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Risk Modelling in Energy Markets

A Value at Risk and Expected Shortfall Approach

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Problem Description

The master thesis aims to compare the predictive performance of different models for Value at Risk and Expected Shortfall for energy markets (electricity, oil, oil products, gas, coal and carbon). Primary markets are NASDAQ OMX, European Energy Exchange, Intercontinental Exchange and New York Mercantile Exchange.

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Preface

This master thesis was written at the Department of Industrial Economics and Technology Management at the Norwegian University of Science and Technology (NTNU) between January 2011 and June 2011.

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We hereby declare that this master thesis has been carried out in accordance with the examination regulations of NTNU.

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Abstract

Value at risk (VaR) and Expected Shortfall (ES) are commonly used risk measures in the financial literature. They have however not been applied to a great extent on energy derivatives. This paper compares the performance of several VaR and ES models for energy commodity futures on some of the world's largest commodity exchanges. In total 14 different VaR models and nine ES models are evaluated; GARCH and GJR-GARCH with normal, student t, GED and skewed student t distributions and EWQR are used to obtain both VaR and ES forecasts. In addition, five CAViaR models are used in the VaR analysis.

EWQR is by far the best ES model. It has very good test results for all markets and quantiles considered. The VaR results vary greatly, and there does not appear to be any clear pattern in which some models are better suited for certain markets or commodities. The VaR models with best performance overall are however EWQR, the adaptive CAViaR and GARCH and GJR-GARCH models with student t and skewed student t distributions.

Keywords: Risk Modelling, Value at Risk, VaR, Expected Shortfall, ES, Expected Tail Loss, ETL, Conditional Value at Risk, CVaR, Quantile Regression, Exponentially Weighted Quantile Regression, EWQR, Conditional Autoregressive Value at Risk, CAViaR, Generalized AutoRegressive Conditional Heteroskedasticity, GARCH,GJR-GARCH, Normal Distribution, Student t, GED, Skewed Student t, Energy Markets, Energy Commodity Futures, Carbon, Electricity, Oil, Oil Products, Natural Gas, Coal,

1. Introduction

Risk management in energy markets is becoming increasingly relevant. A growing number of the world's power markets have been liberalized and multinational power exchanges have emerged. Markets are becoming more integrated, and the trading of forward and futures contracts is increasing. Energy markets differ from traditional financial markets due to the nature of production and consumption (Pilipovic 2007); the volatility of energy commodities is higher, and return distributions tend to be more leptokurtic and skewed. This makes risk modelling a challenging and important task. Risk management is not only relevant for participants in financial trading; suppliers and consumers of energy commodities also have a need for hedging of their operations and investments.

In this paper both Value at Risk (VaR) and Expected Shortfall (ES) will be used to quantify risk. VaR is a popular tool in risk management today. It assists in setting position limits and allocating resources to meet capital requirements needed to cover market risk. ES is a risk measure which has been introduced as a coherent supplement to VaR.

We apply several different models to obtain VaR and ES estimates for the 90%, 95% and 99% quantiles of the loss distribution for both long and short trading positions: Exponentially Weighted Quantile Regression (EWQR), eight Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) models and five models based on the Conditional Autoregressive Value at Risk (CAViaR) framework. The GARCH models are well-established in risk management, but quantile regression based models such as CAViaR and EWQR are valid alternatives.

We consider monthly, quarterly and yearly first position energy futures from four different markets. These markets have been chosen because of their strong position in futures contracts trading of energy commodities.

New York Mercantile Exchange (NYMEX) is the largest energy and metals exchange in the world. In 2008 they became a part of the world's largest futures market, CME Group Inc. (CME Group 2008).Nord Pool was the world's largest power derivatives exchange when it was acquired by the NASDAQ OMX Group. In November 2010 it changed trade name to NASDAQ OMX Commodities Europe (Nasdaq OMX 2011). ICE Futures Europe is one of three futures exchanges operated by Intercontinental Exchange (NYSE: ICE), and hosts trading in half of the world's crude and refined oil futures contracts traded each day (ICE 2011). European Energy Exchange (EEX) is one of the leading trading markets in European energy trading, and the volume of power derivatives traded is about five times higher than the volume traded on the spot market for power (European Energy Exchange AG 2009).

We share the view of Angelidis et al. (2004) that it is better to use risk models that have good out-of-sample forecasts than models that are correctly specified for the in-sample period. Hence, the focus when evaluating the models will be on the out-of-sample performance.

Our analysis shows that the performance of the VaR models differs great between the 14 return series considered. EWQR, the adaptive CAViaR and the GARCH and GJR-GARCH models with student t and skewed student t distributions are the most accurate. EWQR is the best ES model, clearly outperforming the other models at the two-sided tests.

The rest of the paper is organized as follows. Section two provides a review of relevant studies conducted on VaR and ES, and how our approach will complement the existing literature. The third section describes the methodology of estimating VaR and ES with GARCH, EWQR and CAViaR, and section four and five methods of testing the VaR and ES forecasts, respectively. In section six a description of the data samples is given, while section seven contains an analysis of the empirical results. Concluding remarks follow in the last section.

2. Review of Existing Literature

2.1 Models for Value at Risk

There are several different approaches to estimating VaR from time series. Manganelli and Engle (2001) distinguish between three categories of VaR methods: parametric, semiparametric and nonparametric.

A simple way to estimate VaR is through historical simulation (HS), which is a *nonparametric* approach where historic data is used to make sample quantile estimates. Kuester et al. (2006) describes two kinds of historical simulation, naive HS, which is the most used, and filtered historical simulation (FHS). A problem with the HS approach is that it assumes that the next return will be the same as one of the observed returns in the chosen sample, with equal probability of occurrence. A future return cannot deviate from the already observed returns.

Boudoukh, Richardson and Whitlaw (1998) introduce what they call a hybrid approach, which estimates VaR of a portfolio by applying exponentially declining weights to past returns and then finds the appropriate percentile of the time-weighted empirical distribution. This allows the VaR forecasts to deviate from the observed returns, and to emphasize recent returns.

Parametric VaR-methods, such as GARCH, use parameterization of the time-varying stochastic behavior of financial prices. GARCH was introduced by Bollerslev (1986), who based his work on the ARCH model by Engle (1982). In order to estimate the parameters in this model framework, an error distribution must be assumed. Originally the normal distribution was suggested (Bollerslev 1986). This is the easiest distribution to implement, and it is very often used at least as a benchmark. Even though the normal distribution assumption is easy and popular, it has been shown empirically that it is often unsuitable for real world applications (Kuester, Mittnik et al. 2006; Hung, Lee et al. 2008). The distribution of financial returns tend to be leptokurtic; it has heavier tails than predicted by the normal distribution, as well as more returns close to zero (McNeil and Frey 2000). In addition a lot of return series show an asymmetry that the normal distribution is unable to register (Harvey and Siddique 1999; Verhoeven and McAleer 2004). Therefore, other distributions may fit better with reality. The student t distribution (Bollerslev 1987), GED (Subbotin 1923; Nelson 1991) and heavy tails (Hung, Lee et al. 2008), all allow the distribution to be leptokurtic. Hansen’s skewed Student t distribution accounts for asymmetry in addition to leptokurtosis (Hansen 1994; Giot and Laurent 2003).

There exist a lot of extensions to the ARCH/GARCH framework. In fact there are so many of them that Bollerslev, Russell et al. (2010) published a reference guide to ease the navigation through the “alphabet-soup of acronyms and abbreviations”. Many of the different GARCH models have been used in VaR studies, such as EGARCH (Bertsimas, Lauprete et al. 2004; Chan and Gray 2006), APARCH (Giot and Laurent 2003; Huang and Lin 2004) and GJR-GARCH (Bertsimas, Lauprete et al. 2004), all of which account for asymmetry, AR-GARCH (Byström 2005; Kuester, Mittnik et al. 2006), which includes an autoregressive term for the conditional mean, and FIGARCH (Beine, Bénassy-Quéré et al. 2002; Härdle and Mungo 2008) which includes volatility shock persistence.

The *semiparametric* VaR models include extreme value theory (EVT) and quantile regression (QR). Both EVT and QR model the quantile directly instead of modelling the whole distribution. The problem with EVT is that it assumes that the returns are independent and identically distributed, which is normally not the case. To solve this, some kind of filter, for example a GARCH model, is applied to the returns prior to the EVT (Kuester, Mittnik et al. 2006). Having to apply a filter removes some of the advantage of modelling the quantile directly. We refer to Embrechts, Klüppelberg and Mikosch (1996) and Mapa and Suaiso (2009) for a more comprehensive analysis on this subject.

An example of a QR based model is CAViaR, introduced by Engle and Manganelli (2004). It suggests that the quantiles for the different periods are autoregressive. The parameters in the CAViaR models are estimated using quantile regression minimization. Some studies suggest that CAViaR performs well both for stock markets (Engle and Manganelli 2004) and commodities indices (Füss, Adams et al. 2010).

EWQR, developed by Taylor (2008), is another QR based VaR model, in which a weighting parameter has been included to the quantile regression expression. Even though the EWQR formula generally include regressors, Taylor (2008) argues that an EWQR with an intercept and no regressors is reasonable and should perform well. The version without regressors is basically equivalent to the hybrid model by Boudoukh, Richardson and Whitlaw mentioned above, but perhaps with better a theoretical framework.

Regardless of the popularity and extensive use of VaR, it has also been criticized. Beder (1995) declared VaR to be “seductive, but dangerous”, as results are very dependent on the method applied, the assumptions made and data considered. Acerbi and Tasche (2002) claim that VaR should be interpreted as “[…] the minimum loss incurred in the α% worst cases of our portfolio”, and that it therefore is a strange risk measure to consider.

A risk measure needs to meet four axioms; it must be monotonous, sub-additive, positively homogenous and translation invariant (Acerbi and Tasche 2002). With a portfolio made up of sub-portfolios, the risk calculated by VaR will be the sum of the risks of the sub-portfolios. In reality the risk will be lower or at most the sum of each risk because of diversification. Because our study only concerns univariate cases, this doesn’t affect our result. However, it is an important weakness of a risk measure.

2.2 Models for Expected Shortfall

In order to avoid the shortcomings of VaR, Expected Shortfall (ES) was introduced. Expected Tail loss (ETL), Conditional Value at Risk (CVaR), Average Value at Risk (AVaR), Tail Mean (TM), Average Multiple of Tail Event to Risk Measure (AMTERM), Tail Conditional Expectation (TCE) and Worst Conditional Expectation (WCE) are other terms which are used interchangeably for ES, even though there is a theoretical difference between some of them

(Acerbi and Tasche 2002; Rockafellar and Uryasev 2002; Alexander 2008; Härdle and Mungo 2008).

Compared with VaR less research is done on ES, but in the last decade the number of published articles about ES has increased rapidly. The articles concerning ES can be divided into three groups: The first group compares VaR and ES, the second one uses ES as a measure of VaR performance, while the last group considers ES models individually, as complements or extensions to the VaR models.

Most of the articles comparing VaR and ES focus on the differences in theoretical framework, and how ES is a better and coherent risk measure (Beder 1995; Acerbi and Tasche 2002; Bertsimas, Lauprete et al. 2004; Inui and Kijima 2005; Cai and Wang 2008; Lan, Nelson et al. 2010). Yamai and Yoshiba (2005), on the other hand, try to decide which risk measure is best empirically, by comparing their performance in currency markets. They conclude that VaR and ES should be used together, since VaR has the problem that it ignores everything above the VaR, while ES has much greater estimation errors than VaR and is therefore more difficult to model accurately.

ES can be used as a measure of VaR performance in at least two ways. First, as a comparable value, against which for example the average VaR forecast is compared, to verify whether the risk beyond VaR is great for a given market (Gupta and Liang 2005; Härdle and Mungo 2008). Secondly, an ES based loss function can be used to choose the best VaR model (Angelidis and Degiannakis 2006). The problem with using ES in this way is that the accuracy of the ES models is not tested. Therefore more attention should be focused on the third group of ES articles.

Among the ES models that are widely applied in stock or currency markets are EVT, the Stable Paretian Approach, historical simulation, and the normal distribution (McNeil and Frey 2000; Embrechts, Kaufmann et al. 2005; Yamai and Yoshiba 2005; Harmantzis, Miao et al. 2006; Marinelli, D'Addona et al. 2007; Alexander 2008; Chen 2008). These models have many of the same advantages and disadvantages as their corresponding VaR models, and alternative models are therefore still emerging.

Some GARCH specifications have been considered as well with several different error distributions, as the normal distribution, student t, GED and skewed student t (Angelidis, Benos et al. 2004; Embrechts, Kaufmann et al. 2005; Härdle and Mungo 2008; Caillault and Guégan 2009). These are however either calculated numerically (Embrechts, Kaufmann et al. 2005) or by following Dowd’s approach of slicing the distribution’s tail in many slices, estimating the corresponding VaR of each slice and then estimate ES as the average of these “tail VaRs” (Dowd 2002).

Conditional AutoRegressive Expectiles (CARE) is inspired by CAViaR, but it is constructed in a way that it is possible to obtain ES forecasts as well as VaR forecasts. (Taylor 2008; Kuan, Yeh et al. 2009). EWQR is also a model that can be used both for VaR and ES forecasting. It have had promising ES results so far, and is therefore an interesting model for further research (Lin 2008; Taylor 2008).

2.3 Our Contribution to the Existing Literature

Not much literature has been written on risk management by VaR or ES for energy commodity futures. Füss et al. (2010) investigated how different VaR models succeeded for futures indices based on commodities, one of which was an energy index. Others have estimated VaR for energy commodities, in particular oil, gas and oil products, but the focus has been on spot prices and not on futures (David Cabedo and Moya 2003; Giot and Laurent 2003; Chan and Gray 2006; Sadeghi and Shavvalpour 2006; Costello, Asem et al. 2008; Hung, Lee et al. 2008; Aloui and Mabrouk 2010). Even less has work has been done on ES models for energy commodities; to our knowledge there has not been published such an article yet.

The scope of this paper is to apply several VaR and ES models to a wide range of energy commodity futures. In this way our study will make an attribution to the existing literature, both in the variety of models used and the type of markets and financial instruments investigated.

In the existing literature, the quantile regression based VaR models, CAViaR and EWQR, and models in the GARCH framework seem the most promising. They have mainly been applied to stock or currency markets. We therefore wish to compare their performance for energy commodity futures as well. Since there exist too many GARCH based models to consider in this paper, we will focus our attention on the standard GARCH(1,1) model as well as one model which take asymmetry into account; the GJR-GARCH(1,1,1) model. Both GARCH models will be implemented with four different error distributions; the normal, student t, GED and skewed student t distributions.

We will use the same models to predict ES as VaR, except CAViaR, from which it is not clear how to obtain ES. It is straightforward to calculate ES with EWQR, using the expression derived by Taylor (2008). With GARCH, ES has so far been calculated numerically or as an average of many VaRs. We wish to expand the existing literature by finding analytical expressions for GARCH based ES models using the four mentioned error distributions. Yamai and Yoshiba (2005) have already derived from the standard normal distribution an ES expression which depends on the standard deviation. We will use the same approach to derive similar expressions for the other distributions and then use GARCH models to estimate the standard deviation in order to forecast ES.

3. Value at Risk and Expected Shortfall Models

14 different models are considered in this paper: GARCH(1,1) and GJR-GARCH (1,1,1) with four different error distributions each, five CAViaR specifications and EWQR. These models are used to produce day-ahead forecasts for both VaR and ES, with the exception of the CAViaR models, from which ES forecasts are not easily obtained. The expected value of the conditional mean is, for simplicity, assumed to be zero unless otherwise stated. Details regarding parameter estimation and derivations are left in appendix A.

3.1 Definitions

The probability of experiencing a loss higher than VaR_α is α percent. ES is defined as the expected value of the loss, given that it is greater than VaR_α. Mathematically, this can be expressed as:

$$VaR_\alpha = \sup_{x_t}\{x_t | P(X \geq x_t) \geq \alpha\}$$

$$ES_\alpha = E[x_t | X > VaR_\alpha(X)]$$

Here x_t represent the (1-α)th quantile of the distribution of the loss function X. For short positions the loss function is given by the return itself, while for long positions it equals the negative of the return.

3.2 GARCH and GJR-GARCH

Both GARCH(1,1) and GJR-GARCH(1,1,1) are autoregressive models for conditional variance that take volatility clustering into account. VaR and ES are expected to increase as the volatility in a market increases and vice versa. These models should therefore in theory provide a good basis for VaR and ES estimation. Their conditional variance expressions follow:

GARCH(1,1): $$\sigma_t^2 = \beta_0 + \beta_1 r_{t-1}^2 + \beta_2 \sigma_{t-1}^2$$

GJR-GARCH(1,1,1): $$\sigma_t^2 = \beta_0 + \beta_1 r_{t-1}^2 + \beta_2 r_{t-1}^2 I(r_{t-1} < 0) + \beta_3 \sigma_{t-1}^2$$

The difference between the regular GARCH and the GJR-GARCH is that the latter allows the conditional variance to respond asymmetrically for positive and negative returns. In order to estimate the parameters in the expressions above, an error distribution needs to be assumed. Initially the normal distribution was suggested (Bollerslev 1986) but later more heavy tailed or asymmetrical distributions have been more popular, since they tend to fit empirical results better. In this paper four different error distributions are investigated; normal distribution, student t distribution, generalized error distribution (GED) and Hansen's skew student t distribution.

VaR is found from the following expressions, in which $q_{1-\alpha}$ is the $(1-\alpha)$th-quantile of the assumed error distribution, or in other words the inverse cumulative error distribution at $(1-\alpha)$:

$$\widehat{VaR}_{\alpha,t} = q_{1-\alpha}\hat{\sigma}_t$$

ES is then calculated from the following formulas:

Normal distribution:

$$\widehat{ES}_{\alpha,t} = \frac{\hat{\sigma}_t}{\alpha\sqrt{2\pi}} e^{-\frac{q_{1-\alpha}^2}{2}}$$

Student t distribution:

$$\widehat{ES}_{\alpha,t} = \frac{\hat{\sigma}_t \Gamma\left(\frac{\mathrm{v}+1}{2}\right)\sqrt{\mathrm{v}-2}}{\alpha\sqrt{\pi}(\mathrm{v}-1)\Gamma\left(\frac{\mathrm{v}}{2}\right)}\left(\left(1+\frac{q_{1-\alpha}^2}{\hat{\sigma}_t{}^2(v-2)}\right)^{\frac{1}{2}(1-v)}\right)$$

Generalized error distribution:

$$\widehat{ES}_{\alpha,t} = \frac{\hat{\sigma}_t \omega 2^{\frac{1}{v-1}}}{\alpha\Gamma\left(\frac{1}{\mathrm{v}}\right)}\Gamma\left(\frac{2}{\mathrm{v}},\frac{1}{2}\left(\frac{\widehat{VaR}_{\alpha,t}}{|\lambda\widehat{\sigma}_t|}\right)^v\right)$$

Skew student t distribution:

$$\widehat{ES}_{\alpha,t} = \frac{\sigma_t}{\alpha b}\left(I\left(\widehat{VaR}_{\alpha,t} < -\frac{a\hat{\sigma}_t}{b}\right)\left(c(1-\lambda)^2\frac{v-2}{v-1}\left(\left(1+\frac{\widehat{VaR}_u^2}{(v-2)}\right)^{\frac{1-v}{2}}-1\right)+a(1-\lambda)*\right.\right.$$

$$\left.\left(F_{SST}\left(\widehat{VaR}_u\right)-0.5\right)+c(1+\lambda)^2\frac{v-2}{v-1}-\frac{a}{2}(1+\lambda)\right)+I\left(\widehat{VaR}_{\alpha,t} \geq -\frac{a\hat{\sigma}_t}{b}\right)\left(c(1+\lambda)^2*\right.$$

$$\left.\left.\frac{v-2}{v-1}\left(1+\frac{\widehat{VaR}_w^2}{(v-2)}\right)^{\frac{1-v}{2}}-a(1+\lambda)\left(1-F_{SST}\left(\widehat{VaR}_w\right)\right)\right)\right)$$

In the previous expressions $\Gamma(\cdot)$ is the gamma function, $\Gamma(\cdot,\cdot)$ is the incomplete gamma function, $I(\cdot)$ is the indicator function, $F_{SST}(\cdot)$ is the scale family of the cumulative standardized student t distribution, λ and v are parameters that are estimated with maximum likelihood estimation, and

$\omega = 2^{-\frac{1}{v}}\sqrt{\frac{\Gamma\left(\frac{1}{\mathrm{v}}\right)}{\Gamma\left(\frac{3}{\mathrm{v}}\right)}}$, $VaR_u = \frac{\frac{bVaR_{\alpha,t}}{\sigma_t}+a}{1-\lambda}$, $VaR_w = \frac{\frac{bVaR_{\alpha,t}}{\sigma_t}+a}{1+\lambda}$, $a = 4\lambda c\frac{v-2}{v-1}$, $b^2 = 1+3\lambda^2-a^2$ and $c = \frac{\Gamma\left(\frac{\mathrm{v}+1}{2}\right)}{\sqrt{\pi(v-2)}\Gamma\left(\frac{\mathrm{v}}{2}\right)}$

3.3 CAViaR

Instead of assuming an error distribution, CAViaR estimates the relevant quantile directly by a form for quantile regression. The intuition of the CAViaR models is that VaR is autoregressive, and that it also depends on the realized losses in one way or another. The five specifications considered are all first-order autoregressive VaR models.

In the Symmetric Absolute Value CAViaR model, VaR depends on the absolute value of the last period's return. This means that positive and negative losses will have the same impact; hence, the specification is symmetric. The Asymmetric Slope CAViaR model, on the other hand, allows positive and negative losses to be weighted differently.

Symmetric Absolute Value: $VaR_{\alpha,t} = \beta_0 + \beta_1 VaR_{\alpha,t-1} + \beta_2|x_{t-1}|$

Asymmetric Slope: $VaR_{\alpha,t} = \beta_0 + \beta_1 VaR_{\alpha,t-1} + \beta_2 max[x_{t-1},0] - \beta_3 \min[x_{t-1},0]$

The Adaptive CAViaR model increases the VaR when a loss in the last period exceeds the corresponding VaR; otherwise it decreases the VaR slightly.

Adaptive: $VaR_{\alpha,t} = VaR_{\alpha,t-1} + \beta_1 [I(x_{t-1} > VaR_{\alpha,t-1}) - \alpha]$

The Indirect GARCH(1,1) CAViaR model works just like a GARCH(1,1) model, except that an error distribution is not needed to estimate the parameters. The Indirect AR(1)-GARCH(1,1) CAViaR model, which is an extension of the indirect GARCH(1,1) CAViaR model, includes a first-order autoregressive term for the mean equation.

Indirect GARCH(1,1): $VaR_{\alpha,t} = \sqrt{\beta_0 + \beta_1 (VaR_{\alpha,t-1})^2 + \beta_2 x_{t-1}^2}$

Indirect AR(1)-GARCH(1,1):

$$VaR_{\alpha,t} = ax_{t-1} + \sqrt{\beta_0 + \beta_1 (ax_{t-2} - x_{t-1})^2 + \beta_2 (VaR_{\alpha,t-1} - ax_{t-2})^2}$$

3.4 EWQR

EWQR is another quantile regression based model. The main idea is that past observations influence the future, and that the most resent observations are more relevant than distant ones. Therefore a weighting parameter λ is included in the quantile regression minimization formula, which can be expressed as:

$$\min_{\widehat{VaR}_{\alpha,T+1}} \sum_{t=1}^{T} \lambda^{T-t} (\widehat{VaR}_{\alpha,T+1} - x_t) \left(\alpha - I(x_t > \widehat{VaR}_{\alpha,T+1})\right)$$

From this expression the VaR forecast follows directly and ES can easily be obtained:

$$\widehat{ES}_{\alpha,T+1} = \frac{1}{\alpha \sum_{t=1}^{T} \lambda^{T-t}} \sum_{t=1}^{T} \lambda^{T-t} (\widehat{VaR}_{\alpha,T+1} - x_t) \left(\alpha - I(x_t > \widehat{VaR}_{\alpha,T+1})\right)$$

4. Backtesting Value at Risk Forecasts

To assess the accuracy and appropriateness of VaR models, we consider three different tests. The *test for unconditional coverage*, also known as the Kupiec test, checks whether the proportion of losses that are higher than their corresponding VaR is as expected or not (Kupiec 1995). This test rejects models that either overestimate or underestimate VaR (Hung, Lee et al. 2008).

It does not, however, consider whether the extreme returns are randomly distributed or if they appear in clusters (Hung, Lee et al. 2008). This is of particular interest since it is far worse for an investor if the VaR estimates are exceeded many times in a row (Alexander 2008). The problem is addressed by the *test for conditional coverage*, which is a joint test of correct coverage and independence of the violations (Christoffersen 1998). This test rejects models that either overestimate or underestimate VaR or that generate either too many or too few clustered violations (Hung, Lee et al. 2008).

The third test considered in this paper is the *dynamic quantile (DQ) test.* For good VaR models, a VaR violation should be independent of the VaR estimate, as well as earlier VaR violations (Engle and Manganelli 2004). The DQ test checks whether or not this is the case by performing an artificial regression. The form of artificial regression that appears to be used most frequently, is the one that include four lags of VaR violations and the VaR estimate (Engle and Manganelli 1999; Kuester, Mittnik et al. 2006).

Details regarding these tests can be found in appendix B

5. Backtesting Expected Shortfall Forecasts

5.1 An Expected Shortfall Test Dependent on VaR Forecasts (DV)

McNeil and Frey (2000) developed a test, in which the difference between the ES forecasts and the realized losses is calculated for observations where the loss is greater than the VaR forecast. These residuals are then standardized. If the ES forecasts are appropriate, the residuals should now have a zero mean, be independent and identically distributed. A bootstrap test, which is explained in appendix B, checks whether or not the mean of the residuals is statistically different from zero. The test can be either one-sided or two-sided; we have considered both cases after following the reasoning of appendix B.

McNeil and Frey (2000) standardize the residuals by the corresponding forecasts of the conditional volatility. Taylor (2008), on the other hand, chooses to use the conditional quantile estimate (the forecasted Value at Risk), since not all models estimate volatility. We follow Taylor's example, and standardize with the VaR forecasts. The standardized residuals, $z_{\alpha,t}$, can thus be calculated from the following expression:

$$z_{\alpha,t} = \left\{ \frac{x_t - \widehat{ES}_{\alpha,t}}{\widehat{VaR}_{\alpha,t}} \,|\, x_t > \widehat{VaR}_{\alpha,t} \right\}$$

Even though this test has an attractive intuitiveness, it has a weakness; the test results have a strong dependence of the VaR forecasts (Embrechts, Kaufmann et al. 2005). If a model gives terrible VaR forecasts, the ES test results will be poor since only losses greater than the *forecasted* VaR are considered. A test that considers the ES forecasts separately would therefore be more appropriate.

Another problem with this test rises whenever there are few VaR violations. This may be the case for extreme quantiles if the out-of-sample period is not large enough, or if the VaR forecasts are too conservative. Then there are few data to bootstrap, which makes the test results less reliable. In some cases a bootstrap test does not make sense at all, for example when the number of observations is less than two.

5.2 An Expected Shortfall Test Independent of VaR Forecasts (IV)

Embrechts, Kaufmann et al. (2005) introduced an ES measure that is independent of the VaR forecasts. They considered the α % cases in which the difference between the loss and the ES forecast is the greatest, and calculate the average difference. Ideally the number should be zero, so it should be close to zero for good ES forecasts. Embrechts, Kaufmann et al. do not however state how small the measure should be for the forecasts to be considered adequate.

We propose a test that follows the same intuition of looking at the α % worst cases, but instead of calculating the average difference, it performs a bootstrap hypothesis test for the differences alone. Since this test evaluates ES forecasts independent of VaR forecasts, we choose to keep it that way by not standardizing by the VaR forecasts as in the previous ES test. Another measure could be used to standardize the residuals, but the results of a bootstrap test will have similar results whether or not the residuals are standardized (McNeil and Frey 2000). We therefore use the following variable as a basis for a bootstrap test.

$z_{\alpha,t} = \{x_t - \widehat{ES}_{\alpha,t} | x_t - \widehat{ES}_{\alpha,t} > D_\alpha\}$, where D_α is the α-th quantile of $x_t - \widehat{ES}_{\alpha,t}$.

6. Data and Descriptive Statistics

The data considered in this paper are prices of monthly, quarterly and yearly first position energy futures from EEX, NASDAQ OMX (Nord Pool), ICE and NYMEX; monthly peak electricity, brent crude oil, light crude oil, heating oil, gasoline, coal and gas futures, quarterly carbon futures and yearly peak electricity and carbon futures. In total this yields 14 different futures. The prices are gathered from the Reuters EcoWin Pro database.

