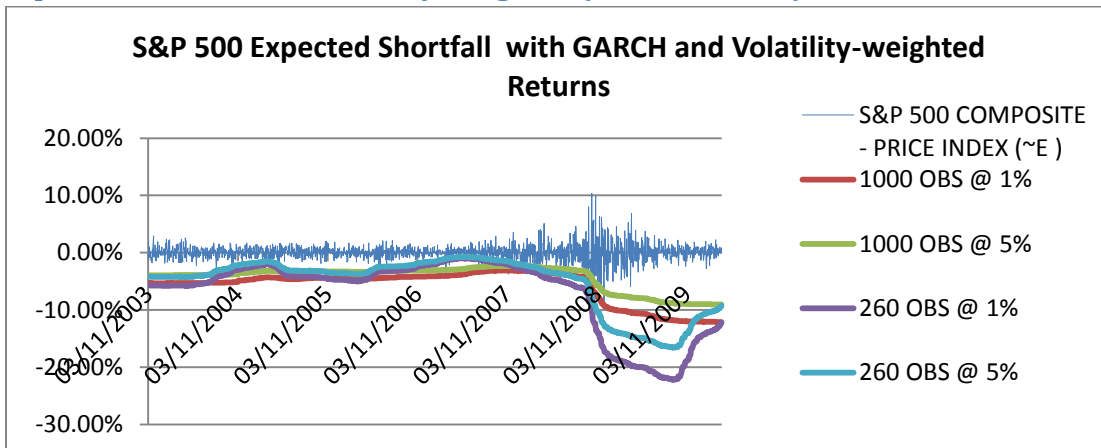


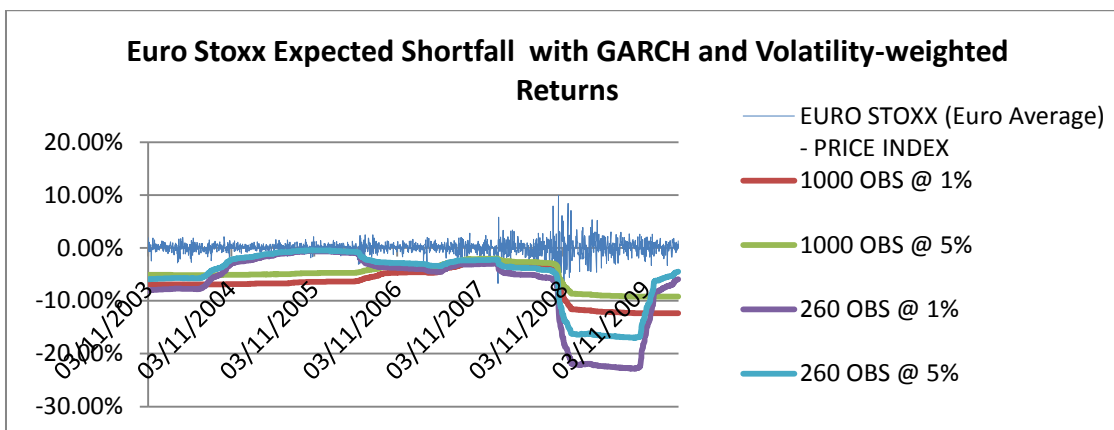
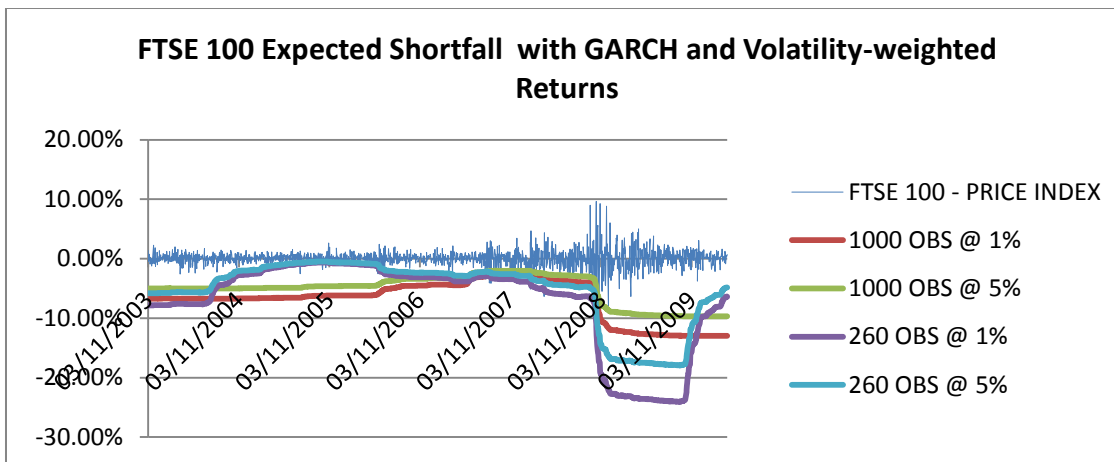
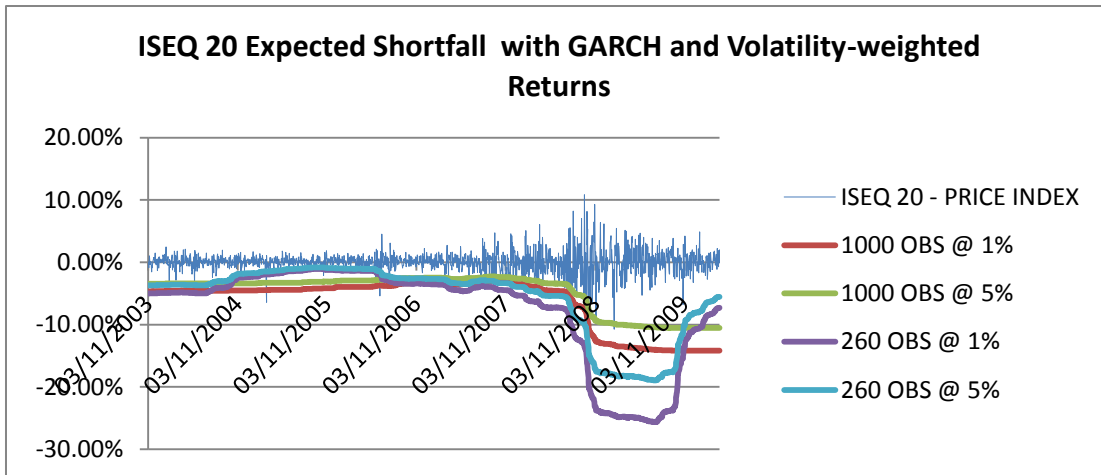
Euro Stoxx Parametric Normal Distribution with GARCH and Volatility-weighted returns

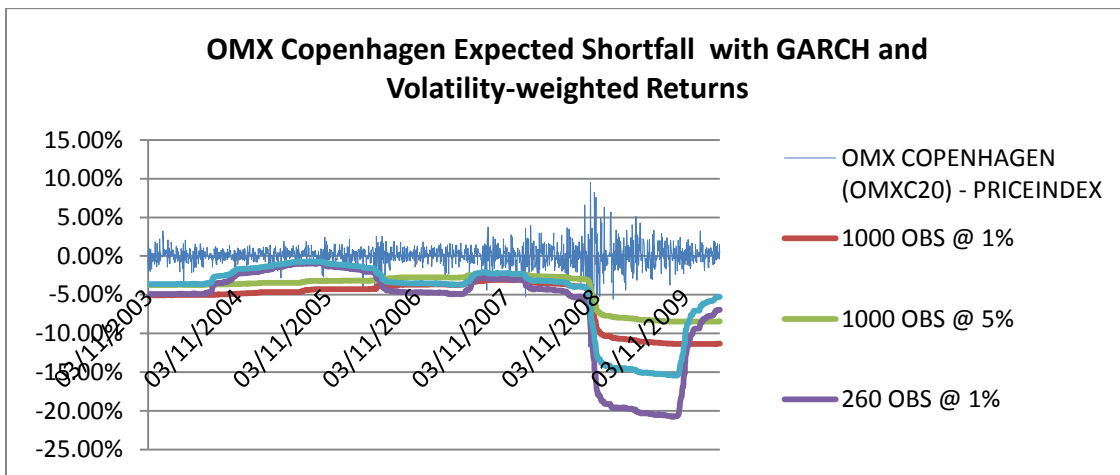
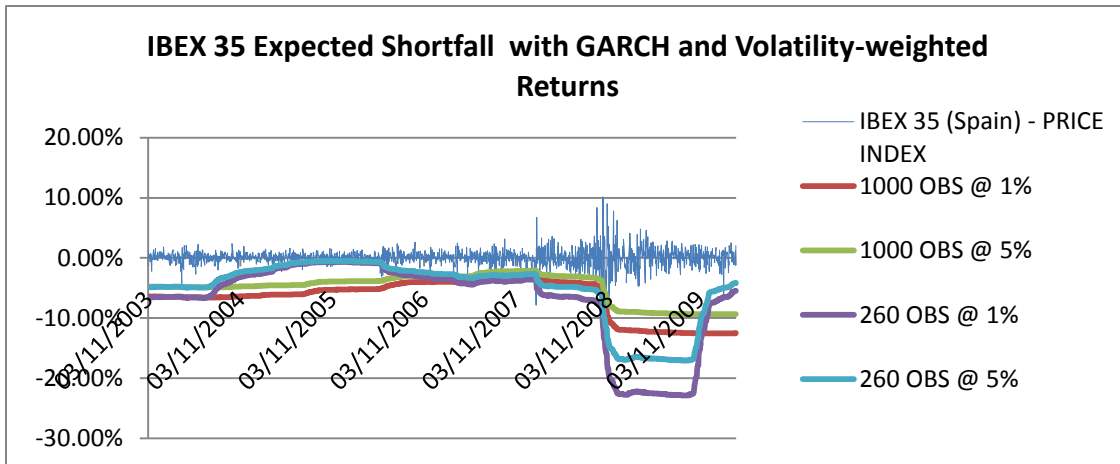