The focus has been on the returns r_t, which can be defined as the logarithmic difference of the price from one day to another (Taylor 2005); $r_t=\ln(P_t/P_{t-1})$. Since daily returns are generally small in monetary units, they have been multiplied by 100 to avoid numerical errors in computer programs. Each price change between the last trading day of a futures contract and the first trading day of the subsequent contract has been excluded from the data set. This is because such price changes are not genuine returns; no trader will ever experience them. Each futures contract has its own rule for when the last trading day occur. The specific rules for the contracts considered in this paper are left in appendix C.

The length of the return series varies between 927 and 3500 data points. In appendix D a table with the length, start date and end date of each series is given, together with a table with descriptive statistics for all series. The last 500 observations are left as an out-of-sample period, against which the models' forecasting performance is backtested.

The means of all the return series are close to zero and the standard deviations are high compared to the means. This indicates that the returns are very volatile. Typical standard deviations for stocks and stock indices are between 0.7% and 2% for daily returns (Taylor 2005). In this study the standard deviations vary between 0.9% and 5.7%. 13 of the 14 commodity futures contracts in this paper have a standard deviation greater than 2%, which suggests that they are more volatile than stocks. The contract with lowest standard deviation is the yearly electricity futures. This makes sense, since the length of the contract makes it less sensitive to short term price variations. The most volatile contract, on the other hand, is the monthly electricity futures on NYMEX.

The kurtosis of the series ranges in value from 4.6 to 40.5. This is significantly higher than the kurtosis of a standard normal distribution, which is 3. A distribution which has a kurtosis higher than 3 is called leptokurtic, which implies a high peak around the mean and fat tails. In other words, there are many returns close to zero as well as numerous extreme returns. All of the series considered are leptokurtic, which contributes to making forecasting a more challenging task.

Comparing the maximum and minimum values with the median supports the notion of having a leptokurtic distribution of the returns. With the exception of yearly electricity futures, all the contracts have some returns with absolute value above 10%. A few of them also display returns well above 30%. The median, on the other hand is very close to zero.

The skewness of the returns varies between -1.4 and 1.9, which means that some of the series are skewed to the right and others to the left. With exception of the electricity futures, all futures for the same commodity are skewed to the same side regardless of which market they are traded on. For example do oil and all oil products have negative skewness, while both gas futures contracts have a positive skewness.

The Jarque-Bera and augmented Dickey-Füller tests refute the null hypothesis of normality and unit root for all the return series, as expected both a priori and after considering the other descriptive statistics.

According to the Ljung-Box test a majority of the futures display autocorrelation within the first five lags, and for the squared returns all of the futures show signs of autocorrelation. This is consistent with the findings of Aloui and Mabrouk (2010) on crude oil and gas commodities and might be explained by the characteristics of energy commodity price behavior; such as mean reversion and spikes (Deng 2000).

Some of the return series display significant difference between the in- and out-of-sample periods. In appendix D the descriptive statistics for both are given. The general trend is that the series are less volatile in the out-of-sample period, with less extreme values and lower standard deviation. The financial crises occurred during the in-sample period, while the out-of sample period is post-crises. This might contribute to the observed difference. Most of the in-sample periods are however larger than the out-of-sample periods, and are therefore more likely to include extreme values.

7. Empirical Results

500 day-ahead VaR and ES forecast are obtained with each of the 14 models for six different quantiles in the return distribution; 1%, 5%, 10%, 90%, 95% and 99%. This corresponds to the 90%, 95% and 99% quantiles in the loss distribution for long and short trading positions, respectively. The number of forecasts is consistent with Engle and Manganelli (2004) and Taylor (2008), and corresponds to around two years of trading. The forecasts are obtained by rolling the sample window and re-estimating the parameters each day for the EWQR and the GARCH models. The parameters are not re-estimated for the CAViaR models, because of limited computing capacity[1].

In the following subsections each model is evaluated for both VaR and ES results. In appendix E all the details regarding the test results are given for further study. There does not

[1]To re-estimate the five CAViaR models' parameters 500 times for each of the 14 futures would require more than three weeks of continuous computations with an average personal computer.

seem to be a clear pattern in which some models are better suited for certain markets or commodities. The results are therefore presented by model rather than market or commodity.

7.1 VaR Results

The VaR models are tested by the three tests described in section 4. Of these, we focus on the results from the coverage tests, since, in our opinion, it is more important for a VaR model to be correctly specified and thus predicting the proportion of losses that exceed VaR correctly, than it is that the probability of a VaR violation is independent of the VaR itself. The coverage tests will therefore be used to assess the appropriateness of the VaR models, while the DQ test will serve as a secondary comparable value in case several models have equally good performance in the coverage tests.

The conditional coverage test does however have a weakness. For the extreme quantiles it is unlikely to witness two consecutive VaR violations, and the test is therefore not able to give a result for these. In order to use the test results in a productive way we will focus on the number of quantiles that pass the test at 5% significance level. The results from the unconditional coverage test and DQ test are more complete, and easier to use for model comparison.

None of the models considered perform well for every return series, and it is not one model that clearly outperforms the others. However, there are some conclusions that can be drawn. The most accurate models are the EWQR, the adaptive CAViaR and the GARCH and GJR-GARCH models with student t and skewed student t distributions. GARCH and GJR-GARCH with normal distribution are the two worst performing VaR models.

7.1.1 VaR Results for EWQR

EWQR is the model that performs best for both gasoline and heating oil on NYMEX. On five of the fourteen return series the model fails none of the quantiles in the unconditional coverage test at 10% significance level, and in total EWQR slightly outperforms the other models according to this test. With a 5% confidence level it fails 13 of the 84 quantiles considered. It is also the model with the highest number of non-failing quantiles in the conditional coverage test. It is on the dynamic quantile test that EWQR has its worst performance. Out of the fourteen models considered, it is the one with the lowest score.

7.1.2 VaR Results for CAViaR

The *symmetric absolute value* CAViaR is together with the *indirect GARCH* CAViaR the models with worst performance. The latter is the best performing model for coal on ICE and light crude oil on NYMEX, but falls through on the rest. Both models have only two series where they clear the unconditional coverage test, and they have the lowest count of reliable quantiles in the conditional coverage test. In the dynamic quantile test they perform in the mid-range.

The *indirect AR-GARCH* CAViaR model can be categorized together with these models. It performs below par for both coverage tests. It is however one of the best models to make sure that the forecast is independent of the previous VaR estimates and violations, according to the dynamic quantile test.

The *asymmetric slope* CAViaR performs slightly better than the *symmetric absolute value*, which is to be expected as it can weigh positive and negative returns differently. It is the best model for carbon futures on NASDAQ OMX and coal futures on NYMEX and it also handles the dynamic quantile test well. Still, it does not perform well on the coverage tests.

The *adaptive* CAViaR is that of the CAViaR models that is most reliable. With exception of the futures for brent crude oil, heating oil and light crude oil, where it fails severely, it has a very stable performance in the coverage tests. It is the best overall model for monthly electricity futures on ICE and EEX and for gas on ICE. Just like EWQR, the problem for the *adaptive* CAViaR is the dynamic quantile test, where it underperforms all the other CAViaR models. Much of the explanation lies in the fact that it is an adaptive model. Once the VaR is breached, it increases significantly, while it decreases slightly otherwise. This makes consecutive breaches of VaR less likely in volatile periods.

Because the parameters in the CAViaR models are not re-estimated, it is natural to assume that they will fit worse the longer the out-of-sample period is. If the parameters were re-estimated for every forecast, the models would probably have a better performance since it would adapt better to changes in the market.

7.1.3 VaR Results for GARCH and GJR-GARCH

The GARCH with normal distribution is the worst performing VaR model considered in this paper. For one of the futures, gas on NYMEX, it passes all the tests. However, several other models do the same, and the test results indicate that this is the easiest series to forecast. Other than that, it has a generally poor performance. The same can be said for the GJR-GARCH with normal distribution.

With Student t distribution the models are significantly improved. The GARCH and GJR-GARCH are the best models for gas futures and electricity futures on NYMEX respectively. The performance is stable and high, both for the coverage tests and the dynamic quantile test. The models with student t distribution prove to be a valid and more reliable alternative for VaR forecasting.

There are no futures series where either of the models with GED distribution are the best models. Overall, they perform better than the models with normal distribution and most of the CAViaR models, but worse than the other models. They distinguish themselves only on the DQ test, where they perform better than most other models.

The GARCH model with skewed student t distribution is the best model for carbon futures on EEX and light crude oil on NYMEX. It passes the unconditional coverage test perfectly for five return series, and is one of the best models both on the coverage tests and the dynamic quantile test. The GJR-GARCH with the same distribution has the best test results for yearly electricity futures on EEX and monthly electricity futures and light crude oil futures on NYMEX. Other than that the performance is quite similar to that of the ordinary GARCH model. Both have five return series where they have no p-values under 10% on the unconditional coverage test.

In our results there is little difference between the GJR-GARCH and the ordinary GARCH when they have the same distribution; the GARCH model actually has a slightly better performance. As the GJR-GARCH is more complicated and requires more computational power, this leads us to suggest that the GARCH model should be preferred for VaR forecasting.

7.2 ES Results

The ES forecasts were tested by the one- and two-sided tests described in section 5. In the following we denote the tests dependent on VaR by DV, and the tests that are independent of the VaR forecasts by IV. The two-sided tests concern whether or not the forecast is correct, while the one-sided tests check if the forecast is underestimated or not. If a model obtains good results in the one-sided tests and poor results in the two-sided tests, it is an indication of overestimated ES forecasts.

The IV tests prove to be stricter than the DV tests, since they reject the null hypotheses more often regardless of which model or market is considered. When there is a great difference between a model's performance in the DV and IV tests, this might be explained by the model having incorrect VaR forecast.

The EWQR model has superior performance to the other models when the two-sided tests are considered. The GARCH and GJR-GARCH models with GED distribution pass almost every quantile for every futures contract in the traditional one-sided tests, but fail to a great extent at the two-sided tests. This suggests that they consistently overestimate ES.

7.2.1 ES Results for EWQR

EWQR is by far the model that performs best. In the DV tests it passes for every quantile for 11 and 12 of the futures for the two- and one-sided respectively. Only for one quantile is the p-value below 5%. In the two-sided IV test EWQR pass every quantile for four series at a 10% significance level. With the exception of GJR-GARCH with a skewed student t distribution, the other models pass every quantile for at most one series. EWQR has the worst performance in the one-sided IV test, which suggests that ES is underestimated. Considering the results from the two-sided test, the underestimation is however not large enough that the ES forecasts are statistically different from the realized shortfalls. Of the models considered in this paper, EWQR is the best at forecasting ES.

7.2.2 ES Results for GARCH and GJR-GARCH

The GJR-GARCH model performs slightly worse than the GARCH model for almost all the distributions. This further promotes the notion from the VaR analysis, that there is no point in using the GJR version instead of an ordinary GARCH.

The GARCH model with normal distribution is surprisingly enough the one that performs best in the two-sided tests. With student-t distribution the GARCH model performs well for the one-sided tests, but falls through on both two-sided tests. The GARCH model with skewed student t distribution does not perform better than that with a student t. GARCH with GED distribution is the model with the worst results in the two-sided tests, but it excels in the one-sided. In other words, the model consistently overestimates ES. An extremely risk averse investor could choose this model, but it would lead to unprofitable allocation of capital.

8. Concluding Remarks

Energy markets differ from traditional financial markets due to the nature of production and consumption. This makes risk modelling a challenging and important task. The approach taken in this paper is to consider different models for two popular risk measures, Value at Risk and Expected Shortfall, in an attempt to model risk for energy commodity futures. We have considered 14 different first position energy futures contracts from NYMEX, NASDAQ OMX, ICE and EEX, and estimated VaR and ES for three different quantiles for both long and short trading positions.

This paper's attribution to the existing literature lies both in the variety of models used and the type of markets and financial instruments investigated. In total 14 different VaR models and nine different ES models are evaluated; GARCH and GJR-GARCH with normal, student t, GED and skewed student t distributions and EWQR have been used to obtain both VaR and ES forecasts. In addition, five CAViaR models have been used in the VaR analysis.

In general, the GJR-GARCH model performs slightly worse than the GARCH model, both for VaR and ES. As the GJR-GARCH is more complicated and requires more computational power, the GARCH model should be preferred. EWQR is by far the best ES model. It has very good test results for all markets and quantiles considered. The GARCH and GJR-GARCH models with GED distribution perform well for the one-sided ES tests, as they do not underestimate ES. They are on the other hand the worst ES models according to the two-sided tests. In other words, they are consistently overestimating ES.

It is not as straightforward to generalize the VaR results, as none of the VaR models perform well for every return series, and there is not one model that clearly outperforms the others. The results vary greatly, and there does not appear to be any clear pattern in which some models are better suited for certain markets or commodities. The models with best performance overall are however EWQR, the adaptive CAViaR and GARCH and GJR-GARCH models with student t and skewed student t distributions. GARCH and GJR-GARCH with normal distribution are the two worst performing VaR models.

A natural extension of the analysis done in this paper would be to compare more models. Additional models should preferably be able to forecast both VaR and ES. A second strategy could be to improve the already considered models. It is possible to extend the EWQR model by including exogenous regressors. The CAViaR models' performance would probably be better if the parameters were re-estimated in a rolling window, as for the other models. In order to avoid the problem of computing capacity the parameters could have been re-estimated periodically instead of every day. There are also several other GARCH based models or error distributions that could be implemented. Another extension that could be relevant, particularly to risk managers that want to assess the risk of whole portfolios, is to consider multivariate VaR and ES models.

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Appendix A: Estimating VaR and ES

A.1 GARCH

GARCH(1,1) can be expressed as the following two equations (assuming a conditional mean of zero):

$$r_t = \varepsilon_t, \qquad \varepsilon_t \sim IID(0, \sigma_t^2)$$

$$\sigma_t^2 = \beta_0 + \beta_1 r_{t-1}^2 + \beta_2 \sigma_{t-1}^2$$

In the same way, GJR-GARCH(1,1,1) can be expressed as:

$$r_t = \varepsilon_t, \qquad \varepsilon_t \sim IID(0, \sigma_t^2)$$

$$\sigma_t^2 = \beta_0 + \beta_1 r_{t-1}^2 + \beta_2 r_{t-1}^2 I(r_{t-1} < 0) + \beta_3 \sigma_{t-1}^2$$

In these expressions, $\beta_i \geq 0 \ \forall \ i$, so that the variance is non-negative. IID means "identically and independently distributed", and I(·) is the indicator function, which is one when the expression between the parentheses are valid and zero otherwise. An error distribution needs to be specified in order to estimate the parameters. In this paper four distributions are considered: the normal distribution, student t, GED and skewed student t. In the next sections the log-likelihood function for each of the distributions is derived. This expression needs to be maximized in order to obtain parameter estimates. The maximization is done numerically.

When an error distribution is assumed it is also possible to derive expressions for ES. This is also presented for each distribution in the following sections.

A.1.1 Assuming a Normal Error Distribution

Let f_{SN} denote the standard normal distribution.

$$f_{SN}(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$$

The scale-family of the standard normal distribution, f_N, which has a mean zero and a variance σ_t that is allowed to change with time, can then be found as:

$$f_N(x_t) = \frac{1}{\sigma_t} f_{SN}\left(\frac{x_t}{\sigma_t}\right) = \frac{1}{\sigma_t\sqrt{2\pi}} e^{-\frac{{x_t}^2}{2{\sigma_t}^2}}$$

From this the maximum likelihood function L follows:

$$L = \prod_{t=1}^{T} \frac{1}{\sigma_t\sqrt{2\pi}} e^{-\frac{{x_t}^2}{2{\sigma_t}^2}}$$

Taking the natural logarithm of this yields the log-likelihood function:
$l = \ln(\mathrm{L}) = \mathrm{T}\ln(1) - \frac{\mathrm{T}}{2}\ln 2\pi - \frac{T}{2}\ln\sigma_t^2 - \frac{1}{2}\sum_{t=1}^{T}\left(\frac{{r_t}^2}{\sigma_t^2}\right) = -\sum_{t=1}^{T}\frac{1}{2}(\ln 2\pi + \ln\sigma_t^2 + \frac{{r_t}^2}{\sigma_t^2}),$
where the relevant expression for the conditional variance is inserted for σ_t^2. The derivation of ES from a GARCH with normal distribution follows.

$$ES_{\alpha,t} = E\left[X_t | x_t \geq VaR_{\alpha,t}\right] = \frac{E\left[x_t * I(x_t \geq VaR_{\alpha,t})\right]}{\alpha} = \frac{1}{\alpha}\int_{VaR_{\alpha,t}}^{\infty} x_t f_N(x_t)\, dx_t$$
$$= \frac{1}{\alpha}\left[\frac{1}{\sigma_t\sqrt{2\pi}}\int_{VaR_{\alpha,t}}^{\infty} x_t e^{-\frac{{x_t}^2}{2{\sigma_t}^2}} dx_t\right] = \frac{1}{\alpha\sigma_t\sqrt{2\pi}}\left[-{\sigma_t}^2 e^{-\frac{{x_t}^2}{2{\sigma_t}^2}}\right]_{VaR_{\alpha,t}}^{\infty}$$
$$= \frac{\sigma_t}{\alpha\sqrt{2\pi}} e^{-\frac{{VaR_{\alpha,t}}^2}{2{\sigma_t}^2}} = \frac{\sigma_t}{\alpha\sqrt{2\pi}} e^{-\frac{q_{1-\alpha}^2 {\sigma_t}^2}{2{\sigma_t}^2}} = \frac{\sigma_t}{\alpha\sqrt{2\pi}} e^{-\frac{q_{1-\alpha}^2}{2}}$$

To obtain a numerical value, the estimated volatility σ_t which is found from a GARCH or GJR-GARCH model is inserted in this expression.

A.1.2 Assuming a Student t Error Distribution

The student t distribution allows for the tails to be heavier than the normal distribution. Let f_{SST} denote the standardized student t distribution, with v > 2 degrees of freedom.

$$f_{SST}(x) = \frac{\Gamma\left(\frac{\mathrm{v}+1}{2}\right)}{\sqrt{\pi(v-2)}\Gamma\left(\frac{\mathrm{v}}{2}\right)}\left(1 + \frac{x^2}{(v-2)}\right)^{-\frac{1}{2}(v+1)}$$

The scale-family of the standardized student t distribution, f_{ST}, which has a mean zero and a variance σ_t that is allowed to change with time, can then be found as:

$$f_{ST}(x_t) = \frac{1}{\sigma_t} f_{SST}\left(\frac{x_t}{\sigma_t}\right) = \frac{\Gamma\left(\frac{\mathrm{v}+1}{2}\right)}{\sigma_t\sqrt{\pi(v-2)}\Gamma\left(\frac{\mathrm{v}}{2}\right)}\left(1 + \frac{{x_t}^2}{{\sigma_t}^2(v-2)}\right)^{-\frac{1}{2}(v+1)}$$

From this the maximum likelihood function L follows:

$$L = \prod_{t=1}^{T}\frac{\Gamma\left(\frac{\mathrm{v}+1}{2}\right)}{\sigma_t\sqrt{\pi(v-2)}\Gamma\left(\frac{\mathrm{v}}{2}\right)}\left(1 + \frac{{x_t}^2}{{\sigma_t}^2(v-2)}\right)^{-\frac{1}{2}(v+1)}$$

Taking the natural logarithm of this yields the log-likelihood function:

$$l = \mathrm{T}\left(\ln\Gamma\left(\frac{\mathrm{v}+1}{2}\right) - \ln\Gamma\left(\frac{\mathrm{v}}{2}\right) - \frac{1}{2}\ln\left(\pi(v-2)\right)\right) - \frac{1}{2}\sum_{t=1}^{T}\ln{\sigma_t}^2$$
$$- \frac{\mathrm{v}+1}{2}\sum_{t=1}^{T}\ln\left(1 + \frac{{r_t}^2}{{\sigma_t}^2(v-2)}\right)$$

The derivation of ES from a GARCH with student t distribution follows.

$$ES_{\alpha,t} = E\left[X_t | x_t \geq VaR_{\alpha,t}\right] = \frac{E\left[x_t * I\left(x_t \geq VaR_{\alpha,t}\right)\right]}{\alpha} = \frac{1}{\alpha}\int_{VaR_{\alpha,t}}^{\infty} x_t f_{ST}(x_t)\, dx_t$$

$$= \frac{1}{\alpha}\int_{VaR_{\alpha,t}}^{\infty} x_t \frac{\Gamma\left(\frac{\text{v}+1}{2}\right)}{\sqrt{\pi(v-2)}\Gamma\left(\frac{\text{v}}{2}\right)\sigma_t}\left(\left(1+\frac{{x_t}^2}{{\sigma_t}^2(v-2)}\right)^{-\frac{1}{2}(v+1)}\right)dx_t$$

$$= \frac{\Gamma\left(\frac{\text{v}+1}{2}\right)}{\alpha\sigma_t\sqrt{\pi(v-2)}\Gamma\left(\frac{\text{v}}{2}\right)}\left[\frac{{\sigma_t}^2(v-2)\left(1+\frac{{x_t}^2}{{\sigma_t}^2(v-2)}\right)^{\frac{1}{2}(1-v)}}{1-v}\right]_{VaR_{\alpha,t}}^{\infty}$$

$$= \frac{\sigma_t\Gamma\left(\frac{\text{v}+1}{2}\right)\sqrt{\text{v}-2}}{\alpha\sqrt{\pi}(1-\text{v})\Gamma\left(\frac{\text{v}}{2}\right)}\left(-\left(1+\frac{{VaR_{\alpha,t}}^2}{{\sigma_t}^2(v-2)}\right)^{\frac{1}{2}(1-v)}\right)$$

$$= \frac{\sigma_t\Gamma\left(\frac{\text{v}+1}{2}\right)\sqrt{\text{v}-2}}{\alpha\sqrt{\pi}(\text{v}-1)\Gamma\left(\frac{\text{v}}{2}\right)}\left(\left(1+\frac{{q_{1-\alpha}}^2{\sigma_t}^2}{{\sigma_t}^2(v-2)}\right)^{\frac{1}{2}(1-v)}\right)$$

$$= \frac{\sigma_t\Gamma\left(\frac{\text{v}+1}{2}\right)\sqrt{\text{v}-2}}{\alpha\sqrt{\pi}(\text{v}-1)\Gamma\left(\frac{\text{v}}{2}\right)}\left(\left(1+\frac{{q_{1-\alpha}}^2}{{\sigma_t}^2(v-2)}\right)^{\frac{1}{2}(1-v)}\right)$$

A.1.3 Assuming a Generalized Error Distribution

The Generalized Error Distribution (GED) is a symmetrical distribution that allows the tails to be either thin or thick, and includes the normal distribution as a special case. Let f_{SGED} denote the standardized GED with v ≥ 1 degrees of freedom.

$$f_{SGED}(x) = \frac{v}{\omega\Gamma\left(\frac{1}{\text{v}}\right)2^{1+\frac{1}{\text{v}}}} x e^{-\frac{1}{2}\left|\frac{x}{\omega}\right|^{v}}$$

where $\omega = 2^{-\frac{1}{v}}\sqrt{\frac{\Gamma\left(\frac{1}{\text{v}}\right)}{\Gamma\left(\frac{3}{\text{v}}\right)}}$

The scale-family of the standardized GED, f_{GED}, which has a mean zero and a variance σ_t that is allowed to change with time, can then be found as:

$$f_{GED}(x_t) = \frac{1}{\sigma_t} f_{SGED}\left(\frac{x_t}{\sigma_t}\right) = \frac{v}{\sigma_t\omega\Gamma\left(\frac{1}{\text{v}}\right)2^{1+\frac{1}{\text{v}}}} x_t e^{-\frac{1}{2}\left|\frac{x_t}{\omega\sigma_t}\right|^{v}}$$

From this the maximum likelihood function L follows:

$$L = \prod_{t=1}^{T} \frac{v}{\sigma_t \omega \Gamma\left(\frac{1}{\mathrm{v}}\right) 2^{1+\frac{1}{\mathrm{v}}}} x_t e^{-\frac{1}{2}\left|\frac{x_t}{\omega\sigma_t}\right|^v}$$

Taking the natural logarithm of this yields the log-likelihood function:

$$l = \mathrm{T}\left(\ln(\mathrm{v}) - \ln(\omega) - \ln\Gamma\left(\frac{1}{\mathrm{v}}\right) - \left(1+\frac{1}{\mathrm{v}}\right)\ln 2\right) - \frac{1}{2}\sum_{t=1}^{T} \ln {\sigma_t}^2 - \frac{1}{2}\sum_{t=1}^{T} \left|\frac{x_t}{\omega\sigma_t}\right|^v$$

The derivation of ES from a GARCH with GED follows.

$$\begin{aligned} ES_{\alpha,t} &= E\left[X_t | x_t \geq VaR_{\alpha,t}\right] = \frac{E\left[x_t * I\left(x_t \geq VaR_{\alpha,t}\right)\right]}{\alpha} = \frac{1}{\alpha}\int_{VaR_{\alpha,t}}^{\infty} x_t f(x_t)\, dx_t \\ &= \frac{1}{\alpha}\int_{VaR_{\alpha,t}}^{\infty} \frac{v}{\omega\sigma_t \Gamma\left(\frac{1}{\mathrm{v}}\right) 2^{1+\frac{1}{\mathrm{v}}}} x_t e^{-\frac{1}{2}\left|\frac{x_t}{\omega\sigma_t}\right|^v} dx_t \\ &= \frac{v}{\alpha\omega\sigma_t \Gamma\left(\frac{1}{\mathrm{v}}\right) 2^{1+\frac{1}{\mathrm{v}}}} \int_{VaR_{\alpha,t}}^{\infty} x_t e^{-\frac{1}{2}\left|\frac{x_t}{\omega\sigma_t}\right|^v} dx_t \end{aligned}$$

Since $VaR_{\alpha,t} > 0$, the absolute value sign for x_t is unnecessary in this interval. Thus,

$$\begin{aligned} ES_{\alpha,t} &= \frac{v}{\alpha\omega\sigma_t \Gamma\left(\frac{1}{\mathrm{v}}\right) 2^{1+\frac{1}{\mathrm{v}}}} \int_{VaR_{\alpha,t}}^{\infty} x_t e^{-\frac{1}{2}\frac{x_t}{|\omega\sigma_t|}^v} dx_t \\ &= \frac{v}{\alpha\omega\sigma_t \Gamma\left(\frac{1}{\mathrm{v}}\right) 2^{1+\frac{1}{\mathrm{v}}}} \left[-\frac{2^{\frac{2}{v}}|\omega|^2 {\sigma_t}^2 \Gamma\left(\frac{2}{\mathrm{v}}, \frac{1}{2}\left(\frac{x_t}{|\omega\sigma_t|}\right)^v\right)}{v}\right]_{VaR_{\alpha,t}}^{\infty} \\ &= \frac{-\sigma_t \omega 2^{\frac{1}{v-1}}}{\alpha\Gamma\left(\frac{1}{\mathrm{v}}\right)} \left[\Gamma\left(\frac{2}{\mathrm{v}}, \frac{1}{2}\left(\frac{x_t}{|\omega\sigma_t|}\right)^v\right)\right]_{VaR_{\alpha,t}}^{\infty} = \frac{\sigma_t \omega 2^{\frac{1}{v-1}}}{\alpha\Gamma\left(\frac{1}{\mathrm{v}}\right)} \Gamma\left(\frac{2}{\mathrm{v}}, \frac{1}{2}\left(\frac{VaR_{\alpha,t}}{|\omega\sigma_t|}\right)^v\right) \end{aligned}$$

A.1.4 Assuming a Skewed Student t Error Distribution

Hansen's skew student-t distribution is a heavy tailed distribution that allows for asymmetry. It is an extension of the student-t distribution, and includes it as a special case when $\lambda=0$ (Hansen 1994). Let f_{SSKEWT} denote standardized skewed student t distribution with v > 2 degrees of freedom and asymmetry parameter $-1 < \lambda < 1$.

$$f_{SSKEWT}(x) = \begin{cases} bc\left(1+\frac{1}{v-2}\left(\frac{bx+a}{1-\lambda}\right)^2\right)^{-\frac{1}{2}(v+1)} & ,for\ x < -\frac{a}{b} \\ bc\left(1+\frac{1}{v-2}\left(\frac{bx+a}{1+\lambda}\right)^2\right)^{-\frac{1}{2}(v+1)} & ,for\ x \geq -\frac{a}{b} \end{cases}$$

Where $a = 4\lambda c\frac{v-2}{v-1}$, $b^2 = 1+3\lambda^2 - a^2$ and $c = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{\pi(v-2)}\Gamma\left(\frac{v}{2}\right)}$.The scale-family of the standardized skewed student t, f_{SKEWT}, which has a mean zero and a variance σ_t that is allowed to change with time, can then be found as:

$$f_{SKEWT}(x_t) = \frac{1}{\sigma_t} f_{SSKEWT}\left(\frac{x_t}{\sigma_t}\right) = \begin{cases} \frac{bc}{\sigma_t}\left(1+\frac{1}{v-2}\left(\frac{\frac{bx_t}{\sigma_t}+a}{1-\lambda}\right)^2\right)^{-\frac{1}{2}(v+1)} & ,for\ \frac{x_t}{\sigma_t} < -\frac{a}{b} \\ \frac{bc}{\sigma_t}\left(1+\frac{1}{v-2}\left(\frac{\frac{bx_t}{\sigma_t}+a}{1+\lambda}\right)^2\right)^{-\frac{1}{2}(v+1)} & ,for\ \frac{x_t}{\sigma_t} \geq -\frac{a}{b} \end{cases}$$