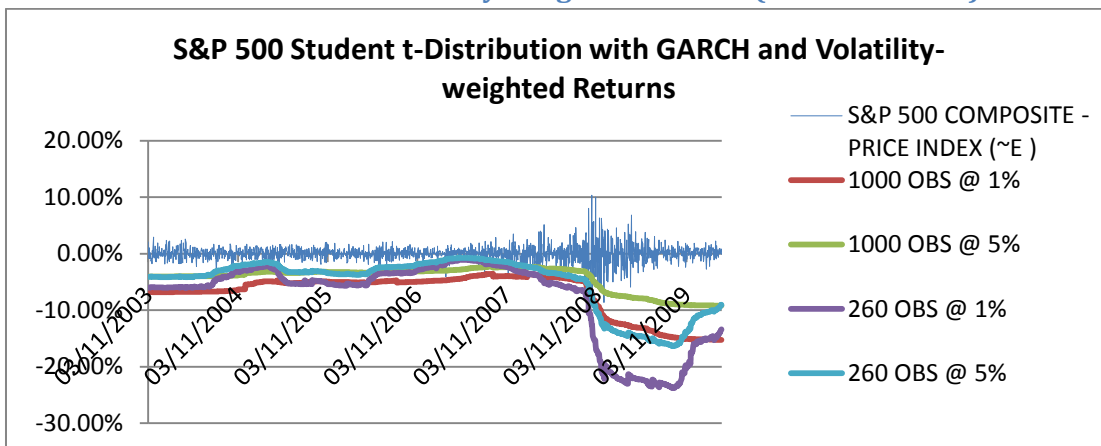
Expected Shortfall with Volatility-weighted (GARCH filtered)



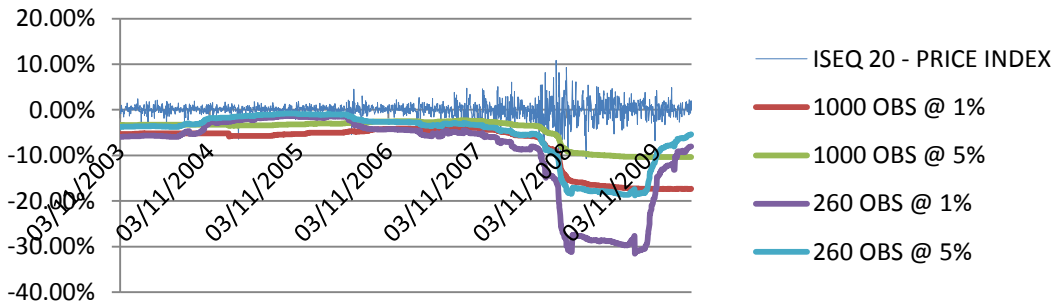




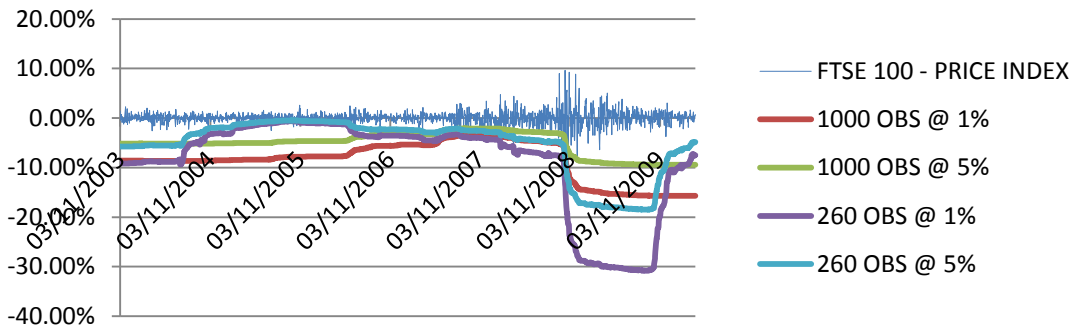
Student t-Distribution with Volatility-weighted Returns (GARCH filtered)



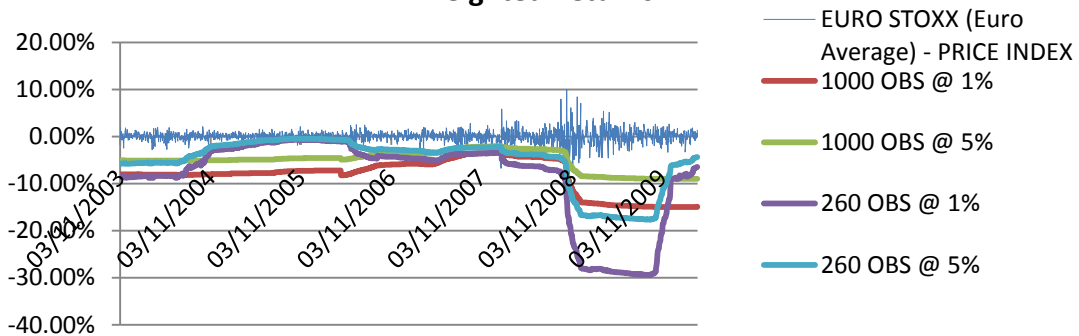
ISEQ 20 Student t-Distribution with GARCH and Volatility-weighted Returns

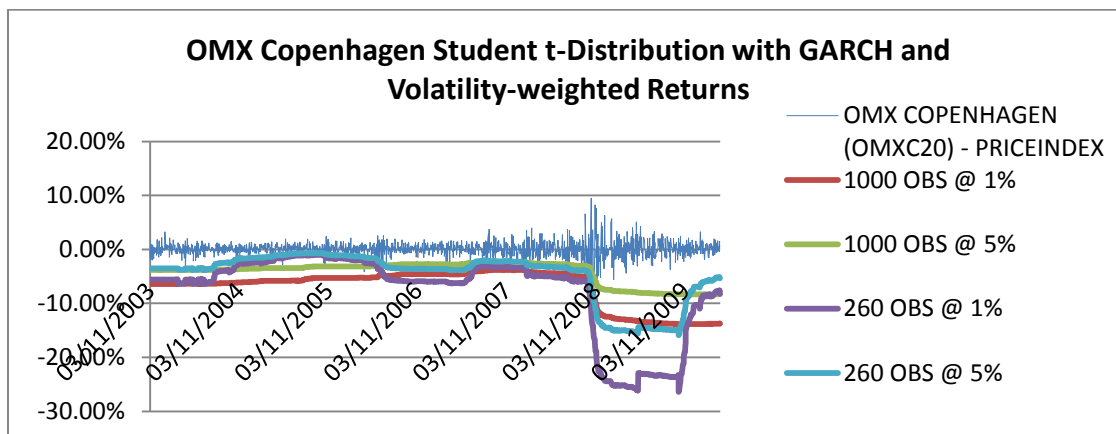
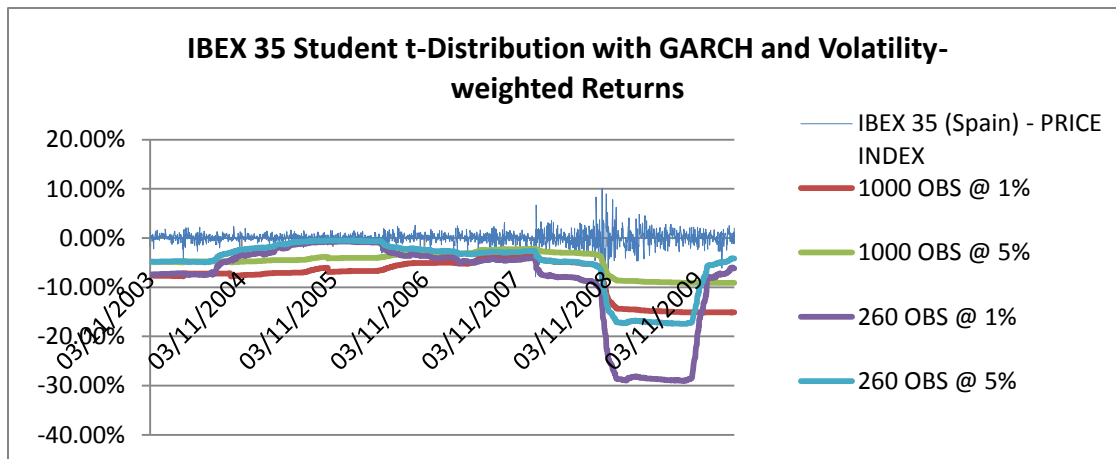