The corresponding log-likelihood function follows.

$$l = T\left(\frac{1}{2}\ln(1+3\lambda^2-a^2) + \ln\Gamma\left(\frac{\mathrm{v}+1}{2}\right) - \ln\Gamma\left(\frac{\mathrm{v}}{2}\right) - \frac{1}{2}\ln\big(\pi(v-2)\big)\right) - \frac{1}{2}\sum_{t=1}^{T}\ln{\sigma_t}^2$$
$$-\left(\frac{\mathrm{v}+1}{2}\right)\sum_{t=1}^{T}\ln\left(1+\frac{1}{(v-2)}\left(\frac{\frac{bx}{\sigma_t}+a}{1-\lambda}\right)^2\right) I\left(\frac{x_t}{\sigma_t} < -\frac{a}{b}\right)$$
$$-\left(\frac{\mathrm{v}+1}{2}\right)\sum_{t=1}^{T}\ln\left(1+\frac{1}{(v-2)}\left(\frac{\frac{bx}{\sigma_t}+a}{1+\lambda}\right)^2\right) I\left(\frac{x_t}{\sigma_t} \geq -\frac{a}{b}\right)$$

The derivation of ES from a GARCH with Hansen's skewed student t distribution follows:

$$ES_{\alpha,t} = E\left[X_t | x_t \geq VaR_{\alpha,t}\right] = \frac{E\left[x_t * I\left(x_t \geq VaR_{\alpha,t}\right)\right]}{\alpha} = \frac{1}{\alpha}\int_{VaR_{\alpha,t}}^{\infty} x_t f(x_t)\, dx_t$$

$$= I\left(VaR_{\alpha,t} < -\frac{a\sigma_t}{b}\right)\frac{1}{\alpha}\left(\int_{VaR_{\alpha,t}}^{-\frac{a\sigma_t}{b}} x_t \frac{bc}{\sigma_t}\left(1+\frac{1}{(v-2)}\left(\frac{\frac{bx_t}{\sigma_t}+a}{1-\lambda}\right)^2\right)^{-\frac{1}{2}(v+1)} dx_t\right.$$

$$\left. + \int_{-\frac{a\sigma_t}{b}}^{\infty} x_t \frac{bc}{\sigma_t}\left(1+\frac{1}{(v-2)}\left(\frac{\frac{bx_t}{\sigma_t}+a}{1+\lambda}\right)^2\right)^{-\frac{1}{2}(v+1)} dx_t\right)$$

$$+ I\left(VaR_{\alpha,t} \geq -\frac{a\sigma_t}{b}\right)\frac{1}{\alpha}\int_{VaR_{\alpha,t}}^{\infty} x_t \frac{bc}{\sigma_t}\left(1+\frac{1}{(v-2)}\left(\frac{\frac{bx_t}{\sigma_t}+a}{1+\lambda}\right)^2\right)^{-\frac{1}{2}(v+1)} dx_t$$

$$ES_{\alpha,t} = \frac{bc}{\alpha\sigma_t}\left(I\left(VaR_{\alpha,t} < -\frac{a\sigma_t}{b}\right)\right.$$

$$* \left(\int_{VaR_{\alpha,t}}^{-\frac{a\sigma_t}{b}} x_t \left(1+\frac{1}{(v-2)}\left(\frac{\frac{bx_t}{\sigma_t}+a}{1-\lambda}\right)^2\right)^{-\frac{1}{2}(v+1)} dx_t\right.$$

$$\left. + \int_{-\frac{a\sigma_t}{b}}^{\infty} x_t \left(1+\frac{1}{(v-2)}\left(\frac{\frac{bx_t}{\sigma_t}+a}{1+\lambda}\right)^2\right)^{-\frac{1}{2}(v+1)} dx_t\right)$$

$$\left. + I\left(VaR_{\alpha,t} \geq -\frac{a\sigma_t}{b}\right)\int_{VaR_{\alpha,t}}^{\infty} x_t \left(1+\frac{1}{(v-2)}\left(\frac{\frac{bx_t}{\sigma_t}+a}{1+\lambda}\right)^2\right)^{-\frac{1}{2}(v+1)} dx_t\right)$$

Let $u = \frac{\frac{bx_t}{\sigma_t}+a}{1-\lambda} \Leftrightarrow x_t = \frac{u(1-\lambda)-a}{b}\sigma_t, \frac{du}{dx_t} = \frac{b}{\sigma_t(1-\lambda)} \Leftrightarrow dx_t = \frac{\sigma_t(1-\lambda)}{b}\, du$

As $x_t = VaR_{\alpha,t} \Rightarrow u = \frac{\frac{bVaR_{\alpha,t}}{\sigma_t}+a}{1-\lambda} = VaR_u$ and $x_t = -\frac{a\sigma_t}{b} \Rightarrow u = 0$.

Let $w = \frac{\frac{bx_t}{\sigma_t}+a}{1+\lambda} \Leftrightarrow x_t = \frac{w(1+\lambda)-a}{b}\sigma_t, \frac{dw}{dx_t} = \frac{b}{\sigma_t(1+\lambda)} \Leftrightarrow dx_t = \frac{\sigma_t(1+\lambda)}{b}\, dw$

As $x_t = VaR_{\alpha,t} \Rightarrow w = \frac{\frac{bVaR_{\alpha,t}}{\sigma_t}+a}{1+\lambda} = VaR_w$, $x_t = -\frac{a\sigma_t}{b} \Rightarrow w = 0$ and $x_t \to \infty \Rightarrow w \to \infty$

It follows by substitution that:

$$ES_{\alpha,t} = \frac{bc}{\alpha\sigma_t}\Bigg(I\left(VaR_{\alpha,t} < -\frac{a\sigma_t}{b}\right) * \left(\int_{VaR_u}^{0} \frac{u(1-\lambda)-a}{b}\sigma_t\left(1+\frac{u^2}{(v-2)}\right)^{-\frac{1}{2}(v+1)} \frac{\sigma_t(1-\lambda)}{b}\,du + \int_{0}^{\infty} \frac{w(1+\lambda)-a}{b}\sigma_t\left(1+\frac{w^2}{(v-2)}\right)^{-\frac{1}{2}(v+1)} \frac{\sigma_t(1+\lambda)}{b}\,dw \right) + I\left(VaR_{\alpha,t} \geq -\frac{a\sigma_t}{b}\right) * \int_{VaR_w}^{\infty} \frac{w(1+\lambda)-a}{b}\sigma_t\left(1+\frac{w^2}{(v-2)}\right)^{-\frac{1}{2}(v+1)} \frac{\sigma_t(1+\lambda)}{b}\,dw \Bigg)$$

$$ES_{\alpha,t} = \frac{\sigma_t c}{\alpha b}\Bigg(I\left(VaR_{\alpha,t} < -\frac{a\sigma_t}{b}\right) * \left((1-\lambda)\int_{VaR_u}^{0} (u(1-\lambda)-a)\left(1+\frac{u^2}{(v-2)}\right)^{-\frac{1}{2}(v+1)} du + (1+\lambda)\int_{0}^{\infty} (w(1+\lambda)-a)\left(1+\frac{w^2}{(v-2)}\right)^{-\frac{1}{2}(v+1)} dw \right) + I\left(VaR_{\alpha,t} \geq -\frac{a\sigma_t}{b}\right)(1+\lambda) * \int_{VaR_w}^{\infty} (w(1+\lambda)-a)\left(1+\frac{w^2}{(v-2)}\right)^{-\frac{1}{2}(v+1)} dw \Bigg)$$

$$
\begin{aligned}
ES_{\alpha,t} = \frac{\sigma_t}{\alpha b}\Bigg(& I\left(VaR_{\alpha,t} < -\frac{a\sigma_t}{b}\right) \\
& * \left(\int_{VaR_u}^{0} cu(1-\lambda)^2\left(1+\frac{u^2}{(v-2)}\right)^{-\frac{1}{2}(v+1)} du \right. \\
& - a(1-\lambda)\int_{VaR_u}^{0} c\left(1+\frac{u^2}{(v-2)}\right)^{-\frac{1}{2}(v+1)} du \\
& + \int_{0}^{\infty} cw(1+\lambda)^2\left(1+\frac{w^2}{(v-2)}\right)^{-\frac{1}{2}(v+1)} dw \\
& \left. - a(1+\lambda)\int_{0}^{\infty} c\left(1+\frac{w^2}{(v-2)}\right)^{-\frac{1}{2}(v+1)} dw \right) + I\left(VaR_{\alpha,t} \geq -\frac{a\sigma_t}{b}\right) \\
& * \int_{VaR_w}^{\infty} cw(1+\lambda)^2\left(1+\frac{w^2}{(v-2)}\right)^{-\frac{1}{2}(v+1)} dw - a(1+\lambda) \\
& * \int_{VaR_w}^{\infty} c\left(1+\frac{w^2}{(v-2)}\right)^{-\frac{1}{2}(v+1)} dw \Bigg)
\end{aligned}
$$

Since $c\left(1+\frac{u^2}{(v-2)}\right)^{-\frac{1}{2}(v+1)} = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{\pi(v-2)}\Gamma\left(\frac{v}{2}\right)}\left(1+\frac{u^2}{(v-2)}\right)^{-\frac{1}{2}(v+1)}$ is the standardized student t distribution with v degrees of freedom, it follows that

$$
\begin{aligned}
ES_{\alpha,t} = \frac{\sigma_t}{\alpha b}\Bigg(& I\left(VaR_{\alpha,t} < -\frac{a\sigma_t}{b}\right) \\
& * \left(c(1-\lambda)^2 \left[\left(-\frac{v-2}{v-1}\right)\left(1+\frac{u^2}{(v-2)}\right)^{\frac{1-v}{2}}\right]_{VaR_u}^{0} \right. \\
& - a(1-\lambda)\big(F_{SST}(0) - F_{SST}(VaR_u)\big) \\
& \left. + c(1+\lambda)^2 \left[\left(-\frac{v-2}{v-1}\right)\left(1+\frac{w^2}{(v-2)}\right)^{\frac{1-v}{2}}\right]_{0}^{\infty} - a(1+\lambda)\big(1 - F_{SST}(0)\big) \right) \\
& + I\left(VaR_{\alpha,t} \geq -\frac{a\sigma_t}{b}\right) \\
& * \left(c(1+\lambda)^2 \left[\left(-\frac{v-2}{v-1}\right)\left(1+\frac{w^2}{(v-2)}\right)^{\frac{1-v}{2}}\right]_{VaR_w}^{\infty} - a(1+\lambda) \right. \\
& \left. * \big(1 - F_{SST}(VaR_w)\big) \right) \Bigg)
\end{aligned}
$$

where $F_{SST}(\cdot)$ is the scale family of the cumulative standardized student t distribution. Since the standardized student t distribution is symmetric, $F_{SST}(0) = 0.5$

$$ES_{\alpha,t} = \frac{\sigma_t}{\alpha b}\left(I\left(VaR_{\alpha,t} < -\frac{a\sigma_t}{b}\right)\right.$$

$$* \left(c(1-\lambda)^2\left(-\frac{v-2}{v-1}\right)\left(1-\left(1+\frac{VaR_u^2}{(v-2)}\right)^{\frac{1-v}{2}}\right)\right.$$

$$- a(1-\lambda)\big(0.5 - F_{SST}(VaR_u)\big) + c(1+\lambda)^2\left(-\frac{v-2}{v-1}\right)(-1)$$

$$\left. - a(1+\lambda)(1-0.5)\right) + I\left(VaR_{\alpha,t} \geq -\frac{a\sigma_t}{b}\right)$$

$$* \left(c(1+\lambda)^2\left(-\frac{v-2}{v-1}\right)\left(-\left(1+\frac{VaR_w^2}{(v-2)}\right)^{\frac{1-v}{2}}\right) - a(1\right.$$

$$\left.\left. + \lambda)\big(1 - F_{SST}(VaR_w)\big)\right)\right)$$

This leads to the ES expression:

$$ES_{\alpha,t} = \frac{\sigma_t}{\alpha b}\left(I\left(VaR_{\alpha,t} < -\frac{a\sigma_t}{b}\right)\right.$$

$$* \left(c(1-\lambda)^2\frac{v-2}{v-1}\left(\left(1+\frac{VaR_u^2}{(v-2)}\right)^{\frac{1-v}{2}} - 1\right) + a(1-\lambda)(F_{SST}(VaR_u) - 0.5)\right.$$

$$\left. + c(1+\lambda)^2\frac{v-2}{v-1} - \frac{a}{2}(1+\lambda)\right) + I\left(VaR_{\alpha,t} \geq -\frac{a\sigma_t}{b}\right)$$

$$\left.* \left(c(1+\lambda)^2\frac{v-2}{v-1}\left(1+\frac{VaR_w^2}{(v-2)}\right)^{\frac{1-v}{2}} - a(1+\lambda)\big(1-F_{SST}(VaR_w)\big)\right)\right)$$

A.2 CAViaR

The following five versions of CAViaR have been used in this paper.

Symmetric Absolute Value: $VaR_{\alpha,t} = \beta_0 + \beta_1 VaR_{\alpha,t-1} + \beta_2 |x_{t-1}|$

Asymmetric Slope: $VaR_{\alpha,t} = \beta_0 + \beta_1 VaR_{\alpha,t-1} + \beta_2 max[x_{t-1}, 0] - \beta_3 \min[x_{t-1}, 0]$

Adaptive: $VaR_{\alpha,t} = VaR_{\alpha,t-1} + \beta_1 [I(x_{t-1} > VaR_{\alpha,t-1}) - \alpha]$

Indirect GARCH(1,1): $VaR_{\alpha,t} = \sqrt{\beta_0 + \beta_1 (VaR_{\alpha,t-1})^2 + \beta_2 x_{t-1}^2}$

Indirect AR(1)-GARCH(1,1):

$$VaR_{\alpha,t} = ax_{t-1} + \sqrt{\beta_0 + \beta_1 (ax_{t-2} - x_{t-1})^2 + \beta_2 (VaR_{\alpha,t-1} - ax_{t-2})^2}$$

The parameters of both the *Symmetric Absolute Value* and *Asymmetric Slope* CAViaR are unconstrained. The *Adaptive* CAViaR model increases the VaR when a loss in the last period exceeds the corresponding VaR. Otherwise the VaR is slightly decreased. For the model to work correctly, the parameter β_1 should be positive. If this is not the case, the model will perform very poorly, since it will increase VaR each time there is no VaR violation, making a successive VaR violation even less likely. The VaR forecasts will then diverge to infinity, which is obviously an undesirable property of any VaR model. For both the *Indirect GARCH* and *Indirect AR-GARCH* models, the parameters β_0, β_1 and β_2 should be non-negative to ensure that the expression under the square root is positive.

Engle and Manganelli (2004) also proposed *an alternative version of the Adaptive CAViaR model*, where the indicator function is replaced by a smoothed version of it. This alternative version is not used in this paper, but is reported here for completeness.

$$VaR_{\alpha,t} = VaR_{\alpha,t-1} + \beta_1 \left\{ \left[1 + exp\left(K[VaR_{\alpha,t-1} - x_{t-1}]\right)\right]^{-1} - \alpha \right\}$$

K is a smoothing parameter, which may be chosen or estimated. When $K \rightarrow \infty$, this version of the Adaptive CAViaR model converges to the other one. Engle and Manganelli (2004) do not give any indication of how to estimate it or choose it appropriately, but instead set K=10 for simplicity.

A.3 EWQR

Exponentially weighted quantile regression (EWQR) was introduced by Taylor (2008) as an extension of quantile regression, where a weighting parameter λ is included. For a specific value of λ the EWQR minimization formula is as follows:

$$\min_{\boldsymbol{\beta}} \sum_{t=1}^{T} \lambda^{T-t} (r_t - \boldsymbol{x}'_t \boldsymbol{\beta})\left(\theta - I(r_t < \boldsymbol{x}'_t \boldsymbol{\beta})\right)$$

$\boldsymbol{\beta}$ is a parameter vector, $\boldsymbol{x}_t$ is a vector of regressors, r_t is the return at period t, T is the length of the estimation window, θ is the quantile considered and I(·) the indicator function. Even though the EWQR formula generally include regressors, Taylor (2008) argues that an EWQR with an intercept and no regressors is reasonable and should perform well. In this paper the case without regressors will be considered. Consequently the estimator $\boldsymbol{x}'_t\boldsymbol{\beta}$ can be substituted with a constant $\hat{q}_{\theta,T+1}$.

$$\min_{\hat{q}_{\theta,T+1}} \sum_{t=1}^{T} \lambda^{T-t}\left(r_t - \hat{q}_{\theta,T+1}\right)\left(\theta - I\left(r_t < \hat{q}_{\theta,T+1}\right)\right)$$

The expression presented in this paper has a slightly different notation:

$$\min_{\widehat{VaR}_{\alpha,T+1}} \sum_{t=1}^{T} \lambda^{T-t}\left(\widehat{VaR}_{\alpha,T+1} - x_t\right)\left(\alpha - I\left(x_t > \widehat{VaR}_{\alpha,T+1}\right)\right)$$

To see that this is an equivalent representation of the formula, consider the two trading positions separately.

Long trading position:

$$\alpha = \theta$$
$$\widehat{VaR}^{L}{}_{\alpha,t} = -\hat{q}_{\theta,t}$$
$$x_t = -r_t$$

Here q_θ denotes the θth quantile of the return distribution. Then,

$$\min_{\widehat{VaR}_{\alpha,T+1}} \sum_{t=1}^{T} \lambda^{T-t}\left(\widehat{VaR}_{\alpha,T+1} - x_t\right)\left(\alpha - I\left(x_t > \widehat{VaR}_{\alpha,T+1}\right)\right)$$
$$= \min_{-\hat{q}_{\theta,T+1}} \sum_{t=1}^{T} \lambda^{T-t}\left(-\hat{q}_{\theta,T+1} - (-r_t)\right)\left(\alpha - I\left(-r_t > -\hat{q}_{\theta,T+1}\right)\right)$$
$$= \min_{\hat{q}_{\theta,T+1}} \sum_{t=1}^{T} \lambda^{T-t}\left(r_t - \hat{q}_{\theta,T+1}\right)\left(\theta - I\left(r_t < \hat{q}_{\theta,T+1}\right)\right)$$

Short trading position:

$$\alpha = 1 - \theta$$
$$\widehat{VaR}^{S}{}_{\alpha,t} = \hat{q}_{\theta,t}$$
$$x_t = r_t$$

$$\min_{\widehat{VaR}_{\alpha,T+1}} \sum_{t=1}^{T} \lambda^{T-t}\left(\widehat{VaR}_{\alpha,T+1} - x_t\right)\left(\alpha - I\left(x_t > \widehat{VaR}_{\alpha,T+1}\right)\right)$$
$$= \min_{\hat{q}_{\theta,T+1}} \sum_{t=1}^{T} \lambda^{T-t}\left(\hat{q}_{\theta,T+1} - r_t\right)\left((1-\theta) - I\left(r_t > \hat{q}_{\theta,T+1}\right)\right)$$

$$= \min_{\hat{q}_{\theta,T+1}} \sum_{t=1}^{T} \lambda^{T-t}\left(\hat{q}_{\theta,T+1} - r_t\right)\left(I\left(r_t < \hat{q}_{\theta,T+1}\right) - \theta\right)$$

$$= \min_{\hat{q}_{\theta,T+1}} \sum_{t=1}^{T} \lambda^{T-t}\left(r_t - \hat{q}_{\theta,T+1}\right)\left(\theta - I\left(r_t < \hat{q}_{\theta,T+1}\right)\right)$$

A key aspect to EWQR is to choose an appropriate λ. A high value of λ corresponds to giving past observations high weights, while with smaller λ values older observations become less significant (Taylor 2008). To optimize λ we follow Taylor's approach of using a rolling window of 250 observations to produce day-ahead forecasts for the rest of the observations in an estimation sample of size n. This is done for several different λ values, and the λ with the lowest corresponding QR Sum is chosen and assumed to be optimal also for out-of-sample forecasting. QR Sum is defined as the standard quantile regression formula, but without the minimization; the quantile forecasts obtained with EWQR is entered instead, as in the expression below.

$$QR\ Sum(\lambda, \theta) = \sum_{t=251}^{n} \left(r_t - \hat{q}_{\theta,t}\right)\left(\theta - I\left(r_t < \hat{q}_{\theta,t}\right)\right)$$

Taylor (2008) proposes to use a grid of values of λ from 0.8 to 1 with step size 0.005, when optimizing λ. This is what is done in this analysis as well. As for the estimation sample, a rolling window of 250 observations is used to forecast out-of-sample. From these quantile forecasts the out-of-sample VaR and ES forecasts can be obtained:

$$\widehat{ES}_{\alpha,T+1} = \frac{1}{\alpha \sum_{t=1}^{T} \lambda^{T-t}} \sum_{t=1}^{T} \lambda^{T-t}\left(r_t - \hat{q}_{\theta,T+1}\right)\left(\theta - I\left(r_t < \hat{q}_{\theta,T+1}\right)\right),$$

or equivalently:

$$\widehat{ES}_{\alpha,T+1} = \frac{1}{\alpha \sum_{t=1}^{T} \lambda^{T-t}} \sum_{t=1}^{T} \lambda^{T-t}\left(\widehat{VaR}_{\alpha,T+1} - x_t\right)\left(\alpha - I\left(x_t > \widehat{VaR}_{\alpha,T+1}\right)\right).$$

A.3.1 Comments on the Rolling Window Size for λ Estimation

In Taylor's articles about EWQR (2007; 2008) the procedure is to use a rolling window corresponding to one year of observations. For financial assets a typical trading year has 250 days which is why a rolling window of 250 observations has been chosen. The logic is that the window has to be big enough to include as many observations that are deemed to influence the current observation, but small enough that it leaves a sufficiently large number of observations to be forecasted. Furthermore, the larger an estimation window is, the smaller the sample error becomes, but a small window is desirable when the parameters should be able to change rapidly (Sheedy 2009). Taylor (2008) tried different window sizes for λ, but found that none of the other tested window sizes improved results significantly.

Appendix B: Backtesting VaR and ES Forecasts

B.1 Backtesting Value at Risk Forecasts

B.1.1 Test for Unconditional Coverage

For a VaR model to be appropriate, the proportion of returns more extreme than the VaR estimates should equal α. The unconditional coverage test checks whether this is the case for a given model, by comparing the two alternative hypotheses, $H_0: E[H_{\alpha,t}] = \alpha$ and $H_1: E[H_{\alpha,t}] \neq \alpha$, where $H_{\alpha,t} = I(x_t > VaR_{\alpha,t})$, using the likelihood ratio test statistic:

$$LR_{uc} = -2\ln\left(\frac{L(\theta)}{L(\hat{\theta})}\right) = -2\ln\left(\frac{\theta^{n_1}(1-\theta)^{n_0}}{\hat{\theta}^{n_1}(1-\hat{\theta})^{n_0}}\right) \overset{a}{\sim} \chi_1^2.$$

L(·) denotes the binomial likelihood function, n_1 is the number of VaR-violations ($H_{\alpha,t} = 1$), n_0 is the number of non-violations ($H_{\alpha,t} = 0$) and $\hat{\theta} = \frac{n_1}{n_1+n_0}$ the observed proportion of violations. Under the null hypothesis, LR_{uc} asymptotically has a chi-squared distribution with one degree of freedom. This test rejects models that either overestimate or underestimate VaR (Hung, Lee et al. 2008).

B.1.2 Test for Conditional Coverage

The test for conditional coverage is a joint test of correct coverage and independence of VaR violations. (Christoffersen 1998). The test statistic is defined as follows:

$$LR_{cc} = -2\ln\left(\frac{\theta^{n_1}(1-\theta)^{n_0}}{\hat{\theta}_{01}^{n_{01}}(1-\hat{\theta}_{01})^{n_{00}}\hat{\theta}_{11}^{n_{11}}(1-\hat{\theta}_{11})^{n_{10}}}\right) \overset{a}{\sim} \chi_2^2$$

Here n_{ij} denotes the observed number of times an observation of value i is followed by an observation of value j, (for i,j = 0,1). For example n_{01} is the observed number of times an observation of value 0 (non-violation) is followed by an observation of value 1 (violation). $n_1 = n_{11} + n_{01}$, while $n_0 = n_{10} + n_{00}$. The estimated probability of going from a 0 to 1, from a non-violation to a violation, is $\hat{\theta}_{01} = \frac{n_{01}}{n_{00}+n_{01}}$ and the estimated probability of going from 1 to 1 is $\hat{\theta}_{11} = \frac{n_{11}}{n_{10}+n_{11}}$.

LR_{cc} is compared to a chi-squared distribution with two degrees of freedom. This test rejects models that either overestimate or underestimate VaR or that generate either too many or too few clustered violations (Hung, Lee et al. 2008).

A drawback of the test is that it is unable to give an answer for the extreme quantiles when there are not a sufficient number of forecasts. Then it becomes unlikely that two returns in a row will exceed the forecasted VaR, resulting in a division by 0, which is unfortunate.

B.1.3 The Dynamic Quantile Test

Engle and Manganelli (1999) argue that a good VaR model should not just be uncorrelated with $H_{\alpha,t}$, like in the conditional coverage test, but that it also should be uncorrelated with the

VaR estimate for the period itself. They then propose another method for assessing VaR models called the dynamic quantile (DQ) test, which takes this into account. The DQ test considers a $Hit_{\alpha,t}$ variable similar to the $H_{\alpha,t}$ in the coverage tests:

$$Hit_t = I(x_t > VaR_{\alpha,t}) - \alpha$$

By comparison $Hit_{\alpha,t} = H_{\alpha,t} - \alpha$. This variable is then regressed on its lags, the period's estimated VaR and other variables if desired. This is called an artificial regression (Engle and Manganelli 1999). The form of artificial regression that is used most often is the one that include four lags and the VaR estimate (Engle and Manganelli 1999; Kuester, Mittnik et al. 2006). This is done also for the analysis in this paper:

$$Hit_t = \beta_0 + \beta_1 Hit_{t-1} + \beta_2 Hit_{t-2} + \beta_3 Hit_{t-3} + \beta_4 Hit_{t-4} + \beta_5 \widehat{VaR}_t + u_t$$

$$\text{where } u_t = \begin{cases} -\alpha & with\ probability\ 1-\alpha \\ 1-\alpha & with\ probability\ \alpha \end{cases}$$

In matrix form the same expression yields: $Hit = X\boldsymbol{\beta} + \boldsymbol{u}.$ The null hypothesis of no influence by the regressors then becomes H_0: $\boldsymbol{\beta} = 0$. The ordinary least squares solution to this is $\widehat{\boldsymbol{\beta}} = (X'X)^{-1}X'Hit \overset{a}{\sim} N(0, \alpha(1-\alpha)(X'X)^{-1})$, from which Engle and Manganelli (1999) derive the DQ test statistic

$$DQ = \frac{\widehat{\boldsymbol{\beta}}'X'X\widehat{\boldsymbol{\beta}}}{\alpha(1-\alpha)} \overset{a}{\sim} \chi^2_6$$

The DQ test statistic is asymptotically distributed as a chi-squared distribution with six degrees of freedom.

B.2 Backtesting Expected Shortfall Forecasts

B.2.1 An Expected Shortfall Test Dependent on VaR (DV)

For the ES test dependent of VaR, a bootstrap test is performed on the following residuals to check whether the ES forecasts are correct.

$$z_{\alpha,t} = \left\{ \frac{x_t - \widehat{ES}_{\alpha,t}}{\widehat{VaR}_{\alpha,t}} | x_t > \widehat{VaR}_{\alpha,t} \right\}$$

B.2.2 An Expected Shortfall Test Independent of VaR (IV)

For the ES test independent of VaR, a bootstrap test is performed on the following residuals instead.

$z_{\alpha,t} = \{x_t - \widehat{ES}_{\alpha,t} | x_t - \widehat{ES}_{\alpha,t} > D_\alpha\}$, where D_α is the α-th quantile of $x_t - \widehat{ES}_{\alpha,t}$.

B.2.3 Bootstrapping

The bootstrap hypothesis test is explained well in chapter 16.4, pages 224-227, of Efron and Tibshirani (1993). The idea is to find an appropriate null distribution of a test statistic empirically, instead of assuming one, and then compare the test statistic with it to test the hypothesis of zero mean.

Consider the test statistic

$$T(\boldsymbol{z}_\alpha) = \frac{\hat{\mu}_z - \mu_z}{\frac{\hat{\sigma}_z}{\sqrt{n_z}}} = \frac{\hat{\mu}_z}{\frac{\hat{\sigma}_z}{\sqrt{n_z}}}$$

where $\hat{\mu}_z$ and $\hat{\sigma}_z$ are the mean and standard deviation of the variable to bootstrap test $z_{\alpha,t}$, respectively, and n_z is the number of losses greater than the VaR forecasts. An appropriate null distribution should follow the null hypothesis, which in this case is to have a zero mean. Since $\hat{\mu}_z$ is not necessarily zero, the following transformation is made to get a zero mean variable.

$$\tilde{z}_{\alpha,t} = z_{\alpha,t} - \hat{\mu}_z$$

By drawing random bootstrap samples $\tilde{\boldsymbol{z}}_\alpha^*$ of size n_z from $\tilde{\boldsymbol{z}}_\alpha$, with replacement, and calculating corresponding test statistic for each sample,

$$T(\tilde{\boldsymbol{z}}_\alpha^*) = \frac{\hat{\mu}_{\tilde{z}^*}}{\frac{\hat{\sigma}_{\tilde{z}^*}}{\sqrt{n_{\tilde{z}^*}}}} = \frac{\hat{\mu}_{\tilde{z}^*}}{\frac{\hat{\sigma}_{\tilde{z}^*}}{\sqrt{n_z}}},$$

an empirical null distribution of T is obtained. The achieved significance level corresponds to the proportion of samples that have $T(\tilde{\boldsymbol{z}}_\alpha^*)$ more extreme than $T(\boldsymbol{z}_\alpha)$ for a two-sided hypothesis test, or the proportion of samples for which $T(\tilde{\boldsymbol{z}}_\alpha^*)$ is higher than $T(\boldsymbol{z}_\alpha)$ for a one-sided hypothesis test of the mean being smaller than or equal to zero.

B.2.4 One-sided Versus Two-sided Hypothesis Test

For both the discussed ES tests it is possible to choose between performing a one-sided or a two-sided hypothesis test of zero mean. McNeil and Frey (2000) use a one-sided test to check for underestimation of ES, formulated as a hypothesis test below.

$$H_0: \mu_z = 0 \qquad\qquad H_1: \mu_z > 0$$

Their argument for performing a one-sided test is that it is more likely for a model to underestimate ES than it is to overestimate it. Another argument could be that a risk manager would prefer to be conservative, thus rather overestimate risk than underestimating it. On the other hand, a model which systematically overestimates risk is not adequate either. This would lead the manager to allocate unnecessary much resources to face a huge, but unrealistic, risk. Thus, a two-sided hypothesis test might be more appropriate, since it tests whether or not a model produces ES forecasts that are accurate.

$$H_0: \mu_z = 0 \qquad\qquad H_1: \mu_z \neq 0$$

In this paper we choose to implement both the one-sided and two-sided hypothesis test for completeness. It will then be easier to compare our results with for example those of McNeil and Frey (2000) or Taylor (2008), and it will also enable us to check whether McNeil and Frey’s expectations about ES models generally underestimating ES are supported by our findings.

Appendix C: Last Trading Day

This appendix contains the rules for when the last trading day for each of the futures series considered in this paper. These are found at the home pages of the respective markets; www.theice.com, www.nasdaqomxcommodities.com, www.cmegroup.com and www.eex.com.

ICE Rotterdam Coal:
The month contracts cease trading at the close of business on the last Friday of the contract delivery period.

ICE Natural Gas:
Trading shall cease at the close of business two business days prior to the first calendar day of the delivery month.

ICE Brent Crude Oil:
Trading shall cease at the end of the designated settlement period on the Business Day (a trading day which is not a public holiday in England and Wales) immediately preceding:

(i) Either the 15th day before the first day of the contract month, if such 15th day is a Business Day
(ii) If such 15th day is not a Business Day the next preceding Business Day.

NASDAQ OMX (Nord Pool) Carbon:
The Last Trading Day for EUA/CER Futures is specified in relation to each Futures Series, and will normally be the last Monday of the contract month. If the last Monday of the month is a non-Banking Day, or there is a non-Banking Day in the four calendar days following the last Monday of the month, the Last Trading Day will normally be the penultimate Monday of the contract month. If the previously stated conditions are also in conflict with the penultimate Monday, the Last Trading Day will normally be the antepenultimate Monday of the contract month, unless stated otherwise in the Product Calendar.

NYMEX Light Crude Oil
Trading terminates at the close of business on the third business day prior to the 25th calendar day of the month preceding the delivery month. If the 25th calendar day of the month is a non-business day, trading shall cease on the third business day prior to the business day preceding the 25th calendar day.

NYMEX Heating Oil:
The last trading day is the last business day of the month preceding the contract month.

NYMEX Gasoline:
The last trading day is the last business day of the month preceding the contract month.

NYMEX Natural Gas:
The last trading day is the third business day prior to the first calendar day of the contract month.

NYMEX Coal:
Trading terminates on the fourth last business day of the month prior to the delivery month.

NYMEX Monthly Electricity Peak:
Trading shall cease one business day prior to the last peak day of the contract month.

EEX Yearly Electricity Peak:
Baseload/Peakload Year Futures (Contract cascades three exchange trading days before beginning of the delivery year)**.**

EEX Monthly Electricity Peak:
First day of expiry for German-Baseload/Peakload-Month-Futures and French-Baseload/Peakload-Month-Futures (Reduction of the contract volume starts two exchange trading days before beginning of the delivery period).

EEX Carbon Emissions:
The last trading day is stated in the product calendar.
The product calendar can be found at:
http://www.eex.com/en/Market%20Data/Market%20Information/Trading%20Calendar

ICE Monthly Electricity Peak:
The last trading day is two business days prior to the first EFA calendar day of the delivery period. Table C1-C3 present the EFA calendar for the years 2002-2011. They are constructed after the following pattern: "EFA blocks have an anchor point of 31/12/01 starting with 4,4,5 week cycles. Month contracts are based on the number of days in an EFA month, namely 28 days in January, February, April, May, July, August, October and November; 35 days in March, June, September, December. Exceptions are December 2004 which will have 42 days and every sixth year there is an additional week added to one of the EFA periods."
(https://www.theice.com/productguide/ProductDetails.shtml?specId=911)

Table C1: EFA calendar 2002-2005

	2002																									
	January				Febuary				March					April				May				June				
Mo	31	7	14	21	28	4	11	18	25	4	11	18	25	1	8	15	22	29	6	13	20	27	3	10	17	24
Tu	1	8	15	22	29	5	12	19	26	5	12	19	26	2	9	16	23	30	7	14	21	28	4	11	18	25
We	2	9	16	23	30	6	13	20	27	6	13	20	27	3	10	17	24	1	8	15	22	29	5	12	19	26
Th	3	10	17	24	31	7	14	21	28	7	14	21	28	4	11	18	25	2	9	16	23	30	6	13	20	27
Fr	4	11	18	25	1	8	15	22	1	8	15	22	29	5	12	19	26	3	10	17	24	31	7	14	21	28
Sa	5	12	19	26	2	9	16	23	2	9	16	23	30	6	13	20	27	4	11	18	25	1	8	15	22	29
Su	6	13	20	27	3	10	17	24	3	10	17	24	31	7	14	21	28	5	12	19	26	2	9	16	23	30

	July				August				September					October				November				December				
Mo	1	8	15	22	29	5	12	19	26	2	9	16	23	30	7	14	21	28	4	11	18	25	2	9	16	23
Tu	2	9	16	23	30	6	13	20	27	3	10	17	24	1	8	15	22	29	5	12	19	26	3	10	17	24
We	3	10	17	24	31	7	14	21	28	4	11	18	25	2	9	16	23	30	6	13	20	27	4	11	18	25
Th	4	11	18	25	1	8	15	22	29	5	12	19	26	3	10	17	24	31	7	14	21	28	5	12	19	26
Fr	5	12	19	26	2	9	16	23	30	6	13	20	27	4	11	18	25	1	8	15	22	29	6	13	20	27
Sa	6	13	20	27	3	10	17	24	31	7	14	21	28	5	12	19	26	2	9	16	23	30	7	14	21	28
Su	7	14	21	28	4	11	18	25	1	8	15	22	29	6	13	20	27	3	10	17	24	1	8	15	22	29

	2003																									
	January				Febuary				March					April				May				June				
Mo	30	6	13	20	27	3	10	17	24	3	10	17	24	31	7	14	21	28	5	12	19	26	2	9	16	23
Tu	31	7	14	21	28	4	11	18	25	4	11	18	25	1	8	15	22	29	6	13	20	27	3	10	17	24
We	1	8	15	22	29	5	12	19	26	5	12	19	26	2	9	16	23	30	7	14	21	28	4	11	18	25
Th	2	9	16	23	30	6	13	20	27	6	13	20	27	3	10	17	24	1	8	15	22	29	5	12	19	26
Fr	3	10	17	24	31	7	14	21	28	7	14	21	28	4	11	18	25	2	9	16	23	30	6	13	20	27
Sa	4	11	18	25	1	8	15	22	1	8	15	22	29	5	12	19	26	3	10	17	24	31	7	14	21	28
Su	5	12	19	26	2	9	16	23	2	9	16	23	30	6	13	20	27	4	11	18	25	1	8	15	22	29

	July				August				September					October				November				December				
Mo	30	7	14	21	28	4	11	18	25	1	8	15	22	29	6	13	20	27	3	10	17	24	1	8	15	22
Tu	1	8	15	22	29	5	12	19	26	2	9	16	23	30	7	14	21	28	4	11	18	25	2	9	16	23
We	2	9	16	23	30	6	13	20	27	3	10	17	24	1	8	15	22	29	5	12	19	26	3	10	17	24
Th	3	10	17	24	31	7	14	21	28	4	11	18	25	2	9	16	23	30	6	13	20	27	4	11	18	25
Fr	4	11	18	25	1	8	15	22	29	5	12	19	26	3	10	17	24	31	7	14	21	28	5	12	19	26
Sa	5	12	19	26	2	9	16	23	30	6	13	20	27	4	11	18	25	1	8	15	22	29	6	13	20	27
Su	6	13	20	27	3	10	17	24	31	7	14	21	28	5	12	19	26	2	9	16	23	30	7	14	21	28

	2004																									
	January				Febuary				March					April				May				June				
Mo	29	5	12	19	26	2	9	16	23	1	8	15	22	29	5	12	19	26	3	10	17	24	31	7	14	21
Tu	30	6	13	20	27	3	10	17	24	2	9	16	23	30	6	13	20	27	4	11	18	25	1	8	15	22
We	31	7	14	21	28	4	11	18	25	3	10	17	24	31	7	14	21	28	5	12	19	26	2	9	16	23
Th	1	8	15	22	29	5	12	19	26	4	11	18	25	1	8	15	22	29	6	13	20	27	3	10	17	24
Fr	2	9	16	23	30	6	13	20	27	5	12	19	26	2	9	16	23	30	7	14	21	28	4	11	18	25
Sa	3	10	17	24	31	7	14	21	28	6	13	20	27	3	10	17	24	1	8	15	22	29	5	12	19	26
Su	4	11	18	25	1	8	15	22	29	7	14	21	28	4	11	18	25	2	9	16	23	30	6	13	20	27

	July				August				September					October				November				December					
Mo	28	5	12	19	26	2	9	16	23	30	6	13	20	27	4	11	18	25	1	8	15	22	29	6	13	20	27
Tu	29	6	13	20	27	3	10	17	24	31	7	14	21	28	5	12	19	26	2	9	16	23	30	7	14	21	28
We	30	7	14	21	28	4	11	18	25	1	8	15	22	29	6	13	20	27	3	10	17	24	1	8	15	22	29
Th	1	8	15	22	29	5	12	19	26	2	9	16	23	30	7	14	21	28	4	11	18	25	2	9	16	23	30
Fr	2	9	16	23	30	6	13	20	27	3	10	17	24	1	8	15	22	29	5	12	19	26	3	10	17	24	31
Sa	3	10	17	24	31	7	14	21	28	4	11	18	25	2	9	16	23	30	6	13	20	27	4	11	18	25	1
Su	4	11	18	25	1	8	15	22	29	5	12	19	26	3	10	17	24	31	7	14	21	28	5	12	19	26	2

	2005																									
	January				Febuary				March					April				May				June				
Mo	3	10	17	24	31	7	14	21	28	7	14	21	28	4	11	18	25	2	9	16	23	30	6	13	20	27
Tu	4	11	18	25	1	8	15	22	1	8	15	22	29	5	12	19	26	3	10	17	24	31	7	14	21	28
We	5	12	19	26	2	9	16	23	2	9	16	23	30	6	13	20	27	4	11	18	25	1	8	15	22	29
Th	6	13	20	27	3	10	17	24	3	10	17	24	31	7	14	21	28	5	12	19	26	2	9	16	23	30
Fr	7	14	21	28	4	11	18	25	4	11	18	25	1	8	15	22	29	6	13	20	27	3	10	17	24	1
Sa	8	15	22	29	5	12	19	26	5	12	19	26	2	9	16	23	30	7	14	21	28	4	11	18	25	2
Su	9	16	23	30	6	13	20	27	6	13	20	27	3	10	17	24	1	8	15	22	29	5	12	19	26	3

	July				August				September					October				November				December				
Mo	4	11	18	25	1	8	15	22	29	5	12	19	26	3	10	17	24	31	7	14	21	28	5	12	19	26
Tu	5	12	19	26	2	9	16	23	30	6	13	20	27	4	11	18	25	1	8	15	22	29	6	13	20	27
We	6	13	20	27	3	10	17	24	31	7	14	21	28	5	12	19	26	2	9	16	23	30	7	14	21	28
Th	7	14	21	28	4	11	18	25	1	8	15	22	29	6	13	20	27	3	10	17	24	1	8	15	22	29
Fr	8	15	22	29	5	12	19	26	2	9	16	23	30	7	14	21	28	4	11	18	25	2	9	16	23	30
Sa	9	16	23	30	6	13	20	27	3	10	17	24	1	8	15	22	29	5	12	19	26	3	10	17	24	31
Su	10	17	24	31	7	14	21	28	4	11	18	25	2	9	16	23	30	6	13	20	27	4	11	18	25	1

Table C2: EFA calendar 2006-2009

2006

	January				Febuary				March					April				May				June				
Mo	2	9	16	23	30	6	13	20	27	6	13	20	27	3	10	17	24	1	8	15	22	29	5	12	19	26
Tu	3	10	17	24	31	7	14	21	28	7	14	21	28	4	11	18	25	2	9	16	23	30	6	13	20	27
We	4	11	18	25	1	8	15	22	1	8	15	22	29	5	12	19	26	3	10	17	24	31	7	14	21	28
Th	5	12	19	26	2	9	16	23	2	9	16	23	30	6	13	20	27	4	11	18	25	1	8	15	22	29
Fr	6	13	20	27	3	10	17	24	3	10	17	24	31	7	14	21	28	5	12	19	26	2	9	16	23	30
Sa	7	14	21	28	4	11	18	25	4	11	18	25	1	8	15	22	29	6	13	20	27	3	10	17	24	1
Su	8	15	22	29	5	12	19	26	5	12	19	26	2	9	16	23	30	7	14	21	28	4	11	18	25	2

	July				August				September					October				November				December				
Mo	3	10	17	24	31	7	14	21	28	4	11	18	25	2	9	16	23	30	6	13	20	27	4	11	18	25
Tu	4	11	18	25	1	8	15	22	29	5	12	19	26	3	10	17	24	31	7	14	21	28	5	12	19	26
We	5	12	19	26	2	9	16	23	30	6	13	20	27	4	11	18	25	1	8	15	22	29	6	13	20	27
Th	6	13	20	27	3	10	17	24	31	7	14	21	28	5	12	19	26	2	9	16	23	30	7	14	21	28
Fr	7	14	21	28	4	11	18	25	1	8	15	22	29	6	13	20	27	3	10	17	24	1	8	15	22	29
Sa	8	15	22	29	5	12	19	26	2	9	16	23	30	7	14	21	28	4	11	18	25	2	9	16	23	30
Su	9	16	23	30	6	13	20	27	3	10	17	24	1	8	15	22	29	5	12	19	26	3	10	17	24	31

2007

	January				Febuary				March					April				May				June				
Mo	1	8	15	22	29	5	12	19	26	5	12	19	26	2	9	16	23	30	7	14	21	28	4	11	18	25
Tu	2	9	16	23	30	6	13	20	27	6	13	20	27	3	10	17	24	1	8	15	22	29	5	12	19	26
We	3	10	17	24	31	7	14	21	28	7	14	21	28	4	11	18	25	2	9	16	23	30	6	13	20	27
Th	4	11	18	25	1	8	15	22	1	8	15	22	29	5	12	19	26	3	10	17	24	31	7	14	21	28
Fr	5	12	19	26	2	9	16	23	2	9	16	23	30	6	13	20	27	4	11	18	25	1	8	15	22	29
Sa	6	13	20	27	3	10	17	24	3	10	17	24	31	7	14	21	28	5	12	19	26	2	9	16	23	30
Su	7	14	21	28	4	11	18	25	4	11	18	25	1	8	15	22	29	6	13	20	27	3	10	17	24	1

	July				August				September					October				November				December				
Mo	2	9	16	23	30	6	13	20	27	3	10	17	24	1	8	15	22	29	5	12	19	26	3	10	17	24
Tu	3	10	17	24	31	7	14	21	28	4	11	18	25	2	9	16	23	30	6	13	20	27	4	11	18	25
We	4	11	18	25	1	8	15	22	29	5	12	19	26	3	10	17	24	31	7	14	21	28	5	12	19	26
Th	5	12	19	26	2	9	16	23	30	6	13	20	27	4	11	18	25	1	8	15	22	29	6	13	20	27
Fr	6	13	20	27	3	10	17	24	31	7	14	21	28	5	12	19	26	2	9	16	23	30	7	14	21	28
Sa	7	14	21	28	4	11	18	25	1	8	15	22	29	6	13	20	27	3	10	17	24	1	8	15	22	29
Su	8	15	22	29	5	12	19	26	2	9	16	23	30	7	14	21	28	4	11	18	25	2	9	16	23	30

2008

	January				Febuary				March					April				May				June				
Mo	31	7	14	21	28	4	11	18	25	3	10	17	24	31	7	14	21	28	5	12	19	26	2	9	16	23
Tu	1	8	15	22	29	5	12	19	26	4	11	18	25	1	8	15	22	29	6	13	20	27	3	10	17	24
We	2	9	16	23	30	6	13	20	27	5	12	19	26	2	9	16	23	30	7	14	21	28	4	11	18	25
Th	3	10	17	24	31	7	14	21	28	6	13	20	27	3	10	17	24	1	8	15	22	29	5	12	19	26
Fr	4	11	18	25	1	8	15	22	29	7	14	21	28	4	11	18	25	2	9	16	23	30	6	13	20	27
Sa	5	12	19	26	2	9	16	23	1	8	15	22	29	5	12	19	26	3	10	17	24	31	7	14	21	28
Su	6	13	20	27	3	10	17	24	2	9	16	23	30	6	13	20	27	4	11	18	25	1	8	15	22	29

	July				August				September					October				November				December				
Mo	30	7	14	21	28	4	11	18	25	1	8	15	22	29	6	13	20	27	3	10	17	24	1	8	15	22
Tu	1	8	15	22	29	5	12	19	26	2	9	16	23	30	7	14	21	28	4	11	18	25	2	9	16	23
We	2	9	16	23	30	6	13	20	27	3	10	17	24	1	8	15	22	29	5	12	19	26	3	10	17	24
Th	3	10	17	24	31	7	14	21	28	4	11	18	25	2	9	16	23	30	6	13	20	27	4	11	18	25
Fr	4	11	18	25	1	8	15	22	29	5	12	19	26	3	10	17	24	31	7	14	21	28	5	12	19	26
Sa	5	12	19	26	2	9	16	23	30	6	13	20	27	4	11	18	25	1	8	15	22	29	6	13	20	27
Su	6	13	20	27	3	10	17	24	31	7	14	21	28	5	12	19	26	2	9	16	23	30	7	14	21	28

2009

	January				Febuary				March					April				May				June				
Mo	29	5	12	19	26	2	9	16	23	2	9	16	23	30	6	13	20	27	4	11	18	25	1	8	15	22
Tu	30	6	13	20	27	3	10	17	24	3	10	17	24	31	7	14	21	28	5	12	19	26	2	9	16	23
We	31	7	14	21	28	4	11	18	25	4	11	18	25	1	8	15	22	29	6	13	20	27	3	10	17	24
Th	1	8	15	22	29	5	12	19	26	5	12	19	26	2	9	16	23	30	7	14	21	28	4	11	18	25
Fr	2	9	16	23	30	6	13	20	27	6	13	20	27	3	10	17	24	1	8	15	22	29	5	12	19	26
Sa	3	10	17	24	31	7	14	21	28	7	14	21	28	4	11	18	25	2	9	16	23	30	6	13	20	27
Su	4	11	18	25	1	8	15	22	1	8	15	22	29	5	12	19	26	3	10	17	24	31	7	14	21	28

	July				August				September					October				November				December					
Mo	29	6	13	20	27	3	10	17	24	31	7	14	21	28	5	12	19	26	2	9	16	23	30	7	14	21	28
Tu	30	7	14	21	28	4	11	18	25	1	8	15	22	29	6	13	20	27	3	10	17	24	1	8	15	22	29
We	1	8	15	22	29	5	12	19	26	2	9	16	23	30	7	14	21	28	4	11	18	25	2	9	16	23	30
Th	2	9	16	23	30	6	13	20	27	3	10	17	24	1	8	15	22	29	5	12	19	26	3	10	17	24	31
Fr	3	10	17	24	31	7	14	21	28	4	11	18	25	2	9	16	23	30	6	13	20	27	4	11	18	25	1
Sa	4	11	18	25	1	8	15	22	29	5	12	19	26	3	10	17	24	31	7	14	21	28	5	12	19	26	2
Su	5	12	19	26	2	9	16	23	30	6	13	20	27	4	11	18	25	1	8	15	22	29	6	13	20	27	3

Table C3: EFA calendar 2010-2011

2010

	January				Febuary				March					April			
Mo	4	11	18	25	1	8	15	22	1	8	15	22	29	5	12	19	26
Tu	5	12	19	26	2	9	16	23	2	9	16	23	30	6	13	20	27
We	6	13	20	27	3	10	17	24	3	10	17	24	31	7	14	21	28
Th	7	14	21	28	4	11	18	25	4	11	18	25	1	8	15	22	29
Fr	8	15	22	29	5	12	19	26	5	12	19	26	2	9	16	23	30
Sa	9	16	23	30	6	13	20	27	6	13	20	27	3	10	17	24	1
Su	10	17	24	31	7	14	21	28	7	14	21	28	4	11	18	25	2

	May				June					July				August			
Mo	3	10	17	24	31	7	14	21	28	5	12	19	26	2	9	16	23
Tu	4	11	18	25	1	8	15	22	29	6	13	20	27	3	10	17	24
We	5	12	19	26	2	9	16	23	30	7	14	21	28	4	11	18	25
Th	6	13	20	27	3	10	17	24	1	8	15	22	29	5	12	19	26
Fr	7	14	21	28	4	11	18	25	2	9	16	23	30	6	13	20	27
Sa	8	15	22	29	5	12	19	26	3	10	17	24	31	7	14	21	28
Su	9	16	23	30	6	13	20	27	4	11	18	25	1	8	15	22	29

	September					October				November				December				
Mo	30	6	13	20	27	4	11	18	25	1	8	15	22	29	6	13	20	27
Tu	31	7	14	21	28	5	12	19	26	2	9	16	23	30	7	14	21	28
We	1	8	15	22	29	6	13	20	27	3	10	17	24	1	8	15	22	29
Th	2	9	16	23	30	7	14	21	28	4	11	18	25	2	9	16	23	30
Fr	3	10	17	24	1	8	15	22	29	5	12	19	26	3	10	17	24	31
Sa	4	11	18	25	2	9	16	23	30	6	13	20	27	4	11	18	25	1
Su	5	12	19	26	3	10	17	24	31	7	14	21	28	5	12	19	26	2

2011

	January				Febuary				March					April			
Mo	3	10	17	24	31	7	14	21	28	7	14	21	28	4	11	18	25
Tu	4	11	18	25	1	8	15	22	1	8	15	22	29	5	12	19	26
We	5	12	19	26	2	9	16	23	2	9	16	23	30	6	13	20	27
Th	6	13	20	27	3	10	17	24	3	10	17	24	31	7	14	21	28
Fr	7	14	21	28	4	11	18	25	4	11	18	25	1	8	15	22	29
Sa	8	15	22	29	5	12	19	26	5	12	19	26	2	9	16	23	30
Su	9	16	23	30	6	13	20	27	6	13	20	27	3	10	17	24	1

	May				June					July				August			
Mo	2	9	16	23	30	6	13	20	27	4	11	18	25	1	8	15	22
Tu	3	10	17	24	31	7	14	21	28	5	12	19	26	2	9	16	23
We	4	11	18	25	1	8	15	22	29	6	13	20	27	3	10	17	24
Th	5	12	19	26	2	9	16	23	30	7	14	21	28	4	11	18	25
Fr	6	13	20	27	3	10	17	24	1	8	15	22	29	5	12	19	26
Sa	7	14	21	28	4	11	18	25	2	9	16	23	30	6	13	20	27
Su	8	15	22	29	5	12	19	26	3	10	17	24	31	7	14	21	28

	September					October				November				December				
Mo	29	5	12	19	26	3	10	17	24	31	7	14	21	28	5	12	19	26
Tu	30	6	13	20	27	4	11	18	25	1	8	15	22	29	6	13	20	27
We	31	7	14	21	28	5	12	19	26	2	9	16	23	30	7	14	21	28
Th	1	8	15	22	29	6	13	20	27	3	10	17	24	1	8	15	22	29
Fr	2	9	16	23	30	7	14	21	28	4	11	18	25	2	9	16	23	30
Sa	3	10	17	24	1	8	15	22	29	5	12	19	26	3	10	17	24	31
Su	4	11	18	25	2	9	16	23	30	6	13	20	27	4	11	18	25	1

Appendix D: Data and Descriptive Statistics

The prices used in this paper are gathered from the Reuters EcoWin Pro database. We have however discovered a couple of errors in the data set, which we have corrected. For Coal Rotterdam on ICE, the price was reported to be 0 on the 23.04.2007, but it turns out that it in reality was 71.8. The 20.04.2007 EcoWin reported the price to be 71.35 while it actually was 72. The mentioned prices can be found at the ICE home page, by choosing the relevant dates: https://www.theice.com/marketdata/reports/ReportCenter.shtml?reportId=10&productId=517&hubId=681.