FTSE 100 Student t-Distribution with GARCH and Volatility-weighted Returns



Euro Stoxx Student t-Distribution with GARCH and Volatility-weighted Returns





Backtesting Results

Table 8 Backtesting results for OS 1 Backtest Results

	Test	S&P 500 COMPOSITE - PRICE INDEX	ISEQ 20 - PRICE INDEX	FTSE 100 - PRICE INDEX	EURO STOXX (Euro Average) - PRICE INDEX	IBEX 35 (Spain) - PRICE INDEX	OMX COPENHAGEN (OMXC20) - PRICEINDEX	5% Critical Value (lower bound)	5% Critical Value (upper bound)
HS	LRuc 1000 Obs @ 1%	5.226175	1.298902	5.226175	5.226175	5.226175	5.226175	0.000982	5.023886
	LRuc 1000 Obs @ 5%	14.99556	14.99556	19.44388	26.67251	26.67251	6.701242	0.000982	5.023886
	LRuc 260 Obs @ 1%	11.60148	14.99556	11.60148	11.60148	14.99556	6.701242	0.000982	5.023886
	LRuc 260 Obs @ 5%	0.083018	0.340961	0.340961	0.083018	1.445384	0.079077	0.000982	5.023886
	Lrind 1000 Obs @ 1%	0	13.10979	0	0	0	0	0.000982	5.023886
	Lrind 1000 Obs @ 5%	23.42371	23.43924	23.42371	23.42371	23.43924	41.27098	0.000982	5.023886
	Lrind 260 Obs @ 1%	90.93561	84.61479	78.01441	84.53557	71.32562	0.080186	0.000982	5.023886
	Lrind 260 Obs @ 5%	23.43924	23.43924	13.10979	0	0	3.227731	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	5.226175	14.40869	5.226175	5.226175	5.226175	5.226175	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	38.41926	38.4348	42.86758	50.09622	50.11175	47.97223	0.050636	7.377759
	Lrcc 260 Obs @ 1%	102.5371	99.61034	89.61589	96.13705	86.32118	6.781428	0.050636	7.377759
	Lrcc 260 Obs @ 5%	23.52226	23.7802	13.45075	0.083018	1.445384	3.306808	0.050636	7.377759

<u>AWHS</u>	LRuc 1000 Obs @ 1%	5.226175	1.298902	5.226175	5.226175	5.226175	5.226175	0.000982	5.023886
	LRuc 1000 Obs @ 5%	14.99556	19.44388	19.44388	26.67251	26.67251	14.99556	0.000982	5.023886
	LRuc 260 Obs @ 1%	26.67251	19.44388	26.67251	26.67251	26.67251	26.67251	0.000982	5.023886
	LRuc 260 Obs @ 5%	14.99556	19.44388	19.44388	26.67251	26.67251	11.60148	0.000982	5.023886
	Lrind 1000 Obs @ 1%	0	13.10979	0	0	0	0	0.000982	5.023886
	Lrind 1000 Obs @ 5%	0	13.10979	0	0	0	0	0.000982	5.023886
	Lrind 260 Obs @ 1%	23.43924	13.10979	13.10979	0	0	32.71441	0.000982	5.023886
	Lrind 260 Obs @ 5%	23.43924	13.10979	13.10979	0	0	23.43924	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	5.226175	14.40869	5.226175	5.226175	5.226175	5.226175	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	14.99556	32.55367	19.44388	26.67251	26.67251	14.99556	0.050636	7.377759
	Lrcc 260 Obs @ 1%	50.11175	32.55367	39.7823	26.67251	26.67251	59.38692	0.050636	7.377759
	Lrcc 260 Obs @ 5%	38.4348	32.55367	32.55367	26.67251	26.67251	35.04072	0.050636	7.377759
<u>Para norm</u>	LRuc 1000 Obs @ 1%	5.226175	1.298902	5.226175	5.226175	5.226175	0.15194	0.000982	5.023886
	LRuc 1000 Obs @ 5%	0.340961	4.918254	3.478034	2.332413	2.332413	0.789005	0.000982	5.023886
	LRuc 260 Obs @ 1%	14.99556	14.99556	19.44388	26.67251	26.67251	6.701242	0.000982	5.023886
	LRuc 260 Obs @ 5%	14.99556	14.99556	11.60148	6.701242	14.99556	6.701242	0.000982	5.023886
	Lrind 1000 Obs @ 1%	0	13.10205	0	0	0	23.40823	0.000982	5.023886
	Lrind 1000 Obs @ 5%	23.40823	23.40823	13.10205	0	0	41.14598	0.000982	5.023886
	Lrind 260 Obs @ 1%	23.43924	23.43924	4.190464	3.227731	23.43924	3.227731	0.000982	5.023886
	Lrind 260 Obs @ 5%	0.512472	57.04074	6.886117	1.443634	1.443634	0.757215	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	5.226175	14.40096	5.226175	5.226175	5.226175	23.56017	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	23.74919	28.32649	16.58009	2.332413	2.332413	41.93499	0.050636	7.377759
	Lrcc 260 Obs @ 1%	38.4348	38.4348	23.63434	29.90024	50.11175	9.928973	0.050636	7.377759
	Lrcc 260 Obs @ 5%	15.50803	72.0363	18.4876	8.144876	16.43919	7.458457	0.050636	7.377759
<u>Stu T</u>	LRuc 1000 Obs @ 1%	2372.381	2372.381	2372.381	2372.381	2372.381	2372.381	0.000982	5.023886
	LRuc 1000 Obs @ 5%	26.67251	19.44388	26.67251	26.67251	26.67251	11.60148	0.000982	5.023886
	LRuc 260 Obs @ 1%	1059.078	0	0	0	0	0	0.000982	5.023886
	LRuc 260 Obs @ 5%	11.60148	14.99556	3.478034	4.918254	6.701242	6.701242	0.000982	5.023886
	Lrind 1000 Obs @ 1%	13.1252	13.1252	13.1252	13.1252	13.1252	13.1252	0.000982	5.023886
	Lrind 1000 Obs @ 5%	314.857	13.1252	13.1252	13.1252	13.1252	13.1252	0.000982	5.023886
	Lrind 260 Obs @ 1%	32.71441	23.43924	49.29847	49.33769	49.37675	41.27098	0.000982	5.023886
	Lrind 260 Obs @ 5%	0	13.10979	0	0	0	32.71441	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	2385.506	2385.506	2385.506	2385.506	2385.506	2385.506	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	341.5295	32.56908	39.79772	39.79772	39.79772	24.72668	0.050636	7.377759
	Lrcc 260 Obs @ 1%	1091.792	23.43924	49.29847	49.33769	49.37675	41.27098	0.050636	7.377759
	Lrcc 260 Obs @ 5%	11.60148	28.10535	3.478034	4.918254	6.701242	39.41565	0.050636	7.377759
<u>ES</u>	LRuc 1000 Obs @ 1%	0	1.298902	0	0	0	0	0.000982	5.023886