Table D1: Start date, end date and the length of the return series after removing the price changes between the last trading day of a futures contract and the first trading day of the subsequent contract. (See appendix C for more details)

	CO_2 EEX	CO_2 Nordpool	El M EEX	El M ICE	El M NYMEX	El Y EEX	Gas ICE
Start	05.10.05	05.07.07	08.01.03	14.09.04	01.08.06	01.07.02	31.01.97
End	11.04.11	11.04.11	11.04.11	11.04.11	11.04.11	11.04.11	11.04.11
Length	1391	927	1993	1597	1126	2217	3430

	Gas NYMEX	Coal ICE	Coal NYMEX	Oil ICE	Gasoline NYMEX	HO NYMEX	LCO NYMEX
Start	03.06.96	01.08.06	02.01.07	03.06.96	03.10.05	03.06.96	14.07.97
End	11.04.11	11.04.11	11.04.11	11.04.11	11.04.11	11.04.11	11.04.11
Length	3500	1152	1024	3500	1324	3500	3299

Table D2: Descriptive Statistics for the Energy commodity futures

	CO2 EEX	CO2 NP	Coal ICE	Coal NYMEX	El MP EEX	El MP ICE	El MP NYMEX
Mean	-0.026099	-0.020080	0.038409	0.019870	-0.161382	-0.099144	-0.445351
Median	0.000000	0.000000	0.000000	0.000000	-0.204918	-0.071082	0.000000
Maximum	34.64810	9.684983	19.10552	11.12256	33.91509	26.96636	24.30778
Minimum	-33.45324	-10.78890	-20.90090	-10.77459	-37.64776	-23.31835	-26.66533
Std. Dev	2.859554	2.154191	1.797325	2.071445	3.349222	2.985190	5.695212
Skewness	-0.166823	-0.357085	-1.375732	-0.421948	1.873721	0.739658	-0.436990
Kurtosis	37.02982	6.331609	40.46536	8.497960	35.29957	15.99622	6.460047
Jarque-Bera	67123.88 (0.0000***)	448.4231 (0.0000***)	67738.73 (0.0000***)	1320.095 (0.0000***)	87800.43 (0.0000***)	11384.62 (0.0000***)	597.5198 (0.0000***)
Augmented Dickey-Füller	-17.60033 (0.0000***)	-28.72033 (0.0000***)	-38.84502 (0.0000***)	-26.51426 (0.0000***)	-37.44907 (0.0000***)	-37.45553 (0.0000***)	-32.12734 (0.0000***)
Q(5)	41.324 (0.0000***)	11.255 (0.0465**)	33.124 (0.0000***)	50.748 (0.0000***)	77.041 (0.0000***)	13.287 (0.0208**)	9.7819 (0.0817*)
$Q^2(5)$	424.98 (0.0000***)	194.03 (0.0000***)	168.71 (0.0000***)	218.04 (0.0000***)	301.29 (0.0000***)	198.88 (0.0000***)	62.332 (0.0000***)
Observations	1391	927	1152	1024	1993	1597	1126

	El YP EEX	Gas ICE	Gas NYMEX	Oil ICE	Gasoline NYMEX	Heating Oil NYMEX	Light Crude Oil NYMEX
Mean	0.017701	-0.114770	-0.099095	0.053965	0.037288	0.039815	0.039061
Median	0.025870	-0.096204	-0.078447	0.117947	0.135543	0.000000	0.067499
Maximum	6.704807	35.77702	32.43538	12.89825	12.99953	10.40314	14.54637
Minimum	-6.154219	-16.50143	-16.69867	-14.43716	-11.50368	-14.89902	-16.54451
Std. Dev	0.991491	3.140458	3.549166	2.307953	2.553516	2.302317	2.436475
Skewness	-0.034303	1.809383	0.205909	-0.151191	-0.164068	-0.055027	-0.171649
Kurtosis	7.647625	21.76132	6.656350	5.651866	5.149029	4.619831	6.494140
Jarque-Bera	1995.774 (0.0000***)	52176.36 (0.0000***)	1974.362 (0.0000***)	1038.892 (0.0000***)	260.7176 (0.0000***)	384.4116 (0.0000***)	1694.431 (0.0000***)
Augmented Dickey-Füller	-40.77566 (0.0000***)	-41.27427 (0.0000***)	-60.09238 (0.0001***)	-61.93710 (0.0001***)	-36.50976 (0.0000***)	-60.32120 (0.0001***)	-58.11021 (0.0001***)
Q(5)	67.484 (0.0000***)	71.339 (0.0000***)	2.5717 (0.7657)	11.790 (0.0377**)	6.9132 (0.2272)	8.7314 (0.1203)	7.7555 (0.1702)
$Q^2(5)$	325.29 (0.0000***)	78.795 (0.0000***)	180.18 (0.0000***)	436.79 (0.0000***)	263.27 (0.0000***)	223.23 (0.0000***)	566.53 (0.0000***)
Observations	2217	3430	3500	3500	1324	3500	3299

Q(5) and $Q^2(5)$ denotes the Ljung-Box test statistics with 5 lags for returns and squared returns respectively. *, ** and *** denotes significance at the 10%, 5% and 1% level, respectively

Table D3: Descriptive statistics, In-sample and Out-of-sample periods, for the Energy commodity futures

	CO2 EEX		CO2 NP		Coal ICE		Coal NYMEX		El MP EEX		El MP ICE		El MP NYMEX	
	In-Sample	Out-of Sample	In-Sample	Out-of Sample	In-Sample	Out-of Sample	In-Sample	Out-of Sample	In-Sample	Out-of Sample	In-Sample	Out-of Sample	In-Sample	Out-of Sample
Mean	-0.057200	0.029323	-0.096518	0.045198	-0.008210	0.099201	-0.012991	0.054308	-0.190435	-0.074632	-0.134249	-0.022124	-0.497002	-0.380683
Median	0.000000	0.063920	0.000000	0.000000	0.000000	0.066116	0.000000	0.075876	-0.273785	-0.048427	-0.100150	-0.033863	-0.009072	0.000000
Maximum	34.64810	5.503707	9.684983	7.117628	19.10552	6.632264	11.12256	8.025294	33.91509	12.18746	26.96636	4.686992	24.30778	22.89704
Minimum	-33.45324	-9.048314	-10.78890	-8.356508	-20.90090	-5.788377	-10.77459	-4.332426	-37.64776	-9.007901	-23.31835	-4.077549	-25.13144	-26.66533
Std. Dev	3.318916	1.768216	2.456425	1.857670	2.146279	1.197908	2.514398	1.472462	3.731056	1.773784	3.501324	1.251891	5.741701	5.641538
Skewness	-0.114122	-0.382364	-0.376478	-0.211858	-1.403225	0.144485	-0.515325	0.414492	1.793556	0.952272	0.688417	0.262297	-0.390009	-0.497828
Kurtosis	31.67263	4.597905	6.332839	4.627495	34.40086	9.118354	7.072524	4.979233	30.40386	14.92040	12.30503	4.460452	5.619999	7.590331
Jarque-Bera	30523.12 (0.0000***)	65.37725 (0.0000***)	207.7134 (0.0000***)	58.92240 (0.0000***)	27000.67 (0.0000***)	781.6201 (0.0000***)	385.3080 (0.0000***)	95.92873 (0.0000***)	47517.16 (0.0000***)	3035.899 (0.0000***)	4044.242 (0.0000***)	50.16916 (0.0000***)	194.9161 (0.0000***)	459.6348 (0.0000***)
Augmented Dickey-Füller	-13.81555 (0.0000***)	-21.55972 (0.0000***)	-18.70171 (0.0000***)	-22.38021 (0.0000***)	-30.90723 (0.0000***)	-20.38887 (0.0000***)	-19.57803 (0.0000***)	-16.69987 (0.0000***)	-32.62462 (0.0000***)	-17.14760 (0.0000***)	-31.16907 (0.0000***)	-19.53247 (0.0000***)	-23.17579 (0.0000***)	-22.30358 (0.0000***)
Q(5)	34.385 (0.0000***)	6.3854 (0.2705)	10.265 (0.0681*)	1.0782 (0.9560)	35.857 (0.0000***)	11.599 (0.0407**)	23.113 (0.0000***)	45.823 (0.0000***)	55.090 (0.0000***)	40.955 (0.0000***)	8.0426 (0.1539)	18.918 (0.0020***)	14.126 (0.0148**)	2.2139 (0.8188)
$Q^2(5)$	268.49 (0.0000***)	24.141 (0.0000***)	99.630 (0.0000***)	28.306 (0.0000***)	93.118 (0.0000***)	81.139 (0.0000***)	94.261 (0.0000***)	30.003 (0.0000***)	218.23 (0.0000***)	19.494 (0.0016***)	115.46 (0.0000***)	45.795 (0.0000***)	12.100 (0.0334**)	67.308 (0.0000***)
Observations	891	500	427	500	652	500	524	500	1493	500	1097	500	626	500

	El YP EEX		Gas ICE		Gas NYMEX		Oil ICE		Gasoline NYMEC		Heating Oil NYMEX		Light Crude Oil NYMEX	
	In-Sample	Out-of Sample	In-Sample	Out-of Sample	In-Sample	Out-of Sample	In-Sample	Out-of Sample	In-Sample	Out-of Sample	In-Sample	Out-of Sample	In-Sample	Out-of Sample
Mean	0.037953	-0.051845	-0.149549	0.089037	-0.085044	-0.183403	0.033925	0.174205	-0.036634	0.159110	0.029565	0.101316	0.026094	0.111652
Median	0.065244	-0.145946	-0.102104	-0.029719	-0.034421	-0.431016	0.114903	0.130174	0.134794	0.137071	-0.010280	0.114692	0.069180	0.033000
Maximum	5.440327	6.704807	33.97698	35.77702	32.43538	14.05762	12.89825	8.523785	12.99953	7.281123	10.40314	7.912581	14.54637	8.418311
Minimum	-6.154219	-2.677700	-16.50143	-8.614417	-16.69867	-9.699926	-14.43716	-6.765490	-11.50368	-7.535470	-14.89902	-6.603466	-16.54451	-9.257203
Std. Dev	1.002322	0.951051	3.122467	3.239588	3.566495	3.445637	2.367885	1.906890	2.824074	2.027307	2.351974	1.979349	2.491111	2.105349
Skewness	-0.340068	1.172901	1.594638	2.934989	0.141915	0.627288	-0.159685	0.060717	-0.133098	-0.106306	-0.063043	0.067103	-0.180531	-0.039952
Kurtosis	7.539357	8.565647	19.64249	32.20691	6.927143	4.806227	5.667017	3.952895	4.891280	3.893933	4.609410	4.050599	6.587968	4.548954
Jarque-Bera	1507.265 (0.0000***)	759.9835 (0.0000***)	35055.48 (0.0000***)	18489.59 (0.0000***)	1937.877 (0.0000***)	100.7587 (0.0000***)	901.8718 (0.0000***)	19.22407 (0.0001***)	125.2411 (0.0000***)	17.59002 (0.0002***)	325.7622 (0.0000***)	23.37020 (0.0000***)	1516.578 (0.0000***)	50.11757 (0.0000***)
Augmented Dickey-Füller	-36.16327 (0.0000***)	-18.87306 (0.0000***)	-37.88992 (0.0000***)	-21.97226 (0.0000***)	-54.55850 (0.0000***)	-14.65948 (0.0000***)	-57.73499 (0.0001***)	-22.03494 (0.0000***)	-28.60972 (0.0000***)	-22.97944 (0.0000***)	-55.78529 (0.0001***)	-22.98591 (0.0000***)	-53.47467 (0.0001***)	-22.77832 (0.0000***)
Q(5)	51.309 (0.0000***)	16.725 (0.0051***)	71.456 (0.0000***)	13.504 (0.0191**)	2.8313 (0.7260)	26.468 (0.0000***)	15.019 (0.0103**)	0.5378 (0.9907)	10.224 (0.0691*)	3.7475 (0.5863)	10.877 (0.0539*)	2.7031 (0.7456)	6.4315 (0.1692)	10.303 (0.0671*)
$Q^2(5)$	358.32 (0.0000***)	16.410 (0.0058***)	104.82 (0.0000***)	3.2437 (0.6625)	134.55 (0.0000***)	86.258 (0.0000***)	373.43 (0.0000***)	13.658 (0.0179**)	165.35 (0.0000***)	15.493 (0.0085***)	171.88 (0.0000***)	45.111 (0.0000***)	501.20 (0.0000***)	18.153 (0.0028***)
Observations	1717	500	1930	500	3000	500	3000	500	824	500	3000	500	2799	500

Q(5) and $Q^2(5)$ denotes the Ljung-Box test statistics with 5 lags for returns and squared returns respectively. *, ** and *** denotes significance at the 10%, 5% and 1% level, respectively

Appendix E: Test Results

Table E1: VaR test results for CO2 futures on EEX

Quantile	CO2 EEX													
	EWQR	Symmetric Absolute Value CAViaR	Asymmetric Slope CAViaR	Indirect GARCH CAViaR	Adaptive CAViaR	Indirect AR-GARCH CAViaR	GARCH Normal	GARCH Student t	GARCH GED	GARCH Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Test for unconditional coverage													
1 %	0.6414	0.1250	0.1250	0.0282**	0.6414	NaN	1.000	0.1250	0.1250	0.1250	0.6414	0.1250	0.1250	0.1250
5 %	0.1313	0.0005***	0.0069***	0.0031***	0.5301	0.0142**	0.0486**	0.2885	0.1313	0.0822*	0.0486**	0.2885	0.0822*	0.0822*
10 %	0.3622	0.0072***	0.0187**	0.0043***	0.6518	0.0118**	0.0629*	0.3622	0.2213	0.2213	0.0288**	0.2862	0.1674	0.1674
90 %	0.4625	0.1238	0.1674	0.1674	0.2862	0.0043***	0.0025***	0.4491	0.1674	0.6518	0.0043***	0.4491	0.1674	0.4491
95 %	0.6776	0.0005***	0.0031***	0.0013***	0.1994	0.0013***	0.0271**	0.0486**	0.0271**	0.1313	0.0271**	0.0486**	0.0271**	0.1313
99 %	0.0282**	0.6414	0.1250	0.3315	NaN	0.3315	0.6414	0.3315	0.3315	0.6414	1.0000	1.0000	0.3315	1.0000
	Test for conditional coverage													
1 %	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5 %	NaN	0.0010***	NaN	0.0071***	0.8206	NaN	0.1175	0.5551	0.2930	0.1924	NaN	0.5551	0.1924	0.1924
10 %	0.5493	0.0132**	0.0339**	0.0136**	0.3407	0.0377**	0.1411	0.6586	0.4565	0.4565	0.0885*	0.5581	0.3601	0.3601
90 %	0.3373	0.2265	0.2653	0.3601	0.5581	0.0118**	0.0103**	0.7506	0.3601	0.8811	0.0170**	0.7506	0.3601	0.7506
95 %	0.9156	0.0010***	0.0071***	NaN	0.4167	NaN	0.0664*	0.1175	0.0664*	0.2930	0.0664*	0.1175	0.0664*	0.2930
99 %	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.1063	0.1063	NaN	0.1063
	Dynamic quantile test													
1 %	0.0001***	0.0000***	0.9288	0.7769	0.0001***	0.3831	0.0000***	0.0000***	0.0000***	0.0000***	0.0002***	0.0000***	0.0000***	0.0000***
5 %	0.2843	0.0355**	0.2102	0.1265	0.0007***	0.3534	0.2777	0.7301	0.4724	0.3733	0.2713	0.7329	0.4021	0.4034
10 %	0.2155	0.1066	0.2403	0.1749	0.0616*	0.0863*	0.3365	0.7487	0.6208	0.6843	0.4053	0.6249	0.4046	0.6225
90 %	0.0003***	0.6582	0.7226	0.7420	0.0012***	0.1680	0.1115	0.9092	0.5934	0.9267	0.0830*	0.7332	0.4002	0.7527
95 %	0.1815	0.0299**	0.1092	0.1146	0.0629*	0.1165	0.3185	0.1712	0.3181	0.2434	0.1184	0.1473	0.1182	0.2449
99 %	0.7407	0.5704	0.8131	0.8420	0.0228**	0.8411	0.7593	0.8335	0.8358	0.7442	0.0007***	0.0006***	0.8154	0.0006***

The table presents both the coverage tests and the dynamic quantile test for the daily forecasts. *, ** and *** denotes significance at the 10%, 5% and 1% level, respectively.

Table E2: VaR test results for CO2 futures on Nasdaq OMX (Nord Pool)

Quantile	CO2 Nasdaq OMX													
	EWQR	Symmetric Absolute Value CAViaR	Asymmetric Slope CAViaR	Indirect GARCH CAViaR	Adaptive CAViaR	Indirect AR-GARCH CAViaR	GARCH Normal	GARCH Student t	GARCH GED	GARCH Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Test for unconditional coverage													
1 %	0.6414	NaN	0.3315	NaN	0.3315	NaN	0.6414	0.1250	0.1250	0.0282**	0.6414	0.0282**	0.0282**	0.0282**
5 %	0.1994	0.0005***	0.2885	0.0005***	0.6776	0.3992	0.0822*	0.6776	0.0822*	0.2885	0.1313	0.8364	0.0486**	0.5301
10 %	0.7642	0.5556	1.0000	0.6575	0.0893*	1.0000	0.0431**	1.0000	0.6518	0.8811	0.1674	0.5461	0.2862	0.5461
90 %	0.6575	0.8811	0.8811	0.2862	0.3622	0.2862	0.0072***	0.2862	0.0893*	0.3622	0.0187**	0.1674	0.0431**	0.3622
95 %	0.8384	0.2885	0.6776	0.5455	0.3992	0.5455	0.0142**	0.1313	0.0142**	0.3992	0.0822*	0.1313	0.0271**	0.3992
99 %	1.0000	0.6414	0.6414	0.3315	0.1250	0.6414	0.6414	0.6414	0.6414	0.6414	1.0000	1.0000	1.0000	1.0000
	Test for conditional coverage													
1 %	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5 %	NaN	NaN	0.5551	NaN	NaN	0.6951	0.1924	0.9156	0.1924	0.5551	0.2930	0.9677	0.1175	0.8206
10 %	0.9085	0.8380	0.8775	0.8920	0.2361	0.5712	0.1140	0.8775	0.8811	0.9071	0.2653	0.8270	0.5209	0.8270
90 %	0.0316**	0.2879	0.0758*	0.3285	0.3478	0.1166	0.0174**	0.3285	0.1868	0.3478	0.0600*	0.2653	0.1140	0.3478
95 %	0.9265	0.5551	0.9156	0.7310	0.6951	0.7310	0.0345**	0.2930	0.0345**	0.6951	0.1924	0.2930	0.0664*	0.6951
99 %	0.1063	0.0583*	0.0583*	NaN	NaN	NaN	0.0583*	0.0583*	0.0583*	0.0583*	0.1063	0.1063	0.1063	0.1063
	Dynamic quantile test													
1 %	0.0002***	0.8374	0.8721	0.6081	0.7691	0.2090	0.0002***	0.9299	0.9334	0.7549	0.0002***	0.7147	0.7139	0.7241
5 %	0.1092	0.0035***	0.3571	0.0035***	0.0064***	0.2563	0.3309	0.0528*	0.3213	0.2254	0.5265	0.3888	0.2715	0.6409
10 %	0.1739	0.2638	0.2221	0.1501	0.1854	0.6143	0.3124	0.4069	0.3722	0.3441	0.5002	0.2824	0.4577	0.2779
90 %	0.0016***	0.2777	0.1445	0.5956	0.0335**	0.6120	0.0726*	0.6646	0.5602	0.6254	0.1361	0.7379	0.4084	0.6423
95 %	0.0703*	0.1287	0.8721	0.0140**	0.1128	0.0108**	0.0626*	0.0537*	0.0574*	0.1860	0.2260	0.0419**	0.0910*	0.1522
99 %	0.0011***	0.0001***	0.0001***	0.9887	0.7618	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0008***	0.0009***	0.0010***	0.0008***

The table presents both the coverage tests and the dynamic quantile test for the daily forecasts. *, ** and *** denotes significance at the 10%, 5% and 1% level, respectively.

Table E3: VaR test results for coal futures on ICE

Quantile	EWQR	Symmetric Absolute Value CAViaR	Asymmetric Slope CAViaR	Indirect GARCH CAViaR	Adaptive CAViaR	Indirect AR-GARCH CAViaR	GARCH Normal	GARCH Student t	GARCH GED	GARCH Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Coal ICE													
	Test for unconditional coverage													
1 %	0.1250	0.6414	0.6414	1.0000	0.1250	1.0000	0.6414	1.0000	0.6630	1.0000	0.6414	1.0000	1.0000	1.0000
5 %	0.5455	0.1994	0.1313	0.0822*	0.6776	0.1313	0.0031***	0.3992	0.02710**	0.1313	0.0013***	0.2885	0.0271**	0.0486**
10 %	0.8811	0.6518	0.3622	1.0000	0.7642	0.7669	0.0000***	0.4491	0.0043***	0.2213	0.0000***	0.4491	0.0118**	0.2862
90 %	0.4491	0.0431**	0.0431**	0.0629	0.3622	0.6518	0.0043***	0.0070***	0.7669	0.0047***	0.0288**	0.0223**	0.5556	0.0223**
95 %	0.3992	0.2885	0.5301	0.8364	0.0822*	0.8364	0.0005***	0.0523*	0.4229	0.0523*	0.2885	0.0337**	0.5455	0.0337**
99 %	0.1250	0.3315	1.0000	1.0000	0.1250	1.0000	0.3315	0.6630	0.6630	0.6630	0.6630	0.6630	0.6630	0.6630
	Test for conditional coverage													
1 %	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5 %	0.0099***	NaN	NaN	NaN	0.0557*	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
10 %	0.0016***	0.0304**	0.0082***	0.6373	0.4862	0.0498**	NaN	0.1114	0.0136**	0.0337**	NaN	0.0417**	0.0231**	0.0173**
90 %	0.0417**	0.0569*	0.1140	0.0699*	0.3551	0.8633	0.0072***	0.0009***	0.2628	0.0008***	0.0621*	0.0009***	0.1667	0.0009***
95 %	0.6951	NaN	0.8206	0.9677	0.1924	0.9677	NaN	0.1423	0.6062	0.1423	0.5551	0.1011	0.7829	0.1011
99 %	NaN	NaN	0.1063	NaN	NaN	0.1063	NaN	NaN	NaN	NaN	0.1419	NaN	NaN	NaN
	Dynamic quantile test													
1 %	0.8879	0.9993	0.9993	0.9997	0.7629	0.9199	0.9995	0.9998	0.9965	0.9998	0.9987	0.9996	0.9992	0.9997
5 %	0.0001***	0.8160	0.7198	0.6615	0.0003***	0.7626	0.2191	0.8267	0.4917	0.7701	0.1839	0.8315	0.4641	0.5756
10 %	0.0001***	0.0737*	0.0378**	0.1374	0.0193**	0.0105**	0.0000***	0.2016	0.1957	0.1494	0.0001***	0.0694*	0.3014	0.0636*
90 %	0.0001***	0.0805*	0.2385	0.1104	0.0005***	0.6026	0.0547*	0.0000***	0.0564*	0.0000***	0.0264**	0.0000***	0.0234**	0.0000***
95 %	0.0048***	0.2017	0.0440**	0.6071	0.0523*	0.6066	0.0907*	0.1926	0.2967	0.1915	0.2019	0.0522*	0.1407	0.0514*
99 %	0.8924	0.9333	0.0021***	0.9756	0.9301	0.0029***	0.7527	0.9425	0.9495	0.9374	0.0046***	0.9060	0.8948	0.8996

The table presents both the coverage tests and the dynamic quantile test for the daily forecasts. *, ** and *** denotes significance at the 10%, 5% and 1% level, respectively.

Table E4: VaR test results for coal futures on NYMEX

Quantile	EWQR	Symmetric Absolute Value CAViaR	Asymmetric Slope CAViaR	Indirect GARCH CAViaR	Adaptive CAViaR	Indirect AR-GARCH CAViaR	GARCH Normal	GARCH Student t	GARCH GED	GARCH Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Coal NYMEX													
	Test for unconditional coverage													
1 %	0.3315	0.0282**	0.0282**	0.1250	0.6414	0.3315	0.3315	0.1250	0.1250	0.1250	0.3315	0.1250	0.1250	0.1250
5 %	0.2346	0.0002***	0.0486**	0.0002***	0.6776	0.0013***	0.0486**	0.5301	0.0822*	0.1994	0.0486**	0.5301	0.1313	0.3992
10 %	0.2436	0.0014***	0.0893*	0.0288**	0.4491	0.0187**	0.0025***	0.6518	0.0629*	0.4491	0.0043***	0.6518	0.0629*	0.5461
90 %	0.3063	0.5461	0.4491	0.7669	0.8818	0.3063	0.1674	0.4625	0.7669	0.3063	0.3622	0.2436	0.8818	0.1907
95 %	0.0129**	0.5301	0.6776	0.5455	0.8364	0.5455	0.8364	0.4229	0.8384	0.4229	1.0000	0.2346	0.8384	0.1678
99 %	0.0199**	0.1250	0.1250	0.1250	0.0282**	0.1250	0.3966	1.0000	1.0000	1.0000	0.6630	1.0000	1.0000	1.0000
	Test for conditional coverage													
1 %	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5 %	0.0169**	0.0003***	0.1175	0.0003***	NaN	NaN	0.1175	0.5122	0.1924	0.1870	0.1175	0.5121	0.2930	0.3908
10 %	0.1102	0.0006***	0.0595*	0.0038***	0.0417**	0.0387**	0.0004***	0.0304**	0.0038***	0.0417**	0.0008***	0.0304**	0.0009***	0.0205**
90 %	0.0021***	0.0059***	0.4522	0.0053***	0.0037***	0.2026	0.0015***	0.0003***	0.0001***	0.0006***	0.0021***	0.0000***	0.0002***	0.0001***
95 %	0.0034***	0.1710	0.9156	0.0484**	0.7340	0.1765	0.0795*	0.0560*	0.0303**	0.0560*	0.1062	0.0169**	0.0303**	0.0181**
99 %	0.0325**	NaN	NaN	NaN	NaN	NaN	0.1489	0.1063	0.1063	0.1063	0.1419	0.1063	0.1063	0.1063
	Dynamic quantile test													
1 %	0.9054	0.7673	0.7467	0.8822	0.1776	0.9459	0.9390	0.8904	0.9002	0.8932	0.9360	0.8978	0.9025	0.8978
5 %	0.0006***	0.0438**	0.2990	0.0411**	0.0006***	0.1789	0.5469	0.7298	0.6508	0.5343	0.5310	0.8240	0.7198	0.7937
10 %	0.0001***	0.0307**	0.1430	0.0206**	0.0034***	0.4390	0.0135**	0.0089***	0.0098***	0.0605*	0.0243**	0.0576*	0.0026***	0.0333**
90 %	0.0000***	0.0233**	0.3789	0.0035***	0.0004***	0.4491	0.0027***	0.0001***	0.0000***	0.0002***	0.0022***	0.0000***	0.0000***	0.0000***
95 %	0.0000***	0.2051	0.5783	0.0102**	0.0974*	0.1243	0.0145**	0.0215**	0.0051***	0.0220**	0.0435**	0.0025***	0.0045***	0.0031***
99 %	0.0016***	0.9293	0.9222	0.8890	0.7839	0.8152	0.0028***	0.0008***	0.0010***	0.0007***	0.0018***	0.0009***	0.0008***	0.0008***

The table presents both the coverage tests and the dynamic quantile test for the daily forecasts. *, ** and *** denotes significance at the 10%, 5% and 1% level, respectively.

Table E5: VaR test results for monthly electricity futures on EEX

Quantile	Monthly electricity futures EEX													
	EWQR	Symmetric Absolute Value CAViaR	Asymmetric Slope CAViaR	Indirect GARCH CAViaR	Adaptive CAViaR	Indirect AR-GARCH CAViaR	GARCH Normal	GARCH Student t	GARCH GED	GARCH Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Test for unconditional coverage													
1 %	0.1060	0.1060	1.0000	0.0282**	0.6414	0.3315	0.6414	0.3315	0.6414	0.6414	1.0000	0.3315	1.0000	1.0000
5 %	0.0211**	0.0142**	0.0031***	0.0031***	0.8364	0.0031***	0.0002***	0.2885	0.0271**	0.5301	0.0000***	0.3992	0.0271**	0.6776
10 %	0.7669	0.0014***	0.0025***	0.0007***	1.0000	0.0007***	0.0000***	0.0288**	0.0007***	0.0629*	0.0000***	0.0431**	0.0004***	0.0893*
90 %	0.3063	0.1238	0.0014***	0.0072***	0.8818	0.0004***	0.0000***	0.0043***	0.0001***	0.0025***	0.0000***	0.0007***	0.0000***	0.0007***
95 %	0.0792*	0.0142**	0.0271**	0.0486**	0.6852	0.0031***	0.0005***	0.0822*	0.0271**	0.0486**	0.0002***	0.0822*	0.0142**	0.0486**
99 %	0.6630	0.0282**	0.1250	0.3315	1.0000	0.1250	0.6414	0.6414	1.0000	0.6414	0.6414	0.3315	0.6414	0.3315
	Test for conditional coverage													
1 %	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5 %	0.0517*	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
10 %	0.1233	0.0059***	0.0103**	0.0033***	1.0000	0.0033***	NaN	0.0448**	0.0028***	0.0699*	NaN	0.1140	0.0016***	0.2361
90 %	0.0190**	0.1810	0.0059***	0.0132**	0.1005	0.0017***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0001***	0.0000***	0.0001***
95 %	0.1177	0.0077***	0.0664*	0.0357**	0.0395**	0.0071***	0.0010***	0.1924	0.0664*	0.1175	0.0003***	0.1924	0.0345**	0.1175
99 %	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
	Dynamic quantile test													
1 %	0.0001***	0.3068	0.9995	0.7777	0.0003***	0.9867	0.9978	0.9793	0.9979	0.9985	0.0048***	0.9826	0.0049***	0.0050***
5 %	0.0003***	0.2631	0.2108	0.1506	0.3359	0.1767	0.0509*	0.7687	0.4992	0.9723	0.0137**	0.8846	0.4980	0.9107
10 %	0.0280**	0.0993*	0.0841*	0.0352**	0.0669*	0.0360**	0.0001***	0.4208	0.1256	0.5738	0.0001***	0.6778	0.0919*	0.8407
90 %	0.0008***	0.3857	0.1100	0.1614	0.0002***	0.0318**	0.0000***	0.0010***	0.0000***	0.0004***	0.0001***	0.0014***	0.0010***	0.0014***
95 %	0.0050***	0.0508*	0.3815	0.0222**	0.0008***	0.0981*	0.0188**	0.0256**	0.1030	0.1601	0.0072***	0.3366	0.2642	0.2265
99 %	0.0000***	0.7833	0.9329	0.9874	0.1194	0.9247	0.9879	0.9683	0.0018***	0.9750	0.8231	0.9662	0.7407	0.9721

The table presents both the coverage tests and the dynamic quantile test for the daily forecasts. *, ** and *** denotes significance at the 10%, 5% and 1% level, respectively.

Table E6: VaR test results for yearly electricity futures on EEX

Quantile	Yearly electricity futures EEX													
	EWQR	Symmetric Absolute Value CAViaR	Asymmetric Slope CAViaR	Indirect GARCH CAViaR	Adaptive CAViaR	Indirect AR-GARCH CAViaR	GARCH Normal	GARCH Student t	GARCH GED	GARCH Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Test for unconditional coverage													
1 %	0.3315	0.0282**	NaN	0.0282**	0.0282**	0.1250	0.33148	0.3315	0.3315	0.1250	0.3315	0.3315	0.3315	0.1250
5 %	0.1168	0.2885	0.1313	0.8384	0.0486**	0.5301	0.1994	0.3992	0.1994	0.3992	0.1994	0.3992	0.1994	0.3992
10 %	0.7642	0.3792	0.1674	0.0070***	0.3622	0.4625	0.0629*	0.8811	0.5461	0.8811	0.1238	0.8818	0.7642	0.7669
90 %	0.5556	0.4491	0.7642	0.3622	0.6518	0.5461	0.1674	0.4491	0.3622	0.5461	0.1238	0.4491	0.2862	0.6518
95 %	0.4229	1.0000	0.4229	0.5455	0.3992	0.8384	0.8384	0.6852	0.8384	0.5455	0.8384	0.6852	0.8384	0.5455
99 %	0.6630	0.0479**	0.1060	0.0199**	0.6414	0.0199**	0.0027***	0.1060	0.0479**	0.1060	0.0077***	0.1060	0.1060	0.1060
	Test for conditional coverage													
1 %	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5 %	0.2899	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
10 %	0.6522	0.5118	0.2653	0.0228**	0.6586	0.4701	0.1486	0.9840	0.8270	0.9071	0.2265	0.6931	0.9371	0.7288
90 %	0.1667	0.0417**	0.1151	0.0779*	0.0304**	0.5552	0.0061***	0.0132**	0.0082***	0.0205**	0.0123**	0.0132**	0.0048***	0.0304**
95 %	0.1870	0.1062	0.1870	0.1765	0.3908	0.9265	0.4149	0.4482	0.4149	0.4591	0.4149	0.4482	0.4149	0.4591
99 %	0.1419	0.0588*	0.0934*	0.0325**	0.0583*	0.0325**	0.0071***	0.0934*	0.0588*	0.0934*	0.0160**	0.0934*	0.0934*	0.0934*
	Dynamic quantile test													
1 %	0.9349	0.7704	0.2953	0.7665	0.7672	0.8284	0.9391	0.9401	0.9395	0.9270	0.9349	0.9346	0.9346	0.9244
5 %	0.0005***	0.3933	0.6366	0.2871	0.2035	0.3001	0.4217	0.6911	0.41670	0.7013	0.4175	0.6813	0.4112	0.6871
10 %	0.0848*	0.1427	0.3857	0.0071***	0.0407**	0.1318	0.3999	0.5093	0.5910	0.4993	0.4389	0.3131	0.4379	0.3416
90 %	0.0250**	0.2008	0.3759	0.3067	0.0284**	0.9308	0.0611*	0.0507*	0.0445**	0.0668*	0.0699*	0.0518*	0.0373**	0.1039
95 %	0.0112**	0.0114**	0.0419**	0.0334**	0.0021***	0.4418	0.1305	0.1572	0.1321	0.1666	0.1339	0.1594	0.1354	0.1690
99 %	0.0027***	0.0394**	0.0374**	0.0195**	0.0000***	0.0200**	0.0000***	0.0337**	0.0283**	0.0376**	0.0040***	0.0362**	0.0348**	0.0406**

The table presents both the coverage tests and the dynamic quantile test for the daily forecasts. *, ** and *** denotes significance at the 10%, 5% and 1% level, respectively.

Table E7: VaR test results for monthly electricity futures on ICE

Quantile	Monthly electricity futures ICE													
	EWQR	Symmetric Absolute Value CAViaR	Asymmetric Slope CAViaR	Indirect GARCH CAViaR	Adaptive CAViaR	Indirect AR-GARCH CAViaR	GARCH Normal	GARCH Student t	GARCH GED	GARCH Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Test for unconditional coverage													
1 %	0.0282**	0.1250	0.1250	0.0282**	NaN	NaN	0.0282**	0.0282**	0.0282**	0.0282**	0.0282**	0.0282**	0.0282**	0.0282**
5 %	0.0008***	0.0000***	0.0000***	0.0000***	0.3992	0.0000***	0.0005***	0.0069***	0.0031***	0.0271**	0.0069***	0.0142**	0.0031***	0.0271**
10 %	0.1116	0.0000***	0.0000***	0.0000***	0.7642	0.0000***	0.0000***	0.0629*	0.0072***	0.0629*	0.0000***	0.0629*	0.0288**	0.0629*
90 %	0.6575	0.0000***	0.0000***	0.0000***	0.7642	0.0000***	0.0007***	0.2213	0.0629*	0.0629*	0.0014***	0.0893*	0.0629*	0.0629*
95 %	0.3992	0.0000***	0.0000***	0.0000***	NaN	0.0000***	0.0069***	0.2885	0.0271**	0.1994	0.0142**	0.1994	0.0486**	0.1313
99 %	0.21489	NaN	NaN	NaN	1.0000	NaN	0.3966	0.3315	0.3315	0.3315	0.6630	0.3315	0.3315	0.3314
	Test for conditional coverage													
1 %	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5 %	0.0027***	NaN	NaN	NaN	0.6951	NaN	NaN	NaN	NaN	0.0664*	0.0164**	0.0345**	NaN	0.0664*
10 %	0.2331	0.0000***	0.0000***	NaN	0.9371	NaN	0.0000***	0.0369**	0.0054***	0.0369**	0.0000***	0.0369**	0.0124**	0.0369**
90 %	0.0021***	0.0000***	NaN	0.0000***	0.9371	NaN	0.0003***	0.0337**	0.0130**	0.0131**	0.0006***	0.0226**	0.0131**	0.0131**
95 %	0.0029***	NaN	NaN	NaN	NaN	NaN	0.0164**	0.2797	0.0664*	0.1870	0.0345**	0.1870	0.1175	0.2930
99 %	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
	Dynamic quantile test													
1 %	0.7601	0.9264	0.9304	0.7808	0.0544*	0.3041	0.7685	0.7678	0.7693	0.7691	0.7730	0.7706	0.7729	0.7711
5 %	0.0000***	0.0026***	0.0025***	0.0023***	0.0996*	0.0023***	0.1011	0.2783	0.2010	0.4295	0.2080	0.2965	0.1968	0.4263
10 %	0.0140**	0.0010***	0.0011***	0.0000***	0.0066***	0.0000***	0.0018***	0.0596**	0.0207**	0.0597*	0.0051***	0.0588*	0.0194**	0.0595*
90 %	0.0002***	0.0000***	0.0000***	0.0001***	0.0315**	0.0000***	0.0001***	0.0079***	0.0011***	0.0012***	0.0002***	0.0029***	0.0015***	0.0014***
95 %	0.0000***	0.0104**	0.0051***	0.0103**	0.0000***	0.0044***	0.0144**	0.0167**	0.0524*	0.0088***	0.0238**	0.0107**	0.0795*	0.1538
99 %	0.0000***	0.8827	0.5012	0.7313	0.3620	0.7617	0.0070***	0.9554	0.9606	0.9547	0.7284	0.9632	0.9692	0.9600

The table presents both the coverage tests and the dynamic quantile test for the daily forecasts. *, ** and *** denotes significance at the 10%, 5% and 1% level, respectively.

Table E8: VaR test results for monthly electricity futures on NYMEX

Quantile	EWQR	Symmetric Absolute Value CAViaR	Asymmetric Slope CAViaR	Indirect GARCH CAViaR	Adaptive CAViaR	Indirect AR-GARCH CAViaR	GARCH Normal	GARCH Student t	GARCH GED	GARCH Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Test for unconditional coverage													
1 %	0.2149	0.0000***	0.0000***	NaN	0.6630	0.0009***	0.0027***	0.2149	0.1060	0.2149	0.0077	0.2149	0.2149	0.6630
5 %	0.8384	0.5301	0.2885	0.3992	0.8364	0.5301	0.4229	0.1678	0.3192	0.2346	0.5455	0.1678	0.4229	0.2346
10 %	0.8818	0.0072***	0.0000***	0.2213	0.5461	0.1238	0.4491	0.3792	0.5556	0.4625	0.4491	0.3792	0.6575	0.3792
90 %	0.0614*	0.6518	0.2862	0.6518	0.0288**	0.7642	0.0007***	0.5461	0.1238	0.6518	0.0043***	0.2213	0.0893*	0.2213
95 %	0.6852	1.0000	0.8384	0.5455	0.5455	0.6776	0.5301	1.0000	0.6776	0.8384	0.6776	1.0000	0.6776	1.0000
99 %	0.1060	0.0199**	0.0077***	0.0479**	0.6414	0.0077***	0.1060	1.0000	0.6630	0.6630	0.0199**	0.3966	0.2149	0.2149
	Test for conditional coverage													
1 %	0.1282	0.0000***	0.0000***	NaN	0.1419	0.0006***	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5 %	0.8407	0.5122	0.2797	0.6951	0.7340	0.5122	NaN	NaN	NaN	NaN	0.7829	0.3860	0.7024	0.4925
10 %	0.2257	0.0231**	0.0000***	0.1956	0.1532	0.0373**	0.7506	0.6743	0.8380	0.7632	0.7506	0.5118	0.7416	0.5118
90 %	0.1738	0.6578	0.5581	0.6578	0.0317**	0.9371	0.0021***	0.7688	0.2738	0.8633	0.0170**	0.4565	0.2361	0.4565
95 %	0.8424	0.8069	0.8407	0.7829	0.4591	0.6313	0.5122	0.8069	0.6313	0.8407	0.6313	0.8069	0.6313	0.8069
99 %	NaN	NaN	0.0160**	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.0325**	NaN	NaN	NaN
	Dynamic quantile test													
1 %	0.0466**	0.0000***	0.0000***	0.2397	0.0129**	0.0000***	0.0037***	0.8119	0.0587*	0.8078	0.0087***	0.6316	0.6282	0.9795
5 %	0.0214**	0.0759*	0.0136	0.0943*	0.0070***	0.0870*	0.2595	0.0116**	0.2796	0.0109**	0.1936	0.1251	0.3514	0.1184
10 %	0.0011***	0.0373**	0.0000***	0.5219	0.0414**	0.1805	0.5163	0.8467	0.7692	0.8586	0.7924	0.6532	0.9166	0.6550
90 %	0.0028***	0.9378	0.9558	0.8306	0.0000***	0.9286	0.0698*	0.9912	0.8098	0.8702	0.1678	0.7301	0.5932	0.7305
95 %	0.3060	0.8751	0.8669	0.8883	0.2535	0.7712	0.8594	0.8741	0.8137	0.8602	0.8687	0.8772	0.8907	0.8762
99 %	0.2591	0.0195**	0.0079***	0.0275**	0.8494	0.0064***	0.0448**	0.9988	0.9906	0.9947	0.0162**	0.9616	0.8350	0.7339

The table presents both the coverage tests and the dynamic quantile test for the daily forecasts. *, ** and *** denotes significance at the 10%, 5% and 1% level, respectively.

Table E9: VaR test results for natural gas futures on ICE

Quantile	Gas ICE													
	EWQR	Symmetric Absolute Value CAViaR	Asymmetric Slope CAViaR	Indirect GARCH CAViaR	Adaptive CAViaR	Indirect AR-GARCH CAViaR	GARCH Normal	GARCH Student t	GARCH GED	GARCH Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Test for unconditional coverage													
1 %	1.000	0.3315	0.6414	1.0000	NaN	1.0000	1.0000	1.0000	0.6414	1.0000	1.0000	1.0000	0.6414	1.0000
5 %	1.000	0.0486**	0.0486**	0.1994	0.1994	0.1994	0.0013***	0.6776	0.0822*	1.0000	0.0031***	0.5301	0.0822*	0.8364
10 %	0.7642	0.6518	1.0000	0.7669	0.4491	0.8818	0.0000***	0.2436	1.0000	0.2436	0.0000***	0.2436	0.7669	0.2436
90 %	0.7669	0.007***	0.0154**	0.0005	0.5461	0.0003***	0.0118**	0.0834*	0.3063	0.1116	0.0288**	0.0614*	0.3063	0.0614*
95 %	0.4229	0.0523*	0.0014***	0.0337**	0.6776	0.0337**	0.6776	0.0337**	0.5455	0.0337**	1.0000	0.0337**	0.3192	0.0337**
99 %	0.2149	0.6630	0.2149	0.6630	0.6414	0.6630	0.2149	0.2149	0.6630	0.3966	0.0479**	0.2149	0.6630	0.3966
	Test for conditional coverage													
1 %	0.1063	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5 %	0.3635	0.0357**	0.0357**	0.0441**	NaN	0.1870	0.0004***	0.0557*	0.0121**	0.1062	0.0011***	0.1710	0.0121**	0.0795*
10 %	0.7526	0.6578	1.0000	0.9385	0.6614	0.9842	0.0000***	0.5032	1.0000	0.5032	0.0000***	0.5032	0.9385	0.5032
90 %	0.9385	0.0228**	0.0258**	0.0021***	0.7688	0.0009***	0.0103**	0.2217	0.4805	0.2747	0.0317**	0.1588	0.3373	0.1588
95 %	0.4468	0.0934*	0.0039	0.0710*	0.6313	0.0512*	0.2340	0.0710*	0.1765	0.0710*	0.3635	0.0710*	0.1879	0.0710*
99 %	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.0588*	NaN	NaN	NaN
	Dynamic quantile test													
1 %	0.0008***	0.9644	0.9989	0.9969	0.9184	0.9969	0.9913	0.9826	0.9885	0.9834	0.9935	0.9822	0.9895	0.9839
5 %	0.0733*	0.1823	0.1926	0.1553	0.3006	0.5260	0.0102**	0.0658*	0.0510*	0.1073	0.0228**	0.2248	0.0504*	0.0896*
10 %	0.0466**	0.2618	0.5189	0.4131	0.0670*	0.4524	0.0005***	0.4030	0.6508	0.4027	0.0048***	0.4015	0.6895	0.4046
90 %	0.2814	0.0251**	0.0082***	0.0047***	0.3535	0.0007***	0.0488**	0.0495**	0.1910	0.0789*	0.1608	0.0547*	0.2128	0.0539*
95 %	0.1997	0.0171**	0.0001***	0.0461**	0.2147	0.0830*	0.2469	0.0439**	0.1801	0.0439**	0.2479	0.0422**	0.1522	0.0416**
99 %	0.4243	0.9935	0.8101	0.9884	0.5144	0.9813	0.8303	0.8310	0.9963	0.9630	0.0026***	0.8357	0.9964	0.9631

The table presents both the coverage tests and the dynamic quantile test for the daily forecasts. *, ** and *** denotes significance at the 10%, 5% and 1% level, respectively.

Table E10: VaR test results for natural gas futures on NYMEX

Quantile	Gas NYMEX													
	EWQR	Symmetric Absolute Value CAViaR	Asymmetric Slope CAViaR	Indirect GARCH CAViaR	Adaptive CAViaR	Indirect AR-GARCH CAViaR	GARCH Normal	GARCH Student t	GARCH GED	GARCH Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Test for unconditional coverage													
1 %	0.6414	0.3315	0.3315	0.1250	1.0000	0.1250	0.3315	0.1250	0.0282**	0.1250	0.3315	0.1250	0.1250	0.1250
5 %	0.8384	0.1994	0.1994	0.3992	0.2885	0.2885	0.3992	0.3992	0.3992	0.5301	0.1313	0.5301	0.1313	0.6776
10 %	1.0000	0.5461	0.3622	0.6575	0.6518	0.8818	0.3622	0.5556	0.7669	0.3792	0.2862	0.7669	0.7642	0.6575
90 %	1.0000	0.8818	0.5556	0.7669	0.8811	0.5556	0.5461	0.7669	0.8818	0.7669	0.6518	1.0000	1.0000	1.0000
95 %	0.3992	0.3992	0.6852	0.8364	0.8364	0.6852	0.5301	0.8384	0.6776	1.0000	0.8364	0.8364	0.8364	0.8364
99 %	0.6630	0.6630	0.3966	0.6630	0.2149	0.6630	0.3966	0.6630	0.6630	0.6630	0.3966	0.6630	0.6630	0.6630
	Test for conditional coverage													
1 %	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5 %	0.9265	0.4167	0.4167	0.6951	0.5551	0.5551	0.6951	0.6951	0.6951	0.8206	0.2930	0.8206	0.2930	0.9156
10 %	0.2530	0.1077	0.3478	0.1442	0.0987*	0.5107	0.3478	0.1129	0.1790	0.0637*	0.3285	0.1790	0.3180	0.1442
90 %	0.8775	0.9842	0.7778	0.9385	0.9840	0.7778	0.6572	0.9385	0.9842	0.9385	0.6651	0.5712	0.5712	0.5712
95 %	0.6951	NaN	NaN	NaN	NaN	NaN	NaN	0.9265	NaN	NaN	NaN	NaN	NaN	NaN
99 %	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
	Dynamic quantile test													
1 %	0.9995	0.9899	0.9898	0.9305	0.7697	0.9324	0.9913	0.9314	0.7818	0.9320	0.9888	0.9315	0.9314	0.9320
5 %	0.8087	0.6643	0.7440	0.8358	0.9270	0.6830	0.8515	0.8475	0.8493	0.8622	0.6069	0.8641	0.6092	0.7364
10 %	0.3044	0.2409	0.2965	0.2169	0.2345	0.2858	0.3194	0.2983	0.4901	0.1535	0.4472	0.2300	0.2213	0.1574
90 %	0.0295**	0.0878*	0.2647	0.0398**	0.4241	0.0661*	0.1531	0.1902	0.1676	0.1906	0.3896	0.0835*	0.0840*	0.0836*
95 %	0.0000***	0.4848	0.0873*	0.5254	0.6648	0.3543	0.8338	0.7386	0.7005	0.4549	0.8090	0.8044	0.8069	0.8053
99 %	0.9633	0.9263	0.0354**	0.9488	0.0000***	0.9885	0.9510	0.9485	0.9477	0.9573	0.9630	0.9839	0.9867	0.9867

The table presents both the coverage tests and the dynamic quantile test for the daily forecasts. *, ** and *** denotes significance at the 10%, 5% and 1% level, respectively.

Table E11: VaR test results for brent crude oil futures on ICE

Quantile	Brent Crude Oil ICE													
	EWQR	Symmetric Absolute Value CAViaR	Asymmetric Slope CAViaR	Indirect GARCH CAViaR	Adaptive CAViaR	Indirect AR-GARCH CAViaR	GARCH Normal	GARCH Student t	GARCH GED	GARCH Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Test for unconditional coverage													
1 %	1.0000	NaN	0.0282**	NaN	NaN	NaN	0.6414	0.1250	0.1250	0.1250	0.6414	0.1250	0.1250	0.1250
5 %	0.0013***	0.1994	0.2885	0.1994	0.0031***	0.1313	0.0822*	0.0822*	0.0822*	0.0822*	0.1313	0.1994	0.1313	0.1313
10 %	0.7642	0.1674	0.2862	0.1674	0.0629*	0.0629*	0.0118**	0.0431**	0.0187**	0.0288**	0.0072***	0.0431**	0.0187**	0.0187**
90 %	0.0118**	0.7669	0.3792	0.8811	0.0629*	0.4491	0.5461	0.8818	0.8811	0.6575	0.5461	1.0000	0.7642	0.7669
95 %	0.5301	0.8364	1.0000	0.5301	0.0271**	0.5301	1.0000	0.8364	0.8364	0.8384	0.8364	1.0000	0.8364	1.0000
99 %	0.1250	0.1250	0.3315	0.1250	0.0282**	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250
	Test for conditional coverage													
1 %	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5 %	0.0028***	0.0065***	0.0126**	0.0065***	0.0001***	0.0241**	0.0121**	0.0121**	0.0121**	0.0121**	0.0241**	0.0441**	0.0241**	0.0241**
10 %	0.2586	0.0061***	0.0173**	0.0061***	0.0131**	0.0131**	0.0002***	0.0004***	0.0004***	0.0010***	0.0004***	0.0019***	0.0004***	0.0004***
90 %	0.0248**	0.4432	0.3798	0.6178	0.0699*	0.7506	0.3540	0.5107	0.6198	0.3735	0.6572	0.5712	0.6522	0.7481
95 %	0.8206	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
99 %	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
	Dynamic quantile test													
1 %	0.7119	0.1314	0.7828	1.000	0.0222**	0.3184	0.9074	0.9170	0.9183	0.9161	0.8659	0.9013	0.9051	0.8989
5 %	0.1043	0.0214**	0.0397**	0.0219**	0.0006***	0.1442	0.0926*	0.0925*	0.0926*	0.0924*	0.1455	0.2248	0.1455	0.1456
10 %	0.1321	0.0280**	0.0596*	0.0333**	0.0313**	0.0866*	0.0061***	0.0096***	0.0157**	0.0213**	0.0140**	0.0203**	0.0108***	0.0109**
90 %	0.0157**	0.0612*	0.1242	0.2211	0.0320**	0.1182	0.6813	0.5888	0.6728	0.3150	0.8018	0.6789	0.8657	0.6459
95 %	0.2074	0.4192	0.6015	0.4637	0.1078	0.4601	0.5815	0.4962	0.5066	0.5205	0.6978	0.6088	0.6883	0.6022
99 %	0.8340	0.9291	0.4376	0.9285	0.7091	0.9284	0.9282	0.9277	0.9280	0.9273	0.9271	0.9255	0.9265	0.9252

The table presents both the coverage tests and the dynamic quantile test for the daily forecasts. *, ** and *** denotes significance at the 10%, 5% and 1% level, respectively.

Table E12: VaR test results for light crude oil futures on NYMEX

Quantile	EWQR	Symmetric Absolute Value CAViaR	Asymmetric Slope CAViaR	Indirect GARCH CAViaR	Adaptive CAViaR	Indirect AR-GARCH CAViaR	GARCH Normal	GARCH Student t	GARCH GED	GARCH Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Light Crude Oil NYMEX													
	Test for unconditional coverage													
1 %	0.1250	0.1250	0.3315	0.1250	NaN	0.1250	0.6414	0.3315	0.3315	0.1250	0.6414	0.3315	0.6414	0.1250
5 %	0.0486**	0.1994	0.0486**	0.3992	0.0142**	0.0486**	0.6776	0.3992	0.3992	0.1313	0.3992	0.5301	0.3992	0.1313
10 %	0.0187**	0.5461	0.3622	0.8811	0.0118**	0.4491	0.0893*	0.5461	0.2213	0.2213	0.1238	0.1674	0.1674	0.1674
90 %	0.0288**	0.7642	0.7669	0.3622	0.0187**	0.2213	0.4491	1.0000	1.0000	0.7669	0.6518	0.5556	0.8818	0.4625
95 %	0.0069***	0.0271**	0.0069***	0.0486**	0.0069***	0.0271**	0.0142**	0.0142**	0.0069***	0.0486**	0.0069***	0.0271**	0.0031***	0.0271**
99 %	0.1250	0.3315	0.0282**	0.1250	0.0282**	0.1250	0.3315	0.1250	0.1250	0.3315	0.3315	0.0282**	0.0282***	0.1250
	Test for conditional coverage													
1 %	NA	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5 %	0.0357**	0.1870	0.0357**	0.6951	0.0345**	NaN	0.2340	0.3908	0.3908	0.1164	0.6951	0.5122	0.3908	0.1164
10 %	0.0067***	0.3218	0.3551	0.5664	0.0035***	0.7506	0.2004	0.1532	0.4565	0.3399	0.2738	0.3601	0.3601	0.3601
90 %	0.0885*	0.9085	0.9385	0.6586	0.0590*	0.4565	0.7506	0.87745	0.8775	0.9385	0.8811	0.7778	0.8227	0.6767
95 %	0.0031***	0.0174**	0.0164**	0.0357**	0.0031***	0.0174**	0.0345**	0.0077***	0.0164**	0.0357**	0.0164**	0.0174**	0.0071***	0.0174**
99 %	NA	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
	Dynamic quantile test													
1 %	0.8476	0.9365	0.9910	0.9364	1.0000	0.9317	0.9980	0.9799	0.9787	0.9328	0.9988	0.9789	0.9963	0.9329
5 %	0.1742	0.3720	0.1137	0.9373	0.1153	0.2545	0.2191	0.1871	0.1877	0.2793	0.9261	0.2419	0.5253	0.5001
10 %	0.0301**	0.0612*	0.1498	0.1354	0.0073***	0.4321	0.0720*	0.1595	0.2893	0.2245	0.1367	0.1961	0.1880	0.1965
90 %	0.0613*	0.1811	0.3293	0.3979	0.0972*	0.3417	0.2201	0.1313	0.2114	0.2989	0.1232	0.0932*	0.1953	0.2374
95 %	0.0269**	0.1343	0.2968	0.1920	0.0251**	0.1390	0.3756	0.1349	0.3005	0.2729	0.2364	0.2020	0.1951	0.2020
99 %	0.8526	0.9227	0.7713	0.9160	0.7094	0.9198	0.9699	0.8794	0.8783	0.9709	0.9789	0.7647	0.7635	0.8879

The table presents both the coverage tests and the dynamic quantile test for the daily forecasts. *, ** and *** denotes significance at the 10%, 5% and 1% level, respectively.

Table E13: VaR test results for gasoline futures on NYMEX

Quantile	RBOB Gasoline - NYMEX													
	EWQR	Symmetric Absolute Value CAViaR	Asymmetric Slope CAViaR	Indirect GARCH CAViaR	Adaptive CAViaR	Indirect AR-GARCH CAViaR	GARCH Normal	GARCH Student t	GARCH GED	GARCH Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Test for unconditional coverage													
1 %	1.0000	0.3315	0.3315	0.6414	0.6414	0.0282**	1.0000	1.0000	1.0000	0.6414	1.0000	1.0000	1.0000	1.0000
5 %	0.1994	0.1313	0.1994	0.0822*	0.0822*	0.1994	0.1994	0.1994	0.1994	0.1313	0.2885	0.2885	0.2885	0.0822*
10 %	0.2862	0.0629*	0.0288**	0.0629*	0.1238	0.1238	0.0187**	0.0431**	0.0187**	0.0187**	0.0072***	0.0118**	0.0072***	0.0043***
90 %	0.5461	0.4491	0.7642	0.0431**	0.2213	0.2862	0.6518	0.7642	0.7642	0.8811	0.3622	0.5461	0.4491	0.7669
95 %	0.0486**	0.0486**	0.1313	0.0271**	0.1313	0.0271**	0.1313	0.1313	0.0822*	0.8364	0.0486**	0.1313	0.0486**	0.6776
99 %	0.6414	0.1060	0.6630	1	0.0282**	0.3966	0.3315	0.0282**	0.0282**	0.6414	0.1250	0.1250	0.1250	0.1250
	Test for conditional coverage													
1 %	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5 %	0.4167	0.2930	0.4167	0.1924	0.0672*	0.4167	0.4167	0.4167	0.4167	0.2930	0.5551	0.5551	0.5551	0.1924
10 %	0.1311	0.0369**	0.0124**	0.0369**	0.0922*	0.0922*	0.0067***	0.0218**	0.0067***	0.0067***	0.0132**	0.0103**	0.0132**	0.0072***
90 %	0.6572	0.3565	0.3180	NaN	0.4507	0.1166	0.3407	0.3180	0.3180	0.2879	0.5819	0.8270	0.6287	0.7481
95 %	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
99 %	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
	Dynamic quantile test													
1 %	0.4462	0.9250	0.9896	0.8891	0.3139	0.7739	0.6833	0.6626	0.6576	0.8205	0.9622	0.9501	0.9469	0.9438
5 %	0.6771	0.7731	0.5703	0.6830	0.1525	0.8258	0.8640	0.8648	0.8639	0.7725	0.6989	0.6995	0.6979	0.6115
10 %	0.0944*	0.2884	0.1299	0.3033	0.1102	0.4251	0.0870*	0.2340	0.0873*	0.0876*	0.1552	0.1231	0.1554	0.1068
90 %	0.0780*	0.2578	0.1320	0.0706*	0.0312**	0.2153	0.1960	0.1540	0.1542	0.1648	0.3085	0.4028	0.3408	0.2315
95 %	0.1421	0.5002	0.3665	0.3661	0.1697	0.1365	0.7045	0.7043	0.5959	0.7879	0.4974	0.7092	0.4976	0.7744
99 %	0.8082	0.0107**	0.6539	0.9979	0.7260	0.0119	0.9893	0.7760	0.7762	0.9995	0.9355	0.9354	0.9351	0.9343

The table presents both the coverage tests and the dynamic quantile test for the daily forecasts. *, ** and *** denotes significance at the 10%, 5% and 1% level, respectively.