	LRuc 1000 Obs @ 5%	26.67251	19.44388	26.67251	26.67251	26.67251	26.67251	0.000982	5.023886
	LRuc 260 Obs @ 1%	14.99556	19.44388	14.99556	11.60148	14.99556	8.894783	0.000982	5.023886
	LRuc 260 Obs @ 5%	11.60148	14.99556	6.701242	6.701242	6.701242	6.701242	0.000982	5.023886
	Lrind 1000 Obs @ 1%	0	13.10979	0	0	0	0	0.000982	5.023886
	Lrind 1000 Obs @ 5%	23.43924	13.10979	23.43924	23.42371	23.43924	32.69106	0.000982	5.023886
	Lrind 260 Obs @ 1%	32.71441	23.43924	41.27098	41.27098	49.37675	41.27098	0.000982	5.023886
	Lrind 260 Obs @ 5%	0	13.10979	0	0	0	32.71441	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	0	14.40869	0	0	0	0	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	50.11175	32.55367	50.11175	50.09622	50.11175	59.36358	0.050636	7.377759
	Lrcc 260 Obs @ 1%	47.70997	42.88312	56.26654	52.87246	64.3723	50.16577	0.050636	7.377759
	Lrcc 260 Obs @ 5%	11.60148	28.10535	6.701242	6.701242	6.701242	39.41565	0.050636	7.377759
<u>VW Para norm</u>	LRuc 1000 Obs @ 1%	0	1.298902	0	0	0	0.15194	0.000982	5.023886
	LRuc 1000 Obs @ 5%	0.15194	0.15194	1.298902	0	0	1.761712	0.000982	5.023886
	LRuc 260 Obs @ 1%	14.99556	14.99556	11.60148	6.701242	14.99556	6.701242	0.000982	5.023886
	LRuc 260 Obs @ 5%	15.2096	3.280086	5.141228	7.296969	7.296969	12.35628	0.000982	5.023886
	Lrind 1000 Obs @ 1%	0	13.10979	0	0	0	0	0.000982	5.023886
	Lrind 1000 Obs @ 5%	23.43924	23.43924	32.71441	41.27098	23.43924	41.27098	0.000982	5.023886
	Lrind 260 Obs @ 1%	84.61479	57.04074	49.29847	64.30703	64.30703	0.757215	0.000982	5.023886
	Lrind 260 Obs @ 5%	23.43924	23.43924	13.10979	0	0	49.37675	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	0	14.40869	0	0	0	0.15194	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	23.59118	23.59118	34.01331	41.27098	23.43924	43.0327	0.050636	7.377759
	Lrcc 260 Obs @ 1%	99.61034	72.0363	60.89995	71.00827	79.30258	7.458457	0.050636	7.377759
	Lrcc 260 Obs @ 5%	38.64884	26.71933	18.25102	7.296969	7.296969	61.73303	0.050636	7.377759
<u>VW Stut</u>	LRuc 1000 Obs @ 1%	0	1.298902	0	0	0	0	0.000982	5.023886
	LRuc 1000 Obs @ 5%	0	1.298902	0	0	0	0.059227	0.000982	5.023886
	LRuc 260 Obs @ 1%	14.99556	19.44388	14.99556	14.99556	19.44388	6.701242	0.000982	5.023886
	LRuc 260 Obs @ 5%	0.15194	0.15194	5.141228	3.280086	1.761712	1.761712	0.000982	5.023886
	Lrind 1000 Obs @ 1%	0	13.10979	0	0	0	0	0.000982	5.023886
	Lrind 1000 Obs @ 5%	21.2965	13.10979	23.43924	23.43924	13.10979	32.6441	0.000982	5.023886
	Lrind 260 Obs @ 1%	21.2965	23.43924	49.29847	49.33769	49.37675	0	0.000982	5.023886
	Lrind 260 Obs @ 5%	0	13.10979	0	0	0	32.71441	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	0	14.40869	0	0	0	0	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	21.2965	14.40869	23.43924	23.43924	13.10979	32.70332	0.050636	7.377759
	Lrcc 260 Obs @ 1%	0.15194	13.26173	5.141228	3.280086	1.761712	34.47612	0.050636	7.377759
	Lrcc 260 Obs @ 5%	0	27.51848	0	0	0	0	0.050636	7.377759
<u>VW ES</u>	LRuc 1000 Obs @ 1%	0	1.298902	0	0	0	0	0.000982	5.023886
	LRuc 1000 Obs @ 5%	0	1.298902	0	0	0	0.059227	0.000982	5.023886
	LRuc 260 Obs @ 1%	14.99556	19.44388	14.99556	11.60148	14.99556	8.894783	0.000982	5.023886
	LRuc 260 Obs @ 5%	0.059227	0.15194	1.761712	1.761712	1.761712	1.761712	0.000982	5.023886
	Lrind 1000 Obs @	0	13.10979	0	0	0	0	0.000982	5.023886

	1%								
	Lrind 1000 Obs @ 5%	23.43924	13.10979	23.43924	23.42371	23.43924	32.69106	0.000982	5.023886
	Lrind 260 Obs @ 1%	32.71441	23.43924	41.27098	41.27098	49.37675	0	0.000982	5.023886
	Lrind 260 Obs @ 5%	0	13.10979	0	0	0	32.71441	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	0	14.40869	0	0	0	0	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	23.43924	14.40869	23.43924	23.42371	23.43924	32.75029	0.050636	7.377759
	Lrcc 260 Obs @ 1%	47.70997	42.88312	56.26654	52.87246	64.3723	8.894783	0.050636	7.377759
	Lrcc 260 Obs @ 5%	0.059227	13.26173	1.761712	1.761712	1.761712	34.47612	0.050636	7.377759

Table 9 Backtesting results for OS 2 Backtest Results

	Test	S&P 500 COMPOSITE - PRICE INDEX	ISEQ 20 - PRICE INDEX	FTSE 100 - PRICE INDEX	EURO STOXX (Euro Average) - PRICE INDEX	IBEX 35 (Spain) - PRICE INDEX	OMX COPENHAGEN (OMXC20) - PRICEINDEX	5% Critical Value (lower bound)	5% Critical Value (upper bound)
<u>HS</u>	LRuc 1000 Obs @ 1%	5.226175	1.298902	5.226175	5.226175	1.298902	5.226175	0.000982	5.023886
	LRuc 1000 Obs @ 5%	4.918254	6.701242	4.918254	0.340961	0.789005	6.701242	0.000982	5.023886
	LRuc 260 Obs @ 1%	26.67251	19.44388	26.67251	26.67251	19.44388	26.67251	0.000982	5.023886
	LRuc 260 Obs @ 5%	19.44388	19.44388	19.44388	11.60148	6.701242	26.67251	0.000982	5.023886
	Lrind 1000 Obs @ 1%	0	13.11751	0	0	13.11751	0	0.000982	5.023886
	Lrind 1000 Obs @ 5%	0	13.11751	0	0	13.11751	0	0.000982	5.023886
	Lrind 260 Obs @ 1%	13.11751	13.11751	13.11751	32.73767	49.41566	0	0.000982	5.023886
	Lrind 260 Obs @ 5%	57.08753	49.41566	57.08753	84.77229	78.22703	49.41566	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	5.226175	14.41641	5.226175	5.226175	14.41641	5.226175	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	4.918254	19.81875	4.918254	0.340961	13.90652	6.701242	0.050636	7.377759
	Lrcc 260 Obs @ 1%	39.79003	32.56139	39.79003	59.41018	68.85954	26.67251	0.050636	7.377759
	Lrcc 260 Obs @ 5%	76.53141	68.85954	76.53141	96.37377	84.92827	76.08817	0.050636	7.377759
<u>AWHS</u>	LRuc 1000 Obs @ 1%	15.2096	70.3767	12.35628	35.86292	52.28628	7.296969	0.000982	5.023886
	LRuc 1000 Obs @ 5%	6.655499	60.61208	15.59567	29.54847	46.67848	19.22517	0.000982	5.023886
	LRuc 260 Obs @ 1%	0.789005	9.288997	1.445384	1.186105	2.567549	1.445384	0.000982	5.023886
	LRuc 260 Obs @ 5%	9.288997	69.59277	17.37273	29.54847	49.35766	23.14784	0.000982	5.023886
	Lrind 1000 Obs @ 1%	91.02258	0.030319	1.058227	3.203467	3.391673	64.30703	0.000982	5.023886
	Lrind 1000 Obs @ 5%	91.10921	0.153817	0.752089	3.203467	1.68659	71.32562	0.000982	5.023886
	Lrind 260 Obs @ 1%	0.182764	2.36554	0.097917	0.417593	2.261154	1.486532	0.000982	5.023886
	Lrind 260 Obs @ 5%	1.24712	2.916958	0.494863	0.417593	3.08855	0.494863	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	106.2322	70.40702	13.41451	39.06638	55.67795	71.604	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	97.76471	60.7659	16.34775	32.75193	48.36507	90.55079	0.050636	7.377759
	Lrcc 260 Obs @ 1%	0.971769	11.65454	1.543302	1.603698	4.828704	2.931916	0.050636	7.377759
	Lrcc 260 Obs @ 5%	10.53612	72.50973	17.86759	29.96606	52.4462	23.64271	0.050636	7.377759
<u>Para norm</u>	LRuc 1000 Obs @ 1%	594.3507	687.7456	569.5514	636.3267	619.4404	705.1365	0.000982	5.023886