Table E14: VaR test results for heating oil futures on NYMEX

Quantile	Heating Oil - Nymex													
	EWQR	Symmetric Absolute Value CAViaR	Asymmetric Slope CAViaR	Indirect GARCH CAViaR	Adaptive CAViaR	Indirect AR-GARCH CAViaR	GARCH Normal	GARCH Student t	GARCH GED	GARCH Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Test for unconditional coverage													
1 %	0.1250	0.0282**	0.3315	0.0282**	NaN	0.1250	0.0282**	NaN	NaN	NaN	0.0282**	NaN	NaN	NaN
5 %	0.0822*	0.2885	0.2885	0.6776	0.0013***	0.5301	0.2885	0.3992	0.2885	0.5301	0.1994	0.3992	0.2885	0.5301
10 %	0.1674	0.4491	0.4491	0.4491	0.0043***	0.2862	0.2213	0.4491	0.4491	0.4491	0.2213	0.4491	0.4491	0.4491
90 %	0.1674	0.0431**	0.0893*	0.2862	0.0893*	0.1674	0.1674	0.5461	0.3622	0.3622	0.1238	0.5461	0.3622	0.4491
95 %	0.1994	0.1313	0.1313	0.0486**	0.0822*	0.0486**	0.1994	0.2885	0.1994	0.1994	0.1994	0.2885	0.1994	0.1994
99 %	0.6414	NaN	NaN	NaN	0.0282**	0.1250	0.0282**	NaN	NaN	NaN	0.0282**	NaN	NaN	NaN
	Test for conditional coverage													
1 %	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5 %	0.0672*	0.0746*	0.0746*	0.2340	0.0028***	0.5122	0.0746*	0.1169	0.0746*	0.1710	0.1870	0.1169	0.0746*	0.1710
10 %	0.0208**	0.0417**	0.0417**	0.0132**	0.0008***	0.0173**	0.0105**	0.0132**	0.0132**	0.0132**	0.0105	0.0132**	0.0132**	0.0132**
90 %	0.2529	0.1275	0.2004	0.5209	0.1245	0.2653	0.3765	0.8270	0.6586	0.6586	0.3036	0.8270	0.5819	0.7506
95 %	0.1870	0.2930	0.2930	0.1175	0.0672*	0.1175	0.1870	0.2797	0.1870	0.1870	0.1870	0.2797	0.1870	0.1870
99 %	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
	Dynamic quantile test													
1 %	0.8582	0.7516	0.9867	0.7551	0.5198	0.8450	0.7772	0.2303	0.5420	0.3993	0.7773	1.0000	0.2390	0.9682
5 %	0.3339	0.2936	0.2951	0.6017	0.1435	0.8934	0.2966	0.2947	0.2954	0.3932	0.4858	0.2930	0.2934	0.3918
10 %	0.1689	0.1102	0.1102	0.0431**	0.0278**	0.0569*	0.0691*	0.0427**	0.0423**	0.0427**	0.0691*	0.0427**	0.0423**	0.0427**
90 %	0.5494	0.2531	0.3744	0.0607*	0.2532	0.0566*	0.1978	0.6911	0.2589	0.6354	0.2624	0.6794	0.3789	0.8104
95 %	0.3913	0.4929	0.4674	0.2330	0.4567	0.2283	0.6652	0.7243	0.6778	0.6917	0.6594	0.7206	0.6725	0.6878
99 %	0.7966	0.2102	0.4930	0.3740	0.0073***	0.7715	0.0000***	0.7313	0.9160	0.4927	0.2947	0.4507	0.1941	0.2534

The table presents both the coverage tests and the dynamic quantile test for the daily forecasts. *, ** and *** denotes significance at the 10%, 5% and 1% level, respectively.

Table E15: ES test results for CO2 futures on EEX

Quantile	CO2 - EEX								
	EWQR	**Garch Normal**	**Garch Student t**	**Garch GED**	**Garch Skew t**	**GJR Normal**	**GJR Student t**	**GJR GED**	**GJR Skew t**
	Two-sided Dependent on VaR								
1 %	0.8120	0.5131	0.5046	0.5046	0.5046	0.3731	0.5046	0.5046	0.5046
5 %	0.8244	0.2701	0.4460	0.0000***	0.0674*	0.4041	0.3133	0.0000***	0.0749*
10 %	0.3913	0.9146	0.2982	0.0000***	0.2057	0.9175	0.2459	0.0000***	0.3214
90 %	0.7510	0.6510	0.1663	0.0000***	0.3370	0.6042	0.2357	0.0000***	0.5266
95 %	0.3119	0.5546	0.9634	0.0019***	0.7608	0.4580	0.8329	0.0004***	0.6577
99 %	NaN	0.5753	0.5591	0.3331	0.5753	0.5629	0.8743	0.3331	0.5962
	Two-sided Independent of VaR								
1 %	0.6009	0.5309	0.3046	0.0017***	0.1072	0.6606	0.2763	0.0104**	0.1067
5 %	0.3357	0.7255	0.2198	0.0000***	0.1309	0.4575	0.1458	0.0000***	0.2021
10 %	0.2273	0.2447	0.1786	0.0000***	0.5275	0.1411	0.1221	0.0000***	0.8509
90 %	0.3393	0.0138**	0.0087***	0.0000***	0.0415**	0.0177**	0.0166**	0.0000***	0.0524*
95 %	0.1928	0.1392	0.0568*	0.0000***	0.1766	0.1741	0.0616*	0.0000***	0.1778
99 %	0.9018	0.5934	0.5934	0.0800*	0.7117	0.5962	0.6127	0.2236	0.6567
	One-sided Dependent on VaR								
1 %	0.3699	0.2152	0.2550	0.7504	0.2550	0.1887	0.2550	0.7504	0.2550
5 %	0.5614	0.0753*	0.7257	1.0000	0.0002***	0.1607	0.7922	1.0000	0.0029***
10 %	0.7763	0.4270	0.8175	1.0000	0.0626*	0.4369	0.8449	1.0000	0.1239
90 %	0.6006	0.2715	0.8493	1.0000	0.7624	0.2483	0.8164	1.0000	0.6801
95 %	0.1181	0.1973	0.4642	0.9981	0.3316	0.1391	0.3640	0.9996	0.2755
99 %	NaN	0.2561	0.2606	0.7015	0.2561	0.2328	0.5192	0.7015	0.2661
	One-sided Independent of VaR								
1 %	0.2803	0.2339	0.7982	0.9989	0.0068***	0.3033	0.7982	0.9906	0.0073***
5 %	0.7577	0.6065	0.8229	1.0000	0.0060***	0.7279	0.8709	1.0000	0.0348**
10 %	0.8407	0.8313	0.8664	1.0000	0.2267	0.8889	0.8988	1.0000	0.3986
90 %	0.1416	0.9862	0.9913	1.0000	0.9601	0.9828	0.9834	1.0000	0.9505
95 %	0.0512*	0.8721	0.9433	1.0000	0.8467	0.8551	0.9399	1.0000	0.8596
99 %	0.4151	0.2569	0.6635	0.9207	0.3371	0.2661	0.6699	0.7769	0.3119

The table presents the results for onesided and twosided ES-tests dependent on VaR and independent of VaR. *, ** and *** denotes significance at the 10%, 5% and 1% respectively.

Table E16: ES test results for CO2 futures on NASDAQ OMX (Nord Pool)

Quantile	CO2 - NASDAQ OMX								
	EWQR	Garch Normal	Garch Student t	Garch GED	Garch Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Two-sided Dependent on VaR								
1 %	0.5715	0.5825	0.5046	0.5046	NaN	0.1239	NaN	NaN	NaN
5 %	0.4871	0.7524	0.0211**	0.0000***	0.0753*	0.7303	0.0015***	0.0000***	0.5686
10 %	0.5542	0.9824	0.0416**	0.0000***	0.7155	0.6250	0.0790*	0.0000***	0.6433
90 %	0.7108	0.5735	0.3241	0.0000***	0.7447	0.2565	0.7783	0.0004***	0.9185
95 %	0.3763	0.1874	0.8236	0.0014***	0.9767	0.1381	0.7721	0.0017***	0.7666
99 %	0.3187	0.1124	0.8473	0.0151**	0.4140	0.0965*	0.6238	0.0131*	0.3365
	Two-sided Independent of VaR								
1 %	0.5861	0.9519	0.0104**	0.0122**	0.0898*	0.0173**	0.0105**	0.0771*	0.1573
5 %	0.1041	0.2516	0.0291**	0.0000***	0.2241	0.1310	0.0074***	0.0000***	0.6193
10 %	0.4003	0.0700*	0.1036	0.0000***	0.6794	0.0953*	0.0632*	0.0000***	0.8753
90 %	0.3559	0.0502*	0.0384**	0.0000***	0.1813	0.2590	0.0866*	0.0000***	0.2797
95 %	0.0984*	0.3968	0.0693*	0.0000***	0.2785	0.9144	0.1770	0.0000***	0.4669
99 %	0.3742	0.1526	0.5313	0.0533*	0.9005	0.0889*	0.8937	0.0788*	0.5362
	One-sided Dependent on VaR								
1 %	0.6840	0.2676	0.7504	0.7450	NaN	0.9378	NaN	NaN	NaN
5 %	0.7097	0.3549	0.9812	1.0000	0.0205**	0.6285	0.9985	1.0000	0.2718
10 %	0.2670	0.4972	0.9683	1.0000	0.3432	0.6791	0.9480	1.0000	0.3050
90 %	0.6290	0.2425	0.7904	1.0000	0.5965	0.0800*	0.5887	0.9996	0.5197
95 %	0.1538	0.0502*	0.5526	0.9986	0.4759	0.0268**	0.3539	0.9983	0.3500
99 %	0.1495	0.0512*	0.4088	0.9918	0.1897	0.0197**	0.3055	0.9874	0.1401
	One-sided Independent of VaR								
1 %	0.6794	0.4993	0.9901	0.9995	0.0104**	0.9947	0.9991	0.9235	0.0607*
5 %	0.9052	0.8294	0.9725	1.0000	0.0721*	0.9092	0.9928	1.0000	0.2943
10 %	0.1659	0.9407	0.9211	1.0000	0.3157	0.9319	0.9479	1.0000	0.4276
90 %	0.1374	0.9536	0.9638	1.0000	0.8748	0.8346	0.9285	1.0000	0.8232
95 %	0.0195**	0.7710	0.9400	1.0000	0.8245	0.4317	0.8779	1.0000	0.7380
99 %	0.1722	0.1040	0.7146	0.9475	0.4363	0.0775*	0.4451	0.9235	0.2892

The table presents the results for onesided and twosided ES-tests dependent on VaR and independent of VaR. *, ** and *** denotes significance at the 10%, 5% and 1% respectively.

Table E17: ES test results for coal futures on ICE

Quantile	Coal - ICE								
	EWQR	Garch Normal	Garch Student t	Garch GED	Garch Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Two-sided Dependent on VaR								
1 %	0.5046	0.3789	0.1300	0.0016***	0.4236	0.1268	0.0782*	0.0218**	0.3621
5 %	0.5585	0.2641	0.5777	0.0083***	0.4217	0.1844	0.5185	0.0074***	0.3336
10 %	0.4871	0.0746*	0.3804	0.0095***	0.9750	0.0964*	0.2754	0.0063***	0.7317
90 %	0.3529	0.6395	0.3364	0.0014***	0.4487	0.1805	0.6768	0.0045***	0.8881
95 %	0.9351	0.1217	0.2155	0.0006***	0.3540	0.2163	0.2603	0.0076***	0.4006
99 %	0.5046	0.3357	0.1689	0.0927*	0.2782	0.1566	0.2529	0.1787	0.3069
	Two-sided Independent of VaR								
1 %	0.3086	0.3684	0.1973	0.0115**	0.4461	0.3533	0.0960*	0.0508*	0.3239
5 %	0.8876	0.1048	0.3394	0.0014***	0.7810	0.1514	0.2139	0.0010***	0.5917
10 %	0.7793	0.0038***	0.2425	0.0005***	0.4450	0.0082***	0.1813	0.0007***	0.3583
90 %	0.1374	0.0572*	0.2100	0.0034***	0.1479	0.7371	0.1587	0.0110***	0.1042
95 %	0.8254	0.2915	0.8876	0.0096***	0.7197	0.5762	0.8400	0.0155**	0.6375
99 %	0.3240	0.3498	0.3730	0.0998*	0.4702	0.1880	0.4596	0.2664	0.5397
	One-sided Dependent on VaR								
1 %	0.2550	0.0597*	0.8799	1.0000	0.6635	0.0612*	0.9312	0.9884	0.6682
5 %	0.6638	0.0729*	0.6918	0.9922	0.1965	0.0464**	0.7244	0.9927	0.1490
10 %	0.7314	0.0024***	0.7796	0.9905	0.4943	0.0050***	0.8285	0.9937	0.6098
90 %	0.7922	0.2902	0.7971	0.9986	0.7464	0.0395**	0.6401	0.9955	0.5416
95 %	0.5023	0.0199**	0.8363	0.9994	0.7704	0.0519*	0.8065	0.9924	0.7442
99 %	0.7504	0.2971	0.8798	0.9093	0.7981	0.0310**	0.8093	0.8278	0.7840
	One-sided Independent of VaR								
1 %	0.7906	0.1547	0.8086	0.9894	0.6685	0.1453	0.9118	0.9888	0.7205
5 %	0.4240	0.9148	0.7975	0.9986	0.5946	0.8779	0.8537	0.9990	0.6848
10 %	0.5867	0.9962	0.8391	0.9995	0.7394	0.9918	0.8714	0.9993	0.7812
90 %	0.9006	0.9443	0.0605*	0.9966	0.0310**	0.6066	0.0350**	0.9890	0.0154**
95 %	0.5674	0.7912	0.4089	0.9904	0.3125	0.2483	0.3804	0.9845	0.2726
99 %	0.6810	0.1478	0.7988	0.9196	0.7439	0.0267**	0.7545	0.7602	0.7030

The table presents the results for onesided and twosided ES-tests dependent on VaR and independent of VaR. *, ** and *** denotes significance at the 10%, 5% and 1% respectively.

Table E18: ES test results for coal futures on NYMEX

Quantile	Coal - NYMEX								
	EWQR	Garch Normal	Garch Student t	Garch GED	Garch Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Two-sided Dependent on VaR								
1 %	0.5591	0.7796	0.5046	0.5046	0.5046	0.7796	0.5046	0.5046	0.5046
5 %	0.2379	0.5497	0.0182**	0.0000***	0.1209	0.6155	0.0240**	0.0000***	0.0866*
10 %	0.0661*	0.6531	0.0089***	0.0000***	0.0656*	0.5982	0.0105**	0.0000***	0.0525*
90 %	0.8213	0.0989*	0.6601	0.0000***	0.6505	0.1644	0.7762	0.0000***	0.6766
95 %	0.8517	0.1524	0.8627	0.0001***	0.6512	0.1885	0.9802	0.0001***	0.8969
99 %	0.7776	0.1186	0.3007	0.0033***	0.1634	0.0650*	0.3966	0.0035***	0.1687
	Two-sided Independent of VaR								
1 %	0.1886	0.3552	0.0494**	0.0017***	0.3313	0.4144	0.0120**	0.0017***	0.2403
5 %	0.1293	0.0123**	0.0111**	0.0000***	0.0238**	0.0134**	0.0115**	0.0000***	0.0287**
10 %	0.0014***	0.0007***	0.003***	0.0000***	0.0114**	0.0016***	0.0031***	0.0000***	0.0130**
90 %	0.0697*	0.5440	0.4318	0.0000***	0.3264	0.5172	0.3297	0.0000***	0.2458
95 %	0.0253**	0.2386	0.5299	0.0004***	0.4059	0.2657	0.4212	0.0005***	0.3420
99 %	0.1806	0.0907*	0.3316	0.0139**	0.2066	0.0891*	0.3713	0.0115**	0.2121
	One-sided Dependent on VaR								
1 %	0.7015	0.3694	0.7450	0.7450	0.7450	0.3694	0.7450	0.7450	0.7450
5 %	0.8657	0.6879	0.9818	1.0000	0.8922	0.6537	0.9760	1.0000	0.9170
10 %	0.9801	0.6426	0.9912	1.0000	0.9433	0.6705	0.9895	1.0000	0.9537
90 %	0.4021	0.0151**	0.3049	1.0000	0.2985	0.0399**	0.3711	1.0000	0.3123
95 %	0.5657	0.0323**	0.4141	0.9999	0.2982	0.0511*	0.4678	0.9999	0.4351
99 %	0.3750	0.0342**	0.1561	0.9988	0.0760*	0.0251**	0.1907	0.9970	0.0753*
	One-sided Independent of VaR								
1 %	0.9175	0.8099	0.9947	0.9990	0.6794	0.7920	0.9995	0.9990	0.7706
5 %	0.0299**	0.9879	0.9889	1.0000	0.9762	0.9866	0.9885	1.0000	0.9713
10 %	0.0000***	0.9993	0.9970	1.0000	0.9886	0.9984	0.9969	1.0000	0.9879
90 %	0.0078***	0.2375	0.1701	1.0000	0.1181	0.2200	0.1139	1.0000	0.0759*
95 %	0.0001***	0.0645*	0.2270	0.9996	0.1594	0.0796*	0.1702	0.9995	0.1235
99 %	0.0080***	0.0121**	0.1330	0.9997	0.0769*	0.0105**	0.1625	0.9991	0.0824*

The table presents the results for onesided and twosided ES-tests dependent on VaR and independent of VaR. *, ** and *** denotes significance at the 10%, 5% and 1% respectively.

Table E19: ES test results for monthly electricity futures on EEX

Quantile	Monthly electricity - EEX								
	EWQR	**Garch Normal**	**Garch Student t**	**Garch GED**	**Garch Skew t**	**GJR Normal**	**GJR Student t**	**GJR GED**	**GJR Skew t**
	Two-sided Dependent on VaR								
1 %	0.5715	0.4639	0.3357	0.3007	0.0302**	0.4262	0.3357	0.0941*	0.0104**
5 %	0.9212	0.3174	0.1835	0.0278**	0.0088***	0.1662	0.1461	0.0211**	0.0075***
10 %	0.7817	0.2629	0.4487	0.0302**	0.0355**	0.1985	0.4058	0.0365**	0.0293**
90 %	0.8318	0.1644	0.8349	0.1931	0.6612	0.2116	0.7581	0.2187	0.6850
95 %	0.6581	0.1904	0.9737	0.0960*	0.5175	0.2163	0.7225	0.0684*	0.3663
99 %	0.6553	0.1870	0.4212	0.2255	0.2078	0.2471	0.5495	0.3530	0.3330
	Two-sided Independent of VaR								
1 %	0.0868*	0.6362	0.0745*	0.0745*	0.079*	0.4483	0.0974	0.0423**	0.0771*
5 %	0.0007***	0.0349**	0.0382**	0.0006***	0.0035***	0.0489*	0.0418**	0.0002***	0.0037***
10 %	0.0760*	0.0010***	0.0168**	0.0000***	0.0009***	0.0021***	0.0265**	0.0000***	0.0020***
90 %	0.0778*	0.0216**	0.0961*	0.0023***	0.0345**	0.0141**	0.0708*	0.0009***	0.0243**
95 %	0.0724*	0.2628	0.2036	0.0066***	0.061*	0.2106	0.1317	0.0013***	0.0465**
99 %	0.1769	0.1684	0.2535	0.2577	0.1090	0.2979	0.3005	0.2064	0.208
	One-sided Dependent on VaR								
1 %	0.2798	0.1490	0.7029	0.7031	0.9772	0.0961*	0.7029	0.9061	0.9903
5 %	0.4582	0.0864*	0.8437	0.9722	0.9912	0.0207**	0.8695	0.9789	0.9925
10 %	0.3857	0.0704*	0.7359	0.9699	0.9648	0.0436**	0.7510	0.9635	0.9708
90 %	0.3966	0.0228**	0.3825	0.8449	0.6308	0.0391**	0.3380	0.8252	0.6139
95 %	0.3063	0.0397**	0.4745	0.9054	0.6936	0.041**	0.5949	0.9319	0.7519
99 %	0.3060	0.0659*	0.7233	0.8009	0.8170	0.0641*	0.7049	0.6839	0.7049
	One-sided Independent of VaR								
1 %	0.0094***	0.2836	0.9332	0.9332	0.9235	0.1182	0.9097	0.9622	0.9235
5 %	0.0000***	0.9653	0.9618	0.9994	0.9965	0.9523	0.9583	0.9998	0.9963
10 %	0.0218**	0.9990	0.9832	1.0000	0.9991	0.9979	0.9737	1.0000	0.998
90 %	0.0032***	0.9784	0.9116	0.9977	0.9656	0.9859	0.9313	0.9991	0.9757
95 %	0.0003***	0.8119	0.8436	0.9934	0.9403	0.8405	0.8805	0.9987	0.9535
99 %	0.0897*	0.0758*	0.7765	0.7633	0.8945	0.0959*	0.7101	0.8013	0.7941

The table presents the results for onesided and twosided ES-tests dependent on VaR and independent of VaR. *, ** and *** denotes significance at the 10%, 5% and 1% respectively.

Table E20: ES test results for yearly electricity futures on EEX

Quantile	Yearly electricity - EEX								
	EWQR	**Garch Normal**	**Garch Student t**	**Garch GED**	**Garch Skew t**	**GJR Normal**	**GJR Student t**	**GJR GED**	**GJR Skew t**
	Two-sided Dependent on VaR								
1 %	0.4507	0.5617	0.1111	0.1111	0.5046	0.5617	0.2206	0.1111	0.5046
5 %	0.9124	0.4918	0.0447**	0.0000***	0.3840	0.6432	0.0667*	0.0000***	0.9900
10 %	0.4993	0.6228	0.0192**	0.0000***	0.0588*	0.5643	0.0196**	0.0000***	0.1266
90 %	0.6139	0.0296**	0.0864*	0.0000***	0.0985	0.0274**	0.0885*	0.0000***	0.1226
95 %	0.7479	0.0417**	0.1215	0.0000***	0.1430	0.0426**	0.1289	0.0000***	0.1325
99 %	0.5191	0.1583	0.4940	0.0025***	0.5148	0.1326	0.5304	0.0036***	0.5110
	Two-sided Independent of VaR								
1 %	0.8974	0.3768	0.0250**	0.0017***	0.4574	0.4509	0.0353**	0.0108**	0.6986
5 %	0.0029***	0.0345**	0.0076***	0.0000***	0.0673*	0.0525*	0.0120**	0.0000***	0.4293
10 %	0.2337	0.0171**	0.0141**	0.0000***	0.0681*	0.0291**	0.0239**	0.0000***	0.2387
90 %	0.2556	0.1928	0.2370	0.0000***	0.2230	0.1909	0.2386	0.0001***	0.2064
95 %	0.0841*	0.1190	0.1928	0.0010***	0.1725	0.1220	0.1969	0.0008***	0.1710
99 %	0.2938	0.3373	0.3654	0.0122**	0.3688	0.3194	0.3654	0.0105**	0.3688
	One-sided Dependent on VaR								
1 %	0.1536	0.2646	0.9275	0.9275	0.7450	0.2646	0.8180	0.9275	0.2496
5 %	0.4544	0.7171	0.9573	1.0000	0.7835	0.6490	0.9399	1.0000	0.4938
10 %	0.7395	0.6704	0.9820	1.0000	0.9564	0.6893	0.9818	1.0000	0.9139
90 %	0.6768	0.0020***	0.0194**	1.0000	0.0253**	0.0012***	0.0202**	1.0000	0.0307**
95 %	0.3682	0.0007***	0.0243**	1.0000	0.0344**	0.0008***	0.0279**	1.0000	0.0304**
99 %	0.2505	0.0245**	0.2055	0.9975	0.2165	0.0187**	0.2275	0.9964	0.2162
	One-sided Independent of VaR								
1 %	0.5456	0.7887	0.9886	0.9989	0.7270	0.7525	0.9886	0.9895	0.3198
5 %	0.0000***	0.9670	0.9924	1.0000	0.9428	0.9528	0.9880	1.0000	0.7553
10 %	0.0860*	0.9841	0.9868	1.0000	0.9471	0.9737	0.9787	1.0000	0.8591
90 %	0.0729*	0.0372**	0.0606*	1.0000	0.0546*	0.0364**	0.0611*	0.9999	0.0457**
95 %	0.0003***	0.0007***	0.0127**	0.9990	0.0100**	0.0009***	0.0158**	0.9992	0.0102**
99 %	0.0440**	0.0179**	0.0323**	0.9995	0.0323**	0.0179**	0.0323**	0.9994	0.0323**

The table presents the results for onesided and twosided ES-tests dependent on VaR and independent of VaR. *, ** and *** denotes significance at the 10%, 5% and 1% respectively.

Table E21: ES test results for monthly electricity futures on ICE

Quantile	Monthly electricity - ICE								
	EWQR	Garch Normal	Garch Student t	Garch GED	Garch Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Two-sided Dependent on VaR								
1 %	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5 %	0.9220	0.5217	0.0541*	0.0000***	0.0003***	0.3625	0.0244**	0.0000***	0.0002***
10 %	0.4809	0.2712	0.0015***	0.0000***	0.0001***	0.2882	0.0014***	0.0000***	0.0000***
90 %	0.4409	0.1520	0.2369	0.0000***	0.3133	0.2039	0.4139	0.0000***	0.2822
95 %	0.9986	0.0260**	0.3620	0.0000***	0.2410	0.0394**	0.4116	0.0000***	0.3082
99 %	0.3586	0.3932	0.3330	0.1111	0.2221	0.2603	0.2221	0.1111	0.2221
	Two-sided Independent of VaR								
1 %	0.3536	0.3365	0.0681*	0.0033***	0.013**	0.3365	0.012**	0.0017***	0.0116**
5 %	0.0002***	0.0002***	0.0000***	0.0000***	0.0000***	0.0008***	0.0000***	0.0000***	0.0000***
10 %	0.0051***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
90 %	0.5921	0.0546*	0.0202**	0.0000***	0.0072	0.0476**	0.0140**	0.0000***	0.0048
95 %	0.5898	0.7918	0.0528*	0.0000***	0.0213**	0.7678	0.0466**	0.0000***	0.0190**
99 %	0.0104**	0.1259	0.0893*	0.0149**	0.0893*	0.1652	0.0893*	0.0115**	0.0847*
	One-sided Dependent on VaR								
1 %	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5 %	0.4722	0.6552	0.9459	1.0000	0.9997	0.6655	0.9756	1.0000	0.9998
10 %	0.7405	0.7970	0.9985	1.0000	0.9999	0.8088	0.9986	1.0000	1.0000
90 %	0.7638	0.0512*	0.8549	1.0000	0.8194	0.0781*	0.7715	1.0000	0.8343
95 %	0.4832	0.0016***	0.7986	1.0000	0.8515	0.0062***	0.7703	1.0000	0.8268
99 %	0.2094	0.1761	0.9621	0.9275	0.9621	0.1125	0.9621	0.9275	0.9621
	One-sided Independent of VaR								
1 %	0.6699	0.6699	0.9324	0.9972	0.9877	0.6699	0.9885	0.9988	0.9891
5 %	0.0000***	0.9998	1.0000	1.0000	1.0000	0.9992	1.0000	1.0000	1.0000
10 %	0.0000***	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
90 %	0.2746	0.9572	0.9817	1.0000	0.9930	0.9613	0.9872	1.0000	0.9952
95 %	0.6907	0.5855	0.9570	1.0000	0.9802	0.5975	0.9607	1.0000	0.9819
99 %	0.0099***	0.0637*	0.9207	0.9856	0.9207	0.0760*	0.9207	0.989	0.9207

The table presents the results for onesided and twosided ES-tests dependent on VaR and independent of VaR. *, ** and *** denotes significance at the 10%, 5% and 1% respectively.