	LRuc 1000 Obs @ 5%	284.0878	330.791	259.2629	304.5274	299.3696	425.9166	0.000982	5.023886
	LRuc 260 Obs @ 1%	284.0878	336.1381	264.1629	314.9381	299.3696	402.7304	0.000982	5.023886
	LRuc 260 Obs @ 5%	279.0581	330.791	254.3957	299.3696	294.2437	294.2437	0.000982	5.023886
	Lrind 1000 Obs @ 1%	0.10969	0.308187	0.321771	0.111721	0.25017	0.035323	0.000982	5.023886
	Lrind 1000 Obs @ 5%	0.10969	0.308187	0.321771	0.026375	0.510592	0.669439	0.000982	5.023886
	Lrind 260 Obs @ 1%	0.10969	0.273969	0.59258	0.111721	0.642097	0.015267	0.000982	5.023886
	Lrind 260 Obs @ 5%	0.10969	0.273969	0.94437	0.084158	0.345857	2.12E-05	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	594.4604	688.0538	569.8732	636.4385	619.6905	705.1718	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	284.1975	331.0992	259.5847	304.5538	299.8802	426.5861	0.050636	7.377759
	Lrcc 260 Obs @ 1%	284.1975	336.4121	264.7555	315.0498	300.0117	402.7457	0.050636	7.377759
	Lrcc 260 Obs @ 5%	279.1678	331.0649	255.3401	299.4538	294.5896	294.2437	0.050636	7.377759
<u>Stu I</u>	LRuc 1000 Obs @ 1%	687.7456	758.0558	661.8944	758.0558	696.4254	758.0558	0.000982	5.023886
	LRuc 1000 Obs @ 5%	304.5274	380.0374	309.7169	363.3421	330.791	391.3222	0.000982	5.023886
	LRuc 260 Obs @ 1%	294.2437	374.4413	314.9381	374.4413	341.5165	374.4413	0.000982	5.023886
	LRuc 260 Obs @ 5%	299.3696	363.3421	289.1498	363.3421	330.791	380.0374	0.000982	5.023886
	Lrind 1000 Obs @ 1%	1.893707	4.45E-05	0.528636	1.564588	0.176109	1.386619	0.000982	5.023886
	Lrind 1000 Obs @ 5%	0.35691	0.001686	0.205992	1.108239	0.103773	0.261395	0.000982	5.023886
	Lrind 260 Obs @ 1%	0.359132	0.119418	0.359524	1.198807	0.176109	0.53351	0.000982	5.023886
	Lrind 260 Obs @ 5%	0.35691	0.000568	0.095397	1.040556	0.0194	0.021714	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	689.6393	758.0558	662.423	759.6204	696.6015	759.4424	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	304.8843	380.039	309.9229	364.4504	330.8947	391.5836	0.050636	7.377759
	Lrcc 260 Obs @ 1%	294.6028	374.5607	315.2976	375.6401	341.6926	374.9748	0.050636	7.377759
	Lrcc 260 Obs @ 5%	299.7265	363.3427	289.2452	364.3827	330.8104	380.0591	0.050636	7.377759
<u>ES</u>	LRuc 1000 Obs @ 1%	586.0518	679.0972	561.3501	636.3267	619.4404	627.8676	0.000982	5.023886
	LRuc 1000 Obs @ 5%	284.0878	336.1381	264.1629	309.7169	294.2437	309.7169	0.000982	5.023886
	LRuc 260 Obs @ 1%	279.0581	325.4752	254.3957	299.3696	289.1498	294.2437	0.000982	5.023886
	LRuc 260 Obs @ 5%	279.0581	330.791	259.2629	299.3696	294.2437	299.3696	0.000982	5.023886
	Lrind 1000 Obs @ 1%	0.016264	0.273969	0.59258	0.111721	0.25017	0.413406	0.000982	5.023886
	Lrind 1000 Obs @ 5%	0.016264	0.101214	0.94437	0.084158	0.204677	0.477242	0.000982	5.023886
	Lrind 260 Obs @ 1%	0.10969	0.362771	0.59258	0.084158	0.25017	0.305882	0.000982	5.023886
	Lrind 260 Obs @ 5%	0.10969	0.308187	0.321771	0.141562	0.25017	0.090129	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	586.0681	679.3711	561.9426	636.4385	619.6905	628.281	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	284.1041	336.2393	265.1073	309.8011	294.4484	310.1941	0.050636	7.377759
	Lrcc 260 Obs @ 1%	279.1678	325.838	254.9883	299.4538	289.3999	294.5496	0.050636	7.377759
	Lrcc 260 Obs @ 5%	279.1678	331.0992	259.5847	299.5112	294.4939	299.4597	0.050636	7.377759
<u>VW Para norm</u>	LRuc 1000 Obs @ 1%	687.7456	758.0558	661.8944	758.0558	696.4254	758.0558	0.000982	5.023886
	LRuc 1000 Obs @ 5%	304.5274	380.0374	309.7169	363.3421	330.791	391.3222	0.000982	5.023886
	LRuc 260 Obs @ 1%	299.3696	363.3421	289.1498	363.3421	330.791	380.0374	0.000982	5.023886
	LRuc 260 Obs @ 5%	294.2437	374.4413	314.9381	374.4413	341.5165	374.4413	0.000982	5.023886
	Lrind 1000 Obs @ 1%	1.893707	4.45E-05	0.528636	1.564588	0.176109	1.386619	0.000982	5.023886
	Lrind 1000 Obs @ 5%	0.35691	0.001686	0.205992	1.108239	0.103773	0.261395	0.000982	5.023886
	Lrind 260 Obs @ 1%	0.359132	0.119418	0.359524	1.198807	0.176109	0.53351	0.000982	5.023886

	Lrind 260 Obs @ 5%	0.35691	0.000568	0.095397	1.040556	0.0194	0.021714	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	689.6393	758.0558	662.423	759.6204	696.6015	759.4424	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	304.8843	380.039	309.9229	364.4504	330.8947	391.5836	0.050636	7.377759
	Lrcc 260 Obs @ 1%	299.7287	363.4615	289.5093	364.5409	330.9671	380.5709	0.050636	7.377759
	Lrcc 260 Obs @ 5%	294.6006	374.4419	315.0335	375.4819	341.5359	374.463	0.050636	7.377759
<u>VW</u> <u>Stu t</u>	LRuc 1000 Obs @ 1%	586.0518	679.0972	553.1815	627.8676	619.4404	602.6818	0.000982	5.023886
	LRuc 1000 Obs @ 5%	0	0	2372.381	2372.381	2372.381	2372.381	0.000982	5.023886
	LRuc 260 Obs @ 1%	274.0606	320.1909	254.3957	294.2437	289.1498	294.2437	0.000982	5.023886
	LRuc 260 Obs @ 5%	279.0581	330.791	259.2629	299.3696	294.2437	299.3696	0.000982	5.023886
	Lrind 1000 Obs @ 1%	0.016264	0.273969	0.94437	0.084158	0.25017	0.629898	0.000982	5.023886
	Lrind 1000 Obs @ 5%	0.00568	0.080202	0.94437	0.059425	0.204677	0.477242	0.000982	5.023886
	Lrind 260 Obs @ 1%	14.30979	16.37985	22.55198	16.55263	18.50605	11.54731	0.000982	5.023886
	Lrind 260 Obs @ 5%	13.1252	13.1252	23.47013	23.47013	13.1252	23.47013	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	586.0681	679.3711	554.1258	627.9518	619.6905	603.3117	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	0.00568	0.080202	2373.325	2372.44	2372.585	2372.858	0.050636	7.377759
	Lrcc 260 Obs @ 1%	288.3704	336.5708	276.9477	310.7963	307.6558	305.791	0.050636	7.377759
	Lrcc 260 Obs @ 5%	292.1833	343.9162	282.7331	322.8397	307.3689	322.8397	0.050636	7.377759
<u>VW</u> <u>ES</u>	LRuc 1000 Obs @ 1%	586.0518	679.0972	561.3501	636.3267	619.4404	627.8676	0.000982	5.023886
	LRuc 1000 Obs @ 5%	284.0878	336.1381	-345.509	309.7169	294.2437	309.7169	0.000982	5.023886
	LRuc 260 Obs @ 1%	279.0581	325.4752	254.3957	299.3696	289.1498	294.2437	0.000982	5.023886
	LRuc 260 Obs @ 5%	279.0581	330.791	259.2629	299.3696	294.2437	299.3696	0.000982	5.023886
	Lrind 1000 Obs @ 1%	0.016264	0.273969	0.59258	0.111721	0.25017	0.413406	0.000982	5.023886
	Lrind 1000 Obs @ 5%	0.016264	0.101214	0.94437	0.084158	0.204677	0.477242	0.000982	5.023886
	Lrind 260 Obs @ 1%	0.10969	0.362771	0.59258	0.084158	0.25017	0.305882	0.000982	5.023886
	Lrind 260 Obs @ 5%	0.10969	0.308187	0.321771	0.141562	0.25017	0.090129	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	586.0681	679.3711	561.9426	636.4385	619.6905	628.281	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	284.1041	336.2393	-344.564	309.8011	294.4484	310.1941	0.050636	7.377759
	Lrcc 260 Obs @ 1%	279.1678	325.838	254.9883	299.4538	289.3999	294.5496	0.050636	7.377759
	Lrcc 260 Obs @ 5%	279.1678	331.0992	259.5847	299.5112	294.4939	299.4597	0.050636	7.377759

Table 10 Backtesting results for OS 1 (GARCH filtered)

	<u>Test</u>	S&P 500 COMPOSITE - PRICE INDEX	ISEQ 20 - PRICE INDEX	FTSE 100 - PRICE INDEX	EURO STOXX (Euro Average) - PRICE INDEX	IBEX 35 (Spain) - PRICE INDEX	OMX COPENHAGEN (OMXC20) - PRICEINDEX	5% Critical Value (lower bound)	5% Critical Value (upper bound)
<u>HS</u>	LRuc 1000 Obs @ 1%	32.05649	1.298902	5.226175	5.226175	5.226175	5.226175	0.000982	5.023886
	LRuc 1000 Obs @ 5%	38.97966	19.44388	26.67251	26.67251	26.67251	11.60148	0.000982	5.023886
	LRuc 260 Obs @ 1%	0.340961	14.99556	11.60148	11.60148	14.99556	4.918254	0.000982	5.023886
	LRuc 260 Obs @ 5%	17.37273	0.789005	0.789005	0	0.340961	0.079077	0.000982	5.023886
	Lrind 1000 Obs @ 1%	0.940012	13.10979	0	0	0	0	0.000982	5.023886

	Lrind 1000 Obs @ 5%	3.923827	23.43924	32.71441	23.42371	23.43924	41.23967	0.000982	5.023886
	Lrind 260 Obs @ 1%	0.361012	78.08556	64.19657	84.45603	78.01441	0.314216	0.000982	5.023886
	Lrind 260 Obs @ 5%	0.007188	13.10979	0	0	0	32.71441	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	32.99651	14.40869	5.226175	5.226175	5.226175	5.226175	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	42.90349	42.88312	59.38692	50.09622	50.11175	52.84115	0.050636	7.377759
	Lrcc 260 Obs @ 1%	0.701973	93.08112	75.79805	96.05751	93.00996	5.23247	0.050636	7.377759
	Lrcc 260 Obs @ 5%	17.37992	13.8988	0.789005	0	0.340961	32.79349	0.050636	7.377759
<u>AWHS</u>	LRuc 1000 Obs @ 1%	0.15194	5.226175	5.226175	5.226175	5.226175	5.226175	0.000982	5.023886
	LRuc 1000 Obs @ 5%	36.53003	19.44388	26.67251	26.67251	26.67251	19.44388	0.000982	5.023886
	LRuc 260 Obs @ 1%	6.701242	19.44388	26.67251	26.67251	26.67251	26.67251	0.000982	5.023886
	LRuc 260 Obs @ 5%	41.48839	19.44388	26.67251	26.67251	26.67251	19.44388	0.000982	5.023886
	Lrind 1000 Obs @ 1%	23.39258	0	0	0	0	0	0.000982	5.023886
	Lrind 1000 Obs @ 5%	41.23967	13.10204	0	0	0	0	0.000982	5.023886
	Lrind 260 Obs @ 1%	0.0587	13.10204	0	0	0	13.10204	0.000982	5.023886
	Lrind 260 Obs @ 5%	0.002568	13.10204	0	0	0	13.10204	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	23.54452	5.226175	5.226175	5.226175	5.226175	5.226175	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	77.7697	32.54592	26.67251	26.67251	26.67251	19.44388	0.050636	7.377759
	Lrcc 260 Obs @ 1%	6.759942	32.54592	26.67251	26.67251	26.67251	39.77455	0.050636	7.377759
	Lrcc 260 Obs @ 5%	41.49096	32.54592	26.67251	26.67251	26.67251	32.54592	0.050636	7.377759
<u>Para norm</u>	LRuc 1000 Obs @ 1%	61.14048	1.298902	5.226175	5.226175	5.226175	1.298902	0.000982	5.023886
	LRuc 1000 Obs @ 5%	41.48839	19.44388	26.67251	26.67251	26.67251	11.60148	0.000982	5.023886
	LRuc 260 Obs @ 1%	0.309264	11.60148	11.60148	6.701242	14.99556	4.918254	0.000982	5.023886
	LRuc 260 Obs @ 5%	17.37273	3.478034	1.445384	1.445384	2.332413	0.083018	0.000982	5.023886
	Lrind 1000 Obs @ 1%	0.484772	13.10979	0	0	0	13.10979	0.000982	5.023886
	Lrind 1000 Obs @ 5%	3.238605	32.71441	32.71441	41.27098	23.43924	3.220477	0.000982	5.023886
	Lrind 260 Obs @ 1%	0.361012	64.36193	56.89928	71.32562	64.30703	0.746953	0.000982	5.023886
	Lrind 260 Obs @ 5%	0.053196	13.10979	0	0	0	32.71441	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	61.62525	14.40869	5.226175	5.226175	5.226175	14.40869	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	44.72699	52.15829	59.38692	67.9435	50.11175	14.82196	0.050636	7.377759
	Lrcc 260 Obs @ 1%	0.670276	75.96341	68.50076	78.02686	79.30258	5.665207	0.050636	7.377759
	Lrcc 260 Obs @ 5%	17.42593	16.58782	1.445384	1.445384	2.332413	32.79743	0.050636	7.377759
<u>Stu T</u>	LRuc 1000 Obs @ 1%	12.35628	1.298902	5.226175	5.226175	5.226175	5.226175	0.000982	5.023886
	LRuc 1000 Obs @ 5%	13.89624	19.44388	26.67251	26.67251	26.67251	14.99556	0.000982	5.023886
	LRuc 260 Obs @ 1%	1.445384	19.44388	14.99556	19.44388	19.44388	6.701242	0.000982	5.023886
	LRuc 260 Obs @ 5%	2.567549	8.894783	8.894783	6.701242	6.701242	3.478034	0.000982	5.023886
	Lrind 1000 Obs @ 1%	0.757215	13.10979	0	0	0	0	0.000982	5.023886
	Lrind 1000 Obs @ 5%	0.385717	13.10979	23.43924	13.10979	13.11751	32.69106	0.000982	5.023886
	Lrind 260 Obs @ 1%	2.873874	41.30217	41.30217	41.27098	41.27098	2.486995	0.000982	5.023886
	Lrind 260 Obs @ 5%	0.365169	13.10979	0	0	0	23.43924	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	13.1135	14.40869	5.226175	5.226175	5.226175	5.226175	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	14.28196	32.55367	50.11175	39.7823	39.79003	47.68662	0.050636	7.377759
	Lrcc 260 Obs @ 1%	4.319258	60.74605	56.29773	60.71486	60.71486	9.188237	0.050636	7.377759
	Lrcc 260 Obs @ 5%	2.932719	22.00457	8.894783	6.701242	6.701242	26.91727	0.050636	7.377759
<u>ES</u>	LRuc 1000 Obs @ 1%	28.38335	1.298902	5.226175	5.226175	5.226175	1.298902	0.000982	5.023886

	LRuc 1000 Obs @ 5%	12.27688	19.44388	26.67251	26.67251	26.67251	14.99556	0.000982	5.023886
	LRuc 260 Obs @ 1%	0.083018	19.44388	14.99556	14.99556	14.99556	6.701242	0.000982	5.023886
	LRuc 260 Obs @ 5%	1.817111	11.60148	8.894783	6.701242	4.918254	3.478034	0.000982	5.023886
	Lrind 1000 Obs @ 1%	1.264674	13.10979	0	0	0	13.10205	0.000982	5.023886
	Lrind 1000 Obs @ 5%	2.109998	13.10979	23.43924	23.43924	23.43924	4.175544	0.000982	5.023886
	Lrind 260 Obs @ 1%	1.715375	32.71441	41.30217	41.27098	49.33769	2.486995	0.000982	5.023886
	Lrind 260 Obs @ 5%	0.014956	13.10979	0	0	0	23.43924	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	29.64802	14.40869	5.226175	5.226175	5.226175	14.40096	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	14.38688	32.55367	50.11175	50.11175	50.11175	19.1711	0.050636	7.377759
	Lrcc 260 Obs @ 1%	1.798393	52.15829	56.29773	56.26654	64.33324	9.188237	0.050636	7.377759
	Lrcc 260 Obs @ 5%	1.832067	24.71127	8.894783	6.701242	4.918254	26.91727	0.050636	7.377759
<u>VW Para norm</u>	LRuc 1000 Obs @ 1%	84.88803	1.298902	5.226175	5.226175	5.226175	1.298902	0.000982	5.023886
	LRuc 1000 Obs @ 5%	49.35766	19.44388	26.67251	26.67251	26.67251	11.60148	0.000982	5.023886
	LRuc 260 Obs @ 1%	23.14784	0.789005	5.480089	2.567549	4.404022	6.655499	0.000982	5.023886
	LRuc 260 Obs @ 5%	72.68491	2.567549	27.34834	13.89624	12.27688	19.22517	0.000982	5.023886
	Lrind 1000 Obs @ 1%	0.365169	13.10979	0	0	0	13.10979	0.000982	5.023886
	Lrind 1000 Obs @ 5%	0.189327	78.08556	124.776	108.2519	124.9143	0.000284	0.000982	5.023886
	Lrind 260 Obs @ 1%	1.566239	119.7013	166.892	139.5511	144.739	0.311942	0.000982	5.023886
	Lrind 260 Obs @ 5%	0.442071	13.10979	0	0	0	32.71441	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	85.2532	14.40869	5.226175	5.226175	5.226175	14.40869	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	49.54698	97.52944	151.4486	134.9244	151.5868	11.60176	0.050636	7.377759
	Lrcc 260 Obs @ 1%	24.71408	120.4903	172.3721	142.1187	149.143	6.967441	0.050636	7.377759
	Lrcc 260 Obs @ 5%	73.12698	15.67734	27.34834	13.89624	12.27688	51.93958	0.050636	7.377759
<u>VW Stut</u>	LRuc 1000 Obs @ 1%	21.47136	1.298902	5.226175	5.226175	5.226175	5.226175	0.000982	5.023886
	LRuc 1000 Obs @ 5%	29.54847	19.44388	26.67251	26.67251	26.67251	19.44388	0.000982	5.023886
	LRuc 260 Obs @ 1%	0	6.701242	0	0.083018	0.789005	0.789005	0.000982	5.023886
	LRuc 260 Obs @ 5%	36.53003	0.083018	13.89624	6.655499	7.926332	9.288997	0.000982	5.023886
	Lrind 1000 Obs @ 1%	0.179139	13.10979	0	0	0	0	0.000982	5.023886
	Lrind 1000 Obs @ 5%	0.01567	49.37675	90.8483	77.94297	71.2625	71.2625	0.000982	5.023886
	Lrind 260 Obs @ 1%	0.089809	90.93561	149.4922	119.1808	135.0719	0.000646	0.000982	5.023886
	Lrind 260 Obs @ 5%	4.02E-06	13.10979	0	0	0	13.10979	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	21.6505	14.40869	5.226175	5.226175	5.226175	5.226175	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	29.56414	68.82063	117.5208	104.6155	97.93501	90.70638	0.050636	7.377759
	Lrcc 260 Obs @ 1%	0.089809	97.63685	149.4922	119.2638	135.8609	0.789652	0.050636	7.377759
	Lrcc 260 Obs @ 5%	36.53003	13.19281	13.89624	6.655499	7.926332	22.39879	0.050636	7.377759
<u>VW ES</u>	LRuc 1000 Obs @ 1%	52.28628	1.298902	5.226175	5.226175	5.226175	5.226175	0.000982	5.023886
	LRuc 1000 Obs @ 5%	29.54847	19.44388	26.67251	26.67251	26.67251	19.44388	0.000982	5.023886
	LRuc 260 Obs @ 1%	9.288997	4.918254	0.309264	0.079077	0.079077	0.079077	0.000982	5.023886
	LRuc 260 Obs @ 5%	34.14073	0.083018	13.89624	5.480089	7.926332	10.74019	0.000982	5.023886
	Lrind 1000 Obs @ 1%	0.989931	13.10979	0	0	0	0	0.000982	5.023886
	Lrind 1000 Obs @ 5%	0.16478	57.04074	102.8143	84.37618	77.79924	90.67262	0.000982	5.023886
	Lrind 260 Obs @ 1%	0.083567	90.93561	149.4922	113.7302	135.0719	0.025242	0.000982	5.023886
	Lrind 260 Obs @ 5%	4.02E-06	13.10979	0	0	0	13.10979	0.000982	5.023886

	Lrcc 1000 Obs @ 1%	53.27621	14.40869	5.226175	5.226175	5.226175	5.226175	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	29.71325	76.48462	129.4868	111.0487	104.4718	110.1165	0.050636	7.377759
	Lrcc 260 Obs @ 1%	9.372564	95.85387	149.8015	113.8093	135.151	0.10432	0.050636	7.377759
	Lrcc 260 Obs @ 5%	34.14074	13.19281	13.89624	5.480089	7.926332	23.84998	0.050636	7.377759

Table 11 Backtesting results for OS 2 (GARCH filtered)

	Test	S&P 500 COMPOSITE - PRICE INDEX	ISEQ 20 - PRICE INDEX	FTSE 100 - PRICE INDEX	EURO STOXX (Euro Average) - PRICE INDEX	IBEX 35 (Spain) - PRICE INDEX	OMX COPEN HAGEN (OMXC20) - PRICE INDEX	5% Critical Value (lower bound)	5% Critical Value (upper bound)
<u>HS</u>	LRuc 1000 Obs @ 1%	0.653892	5.226175	5.226175	5.226175	5.226175	5.226175	0.000982	5.023886
	LRuc 1000 Obs @ 5%	7.926332	4.918254	8.894783	0.789005	0.083018	6.701242	0.000982	5.023886
	LRuc 260 Obs @ 1%	19.44388	19.44388	26.67251	26.67251	19.44388	26.67251	0.000982	5.023886
	LRuc 260 Obs @ 5%	4.918254	14.99556	19.44388	11.60148	6.701242	26.67251	0.000982	5.023886
	Lrind 1000 Obs @ 1%	41.30217	0	0	0	0	0	0.000982	5.023886
	Lrind 1000 Obs @ 5%	13.10979	13.10979	0	0	13.10979	0	0.000982	5.023886
	Lrind 260 Obs @ 1%	1.918867	23.43924	13.10979	5.50287	10.04987	0	0.000982	5.023886
	Lrind 260 Obs @ 5%	0.00107	57.04074	32.71441	3.26891	4.663566	49.37675	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	41.95606	5.226175	5.226175	5.226175	5.226175	5.226175	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	21.03612	18.02804	8.894783	0.789005	13.19281	6.701242	0.050636	7.377759
	Lrcc 260 Obs @ 1%	21.36275	42.88312	39.7823	32.17538	29.49375	26.67251	0.050636	7.377759
	Lrcc 260 Obs @ 5%	4.919324	72.0363	52.15829	14.87039	11.36481	76.04926	0.050636	7.377759
<u>AWHS</u>	LRuc 1000 Obs @ 1%	7.296969	3.280086	0.653892	0.059227	0.059227	0.653892	0.000982	5.023886
	LRuc 1000 Obs @ 5%	1.817111	0.083018	4.918254	8.894783	11.60148	8.894783	0.000982	5.023886
	LRuc 260 Obs @ 1%	2.332413	3.478034	6.701242	8.894783	11.60148	8.894783	0.000982	5.023886
	LRuc 260 Obs @ 5%	2.567549	0.340961	6.701242	11.60148	11.60148	6.701242	0.000982	5.023886
	Lrind 1000 Obs @ 1%	1.437444	8.274355	12.36485	5.495241	32.69106	2.507826	0.000982	5.023886
	Lrind 1000 Obs @ 5%	1.437444	8.259266	12.34938	5.495241	32.71441	2.514723	0.000982	5.023886
	Lrind 260 Obs @ 1%	0.145308	3.217591	10.03462	5.495241	32.69106	1.925439	0.000982	5.023886
	Lrind 260 Obs @ 5%	0.06413	3.217591	10.03462	5.495241	32.69106	2.507826	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	8.734413	11.55444	13.01874	5.554468	32.75029	3.161718	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	3.254555	8.342284	17.26763	14.39002	44.31589	11.40951	0.050636	7.377759
	Lrcc 260 Obs @ 1%	2.477722	6.695625	16.73586	14.39002	44.29254	10.82022	0.050636	7.377759
	Lrcc 260 Obs @ 5%	2.63168	3.558552	16.73586	17.09672	44.29254	9.209068	0.050636	7.377759
<u>Para norm</u>	LRuc 1000 Obs @ 1%	9.711302	1.298902	5.226175	5.226175	1.298902	5.226175	0.000982	5.023886
	LRuc 1000 Obs @ 5%	2.567549	4.918254	19.44388	8.894783	19.44388	14.99556	0.000982	5.023886
	LRuc 260 Obs @ 1%	19.44388	19.44388	26.67251	26.67251	19.44388	26.67251	0.000982	5.023886
	LRuc 260 Obs @ 5%	3.478034	19.44388	19.44388	11.60148	8.894783	26.67251	0.000982	5.023886
	Lrind 1000 Obs @ 1%	78.08556	13.10204	0	0	13.10204	0	0.000982	5.023886
	Lrind 1000 Obs @ 5%	13.10204	13.10204	0	0	13.10204	0	0.000982	5.023886

	Lrind 260 Obs @ 1%	1.443634	13.10204	13.10204	23.40811	4.175544	0	0.000982	5.023886
	Lrind 260 Obs @ 5%	0.270481	56.99377	13.10204	41.27098	13.10204	23.42371	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	87.79686	14.40094	5.226175	5.226175	14.40094	5.226175	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	15.66959	18.02029	19.44388	8.894783	32.54592	14.99556	0.050636	7.377759
	Lrcc 260 Obs @ 1%	20.88751	32.54592	39.77455	50.08062	23.61942	26.67251	0.050636	7.377759
	Lrcc 260 Obs @ 5%	3.748515	76.43765	32.54592	52.87246	21.99682	50.09622	0.050636	7.377759
<u>Stu T</u>	LRuc 1000 Obs @ 1%	0.15194	5.226175	5.226175	5.226175	1.298902	5.226175	0.000982	5.023886
	LRuc 1000 Obs @ 5%	0.789005	19.44388	26.67251	26.67251	19.44388	26.67251	0.000982	5.023886
	LRuc 260 Obs @ 1%	19.44388	26.67251	26.67251	26.67251	19.44388	26.67251	0.000982	5.023886
	LRuc 260 Obs @ 5%	8.894783	19.44388	26.67251	19.44388	19.44388	26.67251	0.000982	5.023886
	Lrind 1000 Obs @ 1%	23.42371	0	0	0	13.10204	0	0.000982	5.023886
	Lrind 1000 Obs @ 5%	13.10204	0	0	0	13.10204	0	0.000982	5.023886
	Lrind 260 Obs @ 1%	41.27098	13.10204	0	13.10204	13.10204	0	0.000982	5.023886
	Lrind 260 Obs @ 5%	84.61479	13.10204	0	0	13.10204	0	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	23.57565	5.226175	5.226175	5.226175	14.40094	5.226175	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	13.89104	19.44388	26.67251	26.67251	32.54592	26.67251	0.050636	7.377759
	Lrcc 260 Obs @ 1%	60.71486	39.77455	26.67251	39.77455	32.54592	26.67251	0.050636	7.377759
	Lrcc 260 Obs @ 5%	93.50957	32.54592	26.67251	19.44388	32.54592	26.67251	0.050636	7.377759
<u>ES</u>	LRuc 1000 Obs @ 1%	3.280086	5.226175	5.226175	5.226175	1.298902	5.226175	0.000982	5.023886
	LRuc 1000 Obs @ 5%	0.789005	19.44388	26.67251	26.67251	19.44388	26.67251	0.000982	5.023886
	LRuc 260 Obs @ 1%	19.44388	26.67251	26.67251	26.67251	19.44388	26.67251	0.000982	5.023886
	LRuc 260 Obs @ 5%	8.894783	19.44388	26.67251	19.44388	19.44388	26.67251	0.000982	5.023886
	Lrind 1000 Obs @ 1%	57.04074	0	0	0	13.10979	0	0.000982	5.023886
	Lrind 1000 Obs @ 5%	13.10979	0	0	0	13.10979	0	0.000982	5.023886
	Lrind 260 Obs @ 1%	41.30217	13.10979	0	13.10979	13.10979	0	0.000982	5.023886
	Lrind 260 Obs @ 5%	84.69369	13.10979	0	0	13.10979	0	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	60.32083	5.226175	5.226175	5.226175	14.40869	5.226175	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	13.8988	19.44388	26.67251	26.67251	32.55367	26.67251	0.050636	7.377759
	Lrcc 260 Obs @ 1%	60.74605	39.7823	26.67251	39.7823	32.55367	26.67251	0.050636	7.377759
	Lrcc 260 Obs @ 5%	93.58847	32.55367	26.67251	19.44388	32.55367	26.67251	0.050636	7.377759
<u>VW Para norm</u>	LRuc 1000 Obs @ 1%	5.226175	5.226175	5.226175	5.226175	5.226175	5.226175	0.000982	5.023886
	LRuc 1000 Obs @ 5%	19.44388	26.67251	26.67251	26.67251	26.67251	26.67251	0.000982	5.023886
	LRuc 260 Obs @ 1%	26.67251	26.67251	26.67251	26.67251	19.44388	26.67251	0.000982	5.023886
	LRuc 260 Obs @ 5%	26.67251	26.67251	26.67251	26.67251	19.44388	26.67251	0.000982	5.023886
	Lrind 1000 Obs @ 1%	0	0	0	0	0	0	0.000982	5.023886
	Lrind 1000 Obs @ 5%	0	0	0	0	13.10979	0	0.000982	5.023886
	Lrind 260 Obs @ 1%	0	0	0	0	13.10979	0	0.000982	5.023886
	Lrind 260 Obs @ 5%	13.10979	0	0	0	0	0	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	5.226175	5.226175	5.226175	5.226175	5.226175	5.226175	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	19.44388	26.67251	26.67251	26.67251	39.7823	26.67251	0.050636	7.377759
	Lrcc 260 Obs @ 1%	26.67251	26.67251	26.67251	26.67251	32.55367	26.67251	0.050636	7.377759
	Lrcc 260 Obs @ 5%	39.7823	26.67251	26.67251	26.67251	19.44388	26.67251	0.050636	7.377759

<u>VW</u> <u>Stu t</u>	LRuc 1000 Obs @ 1%	5.226175	5.226175	5.226175	5.226175	5.226175	5.226175	0.000982	5.023886
	LRuc 1000 Obs @ 5%	26.67251	26.67251	26.67251	26.67251	26.67251	26.67251	0.000982	5.023886
	LRuc 260 Obs @ 1%	26.67251	26.67251	26.67251	26.67251	26.67251	26.67251	0.000982	5.023886
	LRuc 260 Obs @ 5%	26.67251	26.67251	26.67251	26.67251	19.44388	26.67251	0.000982	5.023886
	Lrind 1000 Obs @ 1%	0	0	0	0	0	0	0.000982	5.023886
	Lrind 1000 Obs @ 5%	0	0	0	0	0	0	0.000982	5.023886
	Lrind 260 Obs @ 1%	0	0	0	0	13.10979	0	0.000982	5.023886
	Lrind 260 Obs @ 5%	0	0	0	0	0	0	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	5.226175	5.226175	5.226175	5.226175	5.226175	5.226175	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	26.67251	26.67251	26.67251	26.67251	26.67251	26.67251	0.050636	7.377759
	Lrcc 260 Obs @ 1%	26.67251	26.67251	26.67251	26.67251	39.7823	26.67251	0.050636	7.377759
	Lrcc 260 Obs @ 5%	26.67251	26.67251	26.67251	26.67251	19.44388	26.67251	0.050636	7.377759
<u>VW</u> <u>ES</u>	LRuc 1000 Obs @ 1%	5.226175	5.226175	5.226175	5.226175	5.226175	5.226175	0.000982	5.023886
	LRuc 1000 Obs @ 5%	26.67251	26.67251	26.67251	26.67251	26.67251	26.67251	0.000982	5.023886
	LRuc 260 Obs @ 1%	26.67251	26.67251	26.67251	26.67251	19.44388	26.67251	0.000982	5.023886
	LRuc 260 Obs @ 5%	26.67251	26.67251	26.67251	26.67251	19.44388	26.67251	0.000982	5.023886
	Lrind 1000 Obs @ 1%	0	0	0	0	0	0	0.000982	5.023886
	Lrind 1000 Obs @ 5%	0	0	0	0	0	0	0.000982	5.023886
	Lrind 260 Obs @ 1%	0	0	0	0	13.10979	0	0.000982	5.023886
	Lrind 260 Obs @ 5%	0	0	0	0	13.10979	0	0.000982	5.023886
	Lrcc 1000 Obs @ 1%	5.226175	5.226175	5.226175	5.226175	5.226175	5.226175	0.050636	7.377759
	Lrcc 1000 Obs @ 5%	26.67251	26.67251	26.67251	26.67251	26.67251	26.67251	0.050636	7.377759
	Lrcc 260 Obs @ 1%	26.67251	26.67251	26.67251	26.67251	32.55367	26.67251	0.050636	7.377759
	Lrcc 260 Obs @ 5%	26.67251	26.67251	26.67251	26.67251	32.55367	26.67251	0.050636	7.377759

Table 12 Ireland's Main trading Partners 2009 €m (Source Central Statistics Office)
<http://www.cso.ie/statistics/botmaintnrpartners.htm> Accessed: 07 June 2010

Trading Partner	Imports	Exports	% Imports	% Exports
Great Britain and Northern Ireland	13,617.3	13,510.5	30.4%	16.2%
Other EU Countries	12,889.0	37,465.9	28.7%	44.9%
USA	7,839.3	17,584.6	17.5%	21.1%
Rest of World	10,489.8	14,962.3	23.4%	17.9%
Total	44,835.4	83,523.3		

VBA Script for calculating Age-Weighted Historical Simulation

Sub AWHS()

Dim data(3190) As Variant

```

Dim rescaling As Variant
Dim weighta As Variant
Dim weightb(3190) As Variant
Dim i As Integer
Dim j As Integer

For i = 1 To 3189
data(i) = Cells(i + 1, 2)
'rstar(i)=cells(i+1, 17)
'cells(row, column)
Next i

For i = 2 To 2190
ReDim returns(i - 1) As Variant
weighta = (1 - 0.9999) / (1 - 0.9999 ^ (260)) * 260
For j = 1 To i - 1
weightb(j) = weighta * 0.9999
returns(j) = weightb(j) * data(j)
Next j
percentilen = Application.WorksheetFunction.Percentile(returns, 0.01)
Cells(i, 23) = percentilen
Next i

End Sub

```