Table E22: ES test results for monthly electricity futures on NYMEX

Quantile	Monthly electricity- NYMEX								
	EWQR	Garch Normal	Garch Student t	Garch GED	Garch Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Two-sided Dependent on VaR								
1 %	0.4860	0.0476**	0.3441	0.0002***	0.2241	0.0493**	0.2391	0.0010***	0.1296
5 %	0.0774*	0.0306**	0.8746	0.0000***	0.2154	0.0263**	0.8893	0.0001***	0.2324
10 %	0.1763	0.0204**	0.3577	0.0006***	0.1194	0.0226**	0.5994	0.0002***	0.2113
90 %	0.9719	0.0059***	0.7254	0.0000***	0.9809	0.0040***	0.4447	0.0000***	0.2214
95 %	0.7973	0.0280**	0.2489	0.0000***	0.4766	0.0081***	0.7583	0.0000***	0.7845
99 %	0.9396	0.1091	0.0086***	0.0016***	0.0164**	0.0342**	0.0003***	0.0004***	0.0005***
	Two-sided Independent of VaR								
1 %	0.1091	0.0056***	0.8378	0.0420**	0.0898*	0.0137**	0.7876	0.0127**	0.0382**
5 %	0.0366**	0.0082***	0.1498	0.0008***	0.0258**	0.0107**	0.2326	0.0002***	0.0308**
10 %	0.0881*	0.0307**	0.0992*	0.0017***	0.0333**	0.0385**	0.1660	0.0000***	0.0496**
90 %	0.0142**	0.9336	0.5449	0.0000***	0.9531	0.4149	0.9984	0.0000***	0.6344
95 %	0.4197	0.0749*	0.2931	0.0000***	0.7812	0.0212**	0.7747	0.0000***	0.7471
99 %	0.1079	0.0064***	0.0124**	0.012**	0.0713*	0.0039***	0.0232**	0.0377**	0.011**
	One-sided Dependent on VaR								
1 %	0.2123	0.0031***	0.8029	0.9999	0.1017	0.0119**	0.8539	0.9993	0.0986
5 %	0.0247**	0.0028***	0.4266	1.0000	0.0856*	0.0023***	0.5375	0.9999	0.0864*
10 %	0.0697*	0.0011***	0.1496	0.9994	0.0319**	0.0019***	0.2773	0.9998	0.0749*
90 %	0.5090	0.0001***	0.6305	1.0000	0.4872	0.0006***	0.2097	1.0000	0.0958*
95 %	0.3853	0.0032***	0.8542	1.0000	0.7372	0.0015***	0.6123	1.0000	0.3835
99 %	0.5379	0.0533*	0.9921	1.0000	0.9837	0.0126**	0.9997	0.9996	0.9996
	One-sided Independent of VaR								
1 %	0.0064***	0.0021***	0.4271	0.9896	0.0794*	0.013**	0.3992	0.9881	0.0361**
5 %	0.0077***	0.0002***	0.0568*	0.9992	0.0036***	0.0001***	0.0958*	0.9998	0.0031***
10 %	0.0265**	0.0044***	0.0252**	0.9983	0.0042***	0.0065***	0.0556*	1.0000	0.0092***
90 %	0.0011***	0.4622	0.7193	1.0000	0.5271	0.1918	0.4852	1.0000	0.3052
95 %	0.1919	0.0220**	0.8274	1.0000	0.5895	0.0058***	0.6056	1.0000	0.3649
99 %	0.0293**	0.0042***	0.9888	0.9995	0.9294	0.0007***	0.9771	0.9631	0.9896

The table presents the results for onesided and twosided ES-tests dependent on VaR and independent of VaR. *, ** and *** denotes significance at the 10%, 5% and 1% respectively.

Table E23: ES test results for natural gas futures on ICE

Quantile	Gas - ICE								
	EWQR	Garch Normal	Garch Student t	Garch GED	Garch Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Two-sided Dependent on VaR								
1 %	0.4348	0.5523	0.0862*	0.0151**	0.0757*	0.5104	0.0862*	0.0151**	0.0828*
5 %	0.8993	0.1696	0.1699	0.0002***	0.0047***	0.1918	0.2676	0.0001***	0.0097***
10 %	0.4819	0.3865	0.0424**	0.0000***	0.0092***	0.6476	0.0486**	0.0000***	0.0094***
90 %	0.5718	0.1860	0.2339	0.0199**	0.3241	0.1243	0.2402	0.0204**	0.3886
95 %	0.8168	0.2662	0.4577	0.0429**	0.6845	0.2106	0.4317	0.0240**	0.6520
99 %	0.5927	0.3642	0.6559	0.4049	0.6211	0.3690	0.6497	0.4005	0.6243
	Two-sided Independent of VaR								
1 %	0.7722	0.6972	0.0440**	0.0137**	0.0136**	0.5113	0.0473**	0.0137**	0.0167**
5 %	0.5063	0.0460**	0.0877*	0.0000***	0.0097***	0.0551*	0.1023	0.0000***	0.0104**
10 %	0.9604	0.0025***	0.3413	0.0000***	0.0613*	0.0058***	0.3705	0.0000***	0.0636*
90 %	0.2607	0.4462	0.2000	0.3356	0.225	0.3459	0.1956	0.3646	0.2195
95 %	0.4446	0.3453	0.3120	0.3446	0.3336	0.322	0.3078	0.3558	0.3263
99 %	0.3835	0.3835	0.3869	0.8434	0.4063	0.3835	0.3869	0.8511	0.4063
	One-sided Dependent on VaR								
1 %	0.7962	0.2267	0.9248	0.9926	0.9353	0.1898	0.9248	0.9926	0.9282
5 %	0.5393	0.0452**	0.8842	0.9998	0.9953	0.0593*	0.8389	0.9999	0.9903
10 %	0.7351	0.1604	0.9626	1.0000	0.9909	0.3036	0.9578	1.0000	0.9907
90 %	0.1972	0.0030***	0.0565*	0.9801	0.1062	0.0004***	0.0646*	0.9796	0.1462
95 %	0.5514	0.0106**	0.1673	0.9571	0.2955	0.0035***	0.1537	0.9760	0.2788
99 %	0.2292	0.0207**	0.2796	0.6709	0.2720	0.0217**	0.2812	0.6709	0.2718
	One-sided Independent of VaR								
1 %	0.6002	0.3177	0.9670	0.9888	0.9974	0.1907	0.9637	0.9888	0.9943
5 %	0.2285	0.9596	0.9334	1.0000	0.9903	0.9551	0.9248	1.0000	0.9896
10 %	0.4686	0.9975	0.8002	1.0000	0.9481	0.9943	0.7907	1.0000	0.9468
90 %	0.0075***	0.1213	0.0021***	0.7113	0.0052***	0.0564*	0.0018***	0.7037	0.0048***
95 %	0.0982*	0.0191**	0.0078***	0.6744	0.0168**	0.0066***	0.0070***	0.6680	0.0145**
99 %	0.0610*	0.0610*	0.0644*	0.5497	0.0838*	0.0610*	0.0644*	0.5391	0.0838*

The table presents the results for onesided and twosided ES-tests dependent on VaR and independent of VaR. *, ** and *** denotes significance at the 10%, 5% and 1% respectively.

Table E24: ES test results for natural gas futures on NYMEX

Quantile	Gas - NYMEX								
	EWQR	Garch Normal	Garch Student t	Garch GED	Garch Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Two-sided Dependent on VaR								
1 %	0.1084	0.2221	0.5046	NaN	0.5046	0.3357	0.5046	0.5046	0.5046
5 %	0.3573	0.0728*	0.0114**	0.0000***	0.0010***	0.3137	0.0054***	0.0000***	0.0008***
10 %	0.5252	0.0693*	0.0014***	0.0000***	0.0000***	0.0931*	0.0015***	0.0000***	0.0001***
90 %	0.6975	0.2180	0.7312	0.0000***	0.9592	0.2125	0.5017	0.0000***	0.6784
95 %	0.3791	0.1230	0.7316	0.0001***	0.7955	0.1315	0.3959	0.0000***	0.5333
99 %	0.4737	0.1188	0.4786	0.0036***	0.5941	0.0920*	0.3567	0.0036***	0.4292
	Two-sided Independent of VaR								
1 %	0.1215	0.0904*	0.0122**	0.0017***	0.0116**	0.0704*	0.0098***	0.0017***	0.0215**
5 %	0.1194	0.0140**	0.0015***	0.0000***	0.0000***	0.0135**	0.0008***	0.0000***	0.0001***
10 %	0.1797	0.0106**	0.0047***	0.0000***	0.0009***	0.0079***	0.0039***	0.0000***	0.0005***
90 %	0.5905	0.3739	0.4815	0.0000***	0.6571	0.3459	0.4652	0.0000***	0.6393
95 %	0.7165	0.2117	0.5552	0.0000***	0.7254	0.1613	0.4588	0.0000***	0.6047
99 %	0.3114	0.0533*	0.2752	0.0225**	0.3508	0.0312**	0.1743	0.0248**	0.1799
	One-sided Dependent on VaR								
1 %	0.0622*	0.9621	0.7450	NaN	0.7450	0.9614	0.7450	0.7450	0.7450
5 %	0.1654	0.9378	0.9886	1.0000	0.9990	0.8201	0.9947	1.0000	0.9992
10 %	0.2591	0.9481	0.9986	1.0000	1.0000	0.9381	0.9986	1.0000	0.9999
90 %	0.6381	0.0709*	0.3451	1.0000	0.4613	0.0724*	0.2176	1.0000	0.3161
95 %	0.1535	0.0247**	0.3407	0.9999	0.3715	0.0278**	0.1568	1.0000	0.2310
99 %	0.1797	0.0453**	0.2307	0.9983	0.2750	0.0256**	0.1655	0.9983	0.2039
	One-sided Independent of VaR								
1 %	0.0630*	0.9210	0.9992	0.9988	0.9893	0.9647	0.9976	0.9988	0.9904
5 %	0.0373**	0.9862	0.9985	1.0000	1.0000	0.9873	0.9992	1.0000	0.9999
10 %	0.0688*	0.9900	0.9953	1.0000	0.9991	0.9923	0.9961	1.0000	0.9995
90 %	0.6945	0.1509	0.2060	1.0000	0.3046	0.1406	0.2049	1.0000	0.2992
95 %	0.3373	0.0680*	0.2486	1.0000	0.3387	0.0447**	0.1980	1.0000	0.2735
99 %	0.1068	0.0354**	0.1604	0.9879	0.1967	0.0099***	0.0875*	0.9856	0.0875*

The table presents the results for onesided and twosided ES-tests dependent on VaR and independent of VaR. *, ** and *** denotes significance at the 10%, 5% and 1% respectively.

Table E25: ES test results for brent crude oil futures on ICE

Quantile	Brent Crude Oil - ICE								
	EWQR	Garch Normal	Garch Student t	Garch GED	Garch Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Two-sided Dependent on VaR								
1 %	0.6172	0.2646	0.5046	0.5046	0.5046	0.6200	0.5046	0.5046	0.5046
5 %	0.6942	0.8017	0.2829	0.0000***	0.0229**	0.9507	0.1600	0.0000***	0.0433**
10 %	0.0281**	0.9186	0.3185	0.0000***	0.2906	0.7459	0.3464	0.0000***	0.1925
90 %	0.9820	0.6583	0.0758*	0.0000***	0.2015	0.5942	0.1096	0.0000***	0.2952
95 %	0.3715	0.3148	0.0879*	0.0000***	0.1518	0.4243	0.0928*	0.0000***	0.2820
99 %	0.5046	0.5046	0.5046	0.5046	0.5046	0.5046	0.5046	0.5046	0.5046
	Two-sided Independent of VaR								
1 %	0.5367	0.1666	0.0372**	0.0017***	0.0753*	0.3084	0.033	0.0017***	0.0355**
5 %	0.0090***	0.0251**	0.0020***	0.0000***	0.6220	0.0336**	0.0042***	0.0000***	0.4205
10 %	0.0356**	0.004***	0.0009***	0.0000***	0.1368	0.0055***	0.0031***	0.0000***	0.1802
90 %	0.0149**	0.3693	0.1496	0.0000***	0.5593	0.3164	0.1348	0.0000***	0.5390
95 %	0.1479	0.3504	0.0731*	0.0000***	0.2156	0.3022	0.0781*	0.0000***	0.2357
99 %	0.7522	0.4726	0.0887*	0.0134**	0.1323	0.4627	0.0935*	0.0122**	0.2641
	One-sided Dependent on VaR								
1 %	0.2972	0.8130	0.7450	0.745	0.2550	0.6903	0.7504	0.7504	0.2550
5 %	0.2992	0.3860	0.8270	1.0000	0.0014***	0.5051	0.8846	1.0000	0.0029***
10 %	0.9770	0.4473	0.8260	1.0000	0.1275	0.3603	0.8051	1.0000	0.0731*
90 %	0.4651	0.6560	0.9429	1.0000	0.8779	0.6796	0.9204	1.0000	0.8203
95 %	0.7566	0.7907	0.9149	1.0000	0.8752	0.7353	0.9087	1.0000	0.7963
99 %	0.2550	0.2550	0.7504	0.7504	0.2550	0.2550	0.2550	0.7504	0.2550
	One-sided Independent of VaR								
1 %	0.2660	0.9446	0.9984	0.9995	0.0659*	0.8546	0.9856	0.9997	0.0146**
5 %	0.9910	0.9807	0.9980	1.0000	0.2996	0.9725	0.9958	1.0000	0.1878
10 %	0.9693	0.9961	0.9991	1.0000	0.9177	0.9952	0.9969	1.0000	0.8907
90 %	0.986	0.7935	0.9044	1.0000	0.7028	0.8173	0.9093	1.0000	0.7100
95 %	0.870	0.7751	0.9273	1.0000	0.8419	0.7987	0.9227	1.0000	0.8317
99 %	0.3366	0.7338	0.9228	0.9871	0.9228	0.7417	0.9214	0.9883	0.7906

The table presents the results for onesided and twosided ES-tests dependent on VaR and independent of VaR. *, ** and *** denotes significance at the 10%, 5% and 1% respectively.

Table E26: ES test results for light crude oil futures on NYMEX

Quantile	Light Crude Oil - NYMEX								
	EWQR	Garch Normal	Garch Student t	Garch GED	Garch Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Two-sided Dependent on VaR								
1 %	0.5046	0.7190	0.1111	0.1111	0.5046	0.5908	0.3357	0.0151**	0.5046
5 %	0.5019	0.2116	0.0316**	0.0000***	0.0417**	0.5617	0.0259**	0.0000***	0.0318**
10 %	0.2777	0.9993	0.0278**	0.0000***	0.5618	0.9687	0.2166	0.0000***	0.3137
90 %	0.5935	0.3978	0.1272	0.0000***	0.1743	0.2575	0.0676*	0.0000***	0.1147
95 %	0.8810	0.6296	0.9253	0.0225**	0.9002	0.6438	0.7258	0.0292**	0.9416
99 %	0.5046	0.5591	0.5046	0.5046	0.5591	0.5591	NaN	NaN	0.5046
	Two-sided Independent of VaR								
1 %	0.0527*	0.3397	0.0078***	0.0082***	0.0738*	0.7870	0.0127**	0.0115**	0.0227**
5 %	0.0139**	0.1360	0.0058***	0.0000***	0.3217	0.2323	0.0108**	0.0000***	0.2317
10 %	0.0018***	0.1192	0.0123**	0.0000***	0.6027	0.1821	0.0172**	0.0000***	0.7333
90 %	0.0482**	0.1323	0.0600*	0.0000***	0.1250	0.0963*	0.0527*	0.0000***	0.1116
95 %	0.2375	0.2466	0.1303	0.0005***	0.2004	0.2268	0.1183	0.0000***	0.1819
99 %	0.6161	0.8058	0.5799	0.0800*	0.6650	0.8844	0.5244	0.0814*	0.5982
	One-sided Dependent on VaR								
1 %	0.7450	0.6592	0.9275	0.9654	0.2550	0.3192	0.7029	0.9918	0.2550
5 %	0.7381	0.8583	0.9706	1.0000	0.0052***	0.6964	0.9757	1.0000	0.0032***
10 %	0.8355	0.4908	0.9760	1.0000	0.2650	0.4722	0.8689	1.0000	0.1345
90 %	0.6413	0.7110	0.8735	1.0000	0.8319	0.7682	0.9324	1.0000	0.8857
95 %	0.3899	0.2531	0.4018	0.9775	0.3951	0.2709	0.5870	0.9708	0.4145
99 %	0.2550	0.2606	0.2550	0.7504	0.2606	0.2606	NaN	NaN	0.2550
	One-sided Independent of VaR								
1 %	0.9735	0.8693	0.9979	0.9988	0.0676*	0.6332	0.9932	0.9989	0.0174**
5 %	0.9868	0.8940	0.9942	1.0000	0.1400	0.8384	0.9894	1.0000	0.0893*
10 %	0.9982	0.9125	0.9884	1.0000	0.6762	0.8787	0.9843	1.0000	0.6192
90 %	0.9520	0.8739	0.9400	1.0000	0.8818	0.9054	0.9474	1.0000	0.8906
95 %	0.7760	0.7668	0.8698	0.9995	0.8060	0.7761	0.8817	1.0000	0.8187
99 %	0.2796	0.3639	0.6635	0.9207	0.6372	0.5192	0.6635	0.9191	0.6619

The table presents the results for onesided and twosided ES-tests dependent on VaR and independent of VaR. *, ** and *** denotes significance at the 10%, 5% and 1% respectively.

Table E27: ES test results for gasonline futures on NYMEX

Quantile	Gasoline - NYMEX								
	EWQR	Garch Normal	Garch Student t	Garch GED	Garch Skew t	GJR Normal	GJR Student t	GJR GED	GJR Skew t
	Two-sided Dependent on VaR								
1 %	0.9580	0.2474	0.7725	0.0017***	0.1004	0.1520	0.2161	0.0017***	0.0122**
5 %	0.5473	0.2240	0.3643	0.0000***	0.0003***	0.2853	0.3915	0.0000***	0.0021***
10 %	0.6236	0.1919	0.4009	0.0000***	0.0031***	0.1383	0.2161	0.0000***	0.0023***
90 %	0.1731	0.0652*	0.0362**	0.0000***	0.4027	0.0635*	0.0242**	0.0000***	0.1025
95 %	0.9241	0.4969	0.2659	0.0000***	0.3201	0.5862	0.1763	0.0000***	0.3661
99 %	0.8797	0.5495	NaN	NaN	0.5779	0.5046	0.5046	0.5046	0.5046
	Two-sided Independent of VaR								
1 %	0.4456	0.2445	0.7713	0.0017***	0.0197**	0.1469	0.2380	0.0017***	0.0017***
5 %	0.7251	0.6487	0.3908	0.0000***	0.0002***	0.7439	0.5571	0.0000***	0.0001***
10 %	0.0993*	0.2046	0.1617	0.0000***	0.0653*	0.1569	0.1348	0.0000***	0.1041
90 %	0.1012	0.0395**	0.0284**	0.0000***	0.4172	0.0189**	0.0162**	0.0000***	0.2980
95 %	0.0258**	0.0492**	0.0278**	0.0000***	0.2875	0.0328**	0.0174**	0.0000***	0.2756
99 %	0.9133	0.3617	0.2971	0.0017***	0.4953	0.2406	0.2126	0.0108**	0.3830
	One-sided Dependent on VaR								
1 %	0.4876	0.1373	0.3928	0.9995	0.0387**	0.0147**	0.0338**	0.9992	0.0114**
5 %	0.2488	0.0851*	0.1590	1.0000	0.0000***	0.1196	0.1766	1.0000	0.0000***
10 %	0.6721	0.0682*	0.1757	1.0000	0.0000***	0.0449**	0.0807*	1.0000	0.0000***
90 %	0.8962	0.9471	0.9677	1.0000	0.7765	0.9494	0.9781	1.0000	0.9307
95 %	0.5350	0.7130	0.8220	1.0000	0.8004	0.6559	0.8557	1.0000	0.7654
99 %	0.4250	0.7049	NaN	NaN	0.6839	0.2496	0.745	0.745	0.2496
	One-sided Independent of VaR								
1 %	0.1558	0.1373	0.3928	0.9992	0.0097***	0.0316**	0.0717*	0.9995	0.0007***
5 %	0.6153	0.6688	0.7892	1.0000	0.0000***	0.6168	0.7082	1.0000	0.0000***
10 %	0.9297	0.8825	0.9040	1.0000	0.0216**	0.9046	0.9158	1.0000	0.0338**
90 %	0.9293	0.9641	0.9730	1.0000	0.7611	0.9818	0.9844	1.0000	0.8238
95 %	0.9818	0.9529	0.9724	1.0000	0.8025	0.9675	0.9826	1.0000	0.8072
99 %	0.5173	0.6791	0.7093	0.9990	0.6775	0.7966	0.7966	0.9994	0.7124

The table presents the results for onesided and twosided ES-tests dependent on VaR and independent of VaR. *, ** and *** denotes significance at the 10%, 5% and 1% respectively.

Table E28: ES test results for heating oil futures on NYMEX

Quantile	Heating Oil - NYMEX								
	EWQR	**Garch Normal**	**Garch Student t**	**Garch GED**	**Garch Skew t**	**GJR Normal**	**GJR Student t**	**GJR GED**	**GJR Skew t**
	Two-sided Dependent on VaR								
1 %	0.5046	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5 %	0.1269	0.2031	0.0012***	0.0000***	0.0001***	0.3374	0.0012***	0.0000***	0.0001***
10 %	0.0896*	0.5276	0.0563*	0.0000***	0.018**	0.5191	0.0551*	0.0000***	0.0174**
90 %	0.3298	0.1912	0.0087***	0.0000***	0.015**	0.2428	0.0077***	0.0000***	0.0069***
95 %	0.5323	0.1005	0.0032***	0.0000***	0.0051***	0.085	0.0036***	0.0000***	0.0055***
99 %	0.6475	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
	Two-sided Independent of VaR								
1 %	0.0594*	0.0115**	0.0017***	0.0017***	0.0029***	0.0115**	0.0017***	0.0110**	0.0128**
5 %	0.0010***	0.0136**	0.0000***	0.0000***	0.0000***	0.0156**	0.0002***	0.0000***	0.0000***
10 %	0.0011***	0.0429**	0.0058***	0.0000***	0.0015***	0.0418**	0.0059***	0.0000***	0.0013***
90 %	0.0261**	0.0145**	0.0059***	0.0000***	0.0029***	0.0112**	0.0045***	0.0000***	0.0027***
95 %	0.0263**	0.0096***	0.0006***	0.0000***	0.0003***	0.0074***	0.0007***	0.0000***	0.0004***
99 %	0.5943	0.0017***	0.0208**	0.0017***	0.0208	0.011**	0.0208**	0.0017***	0.0208**
	One-sided Dependent on VaR								
1 %	0.7450	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5 %	0.9232	0.8909	0.9992	1.0000	0.9999	0.8256	0.9992	1.0000	0.9999
10 %	0.9412	0.7355	0.9678	1.0000	0.9877	0.7385	0.9681	1.0000	0.9880
90 %	0.8227	0.8923	0.9932	1.0000	0.9893	0.8687	0.9938	1.0000	0.9942
95 %	0.7271	0.9402	0.9977	1.0000	0.9958	0.9481	0.9973	1.0000	0.9952
99 %	0.6652	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
	One-sided Independent of VaR								
1 %	0.9896	0.9991	0.9988	0.9993	0.9993	0.9989	0.9993	0.9993	0.9975
5 %	0.9990	0.9896	1.0000	1.0000	1.0000	0.9873	0.9998	1.0000	1.0000
10 %	0.9992	0.9725	0.9959	1.0000	0.9989	0.9731	0.9959	1.0000	0.999
90 %	0.9798	0.9868	0.9943	1.0000	0.9974	0.9906	0.9956	1.0000	0.9974
95 %	0.9806	0.9912	0.9994	1.0000	0.9997	0.9931	0.9993	1.0000	0.9996
99 %	0.6699	0.9993	0.9892	0.9992	0.9892	0.9990	0.9892	0.9993	0.9892

The table presents the results for onesided and twosided ES-tests dependent on VaR and independent of VaR. *, ** and *** denotes significance at the 10%, 5% and 1% respectively.

Table E29: Total VaR test results for the unconditional coverage test

10 %	CO2 EEX	CO2 Nasdaq	Coal ICE	Coal Nymex	El M EEX	El M ICE	El M Nymex	El Y EEX	Gas ICE	Gas Nymex	Oil ICE	Gasoline	Heating Oil	LC Oil	Number of breaches	Total
EWQR	0	0	0	0	1	0	1	0	0	0	0	0	1	0	3	16
CAViaR1	0	0	0	0	0	0	0	0	1	0	0	1	0	0	2	29
CAViaR2	0	0	0	1	0	0	0	0	0	0	0	0	1	0	2	27
CAViaR3	0	0	1	0	0	0	0	0	0	0	0	2	0	0	3	29
CAViaR4	0	1	1	0	0	0	0	0	0	0	2	1	2	0	7	23
CAViaR5	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	25
Garch-N	1	1	0	0	0	0	0	1	0	0	1	0	0	1	5	37
Garch-t	0	0	1	0	1	1	0	0	1	0	1	0	0	0	5	16
Garch-GED	0	2	0	2	0	1	0	0	1	0	1	1	0	0	8	26
Garch-skew t	1	0	1	0	1	2	0	0	0	0	1	0	0	0	6	16
GJR-Garch-N	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	33
GJR-Garch-t	0	0	0	0	1	2	0	0	1	0	0	0	0	0	4	17
GJR-Garch-GED	1	0	0	1	0	1	1	0	1	0	0	0	0	0	5	25
GJR-Garch-skew t	1	0	0	0	1	2	0	0	1	0	0	1	0	0	6	18
5 %																
EWQR	1	0	0	2	1	1	0	0	0	0	1	1	0	3	10	13
CAViaR1	0	0	1	1	3	0	1	2	1	0	0	1	2	1	13	27
CAViaR2	1	0	1	2	1	0	0	0	2	0	1	1	0	2	11	25
CAViaR3	1	0	0	0	2	1	1	2	1	0	0	2	2	1	13	26
CAViaR4	0	0	0	1	0	0	1	2	0	0	2	1	1	4	12	16
CAViaR5	2	0	0	1	0	0	0	1	1	0	0	2	1	2	10	24
Garch-N	2	2	0	1	0	1	0	0	1	0	1	1	2	1	12	32
Garch-t	1	0	0	0	1	1	0	0	1	0	1	2	0	1	8	11
Garch-GED	1	1	1	0	2	2	0	1	0	1	1	2	0	0	12	18
Garch-skew t	0	1	0	0	1	2	0	0	1	0	1	1	0	1	8	10
GJR-Garch-N	3	1	1	1	0	2	1	0	2	0	0	1	2	0	14	32
GJR-Garch-t	1	1	2	0	1	2	0	0	1	0	1	1	0	2	12	13
GJR-Garch-GED	1	4	2	0	2	3	0	0	0	0	1	1	0	0	14	20
GJR-Garch-skew t	0	1	3	0	1	2	0	0	1	0	1	0	0	1	10	12
1 %																
EWQR	0	0	0	0	0	1	0	0	0	0	1	0	0	1	3	
CAViaR1	3	1	0	2	1	4	2	0	1	0	0	0	0	0	14	
CAViaR2	2	0	0	0	3	4	3	0	1	0	0	0	0	1	14	
CAViaR3	3	1	0	1	3	4	0	1	0	0	0	0	0	0	13	
CAViaR4	0	0	0	0	0	0	0	0	0	0	1	0	2	1	4	
CAViaR5	2	0	0	1	4	4	2	0	1	0	0	0	0	0	14	
Garch-N	1	1	4	1	4	4	2	1	2	0	0	0	0	0	20	
Garch-t	0	0	1	0	1	1	0	0	0	0	0	0	0	0	3	
Garch-GED	0	0	1	0	2	2	0	0	0	0	0	0	0	1	6	
Garch-skew t	0	0	1	0	1	0	0	0	0	0	0	0	0	0	2	
GJR-Garch-N	1	0	2	1	4	3	1	1	2	0	1	1	0	1	18	
GJR-Garch-t	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	
GJR-Garch-GED	0	0	0	0	2	1	0	0	0	0	0	1	0	2	6	
GJR-Garch-skew t	0	0	0	0	1	0	0	0	0	0	0	1	0	0	2	

The tables show number of p-values below 10%, 5% and 1% respectively

Table E30: Total VaR test results for the conditional coverage test

10 %	CO2 EEX	CO2 Nasdaq	Coal ICE	Coal Nymex	El M EEX	El M ICE	El M Nymex	El Y EEX	Gas ICE	Gas Nymex	Oil ICE	Gasoline	Heating Oil	LC Oil	Number of breaches	Total
EWQR	0	0	0	0	1	0	0	0	0	0	0	0	1	1	3	21
CAViaR1	0	1	1	0	0	0	0	1	1	0	0	0	1	0	5	26
CAViaR2	0	2	0	1	1	0	0	1	0	0	0	0	1	0	6	23
CAViaR3	0	0	1	0	0	0	0	1	1	0	0	0	0	0	3	22
CAViaR4	0	0	1	0	0	0	0	1	0	1	0	2	1	1	7	19
CAViaR5	0	0	0	0	0	0	0	0	1	0	0	1	0	0	2	17
Garch-N	1	1	0	1	0	0	0	0	0	0	0	0	1	0	4	26
Garch-t	0	1	0	1	0	0	0	1	2	0	0	0	0	0	5	18
Garch-GED	1	1	0	0	1	1	0	1	0	1	0	0	1	0	7	23
Garch-skew t	0	1	0	1	1	1	0	1	1	0	0	0	0	0	6	19
GJR-Garch-N	2	1	1	0	0	0	0	0	1	0	0	0	0	0	5	25
GJR-Garch-t	0	0	0	0	0	0	0	1	1	0	0	0	0	0	2	17
GJR-Garch-GED	1	1	0	0	0	0	0	1	0	0	0	0	1	0	4	20
GJR-Garch-skew t	0	0	0	0	0	1	0	1	2	0	0	0	0	0	4	18
5 %																
EWQR	0	1	1	2	1	0	0	0	0	0	1	0	1	1	8	18
CAViaR1	1	0	1	0	0	0	1	1	2	0	0	1	1	1	9	21
CAViaR2	1	0	1	0	1	0	1	0	2	0	2	1	1	2	12	17
CAViaR3	1	0	0	1	2	0	0	2	1	0	0	1	1	1	10	19
CAViaR4	0	0	0	1	1	0	1	1	0	0	1	0	0	1	6	12
CAViaR5	2	0	1	1	0	0	1	1	0	0	2	0	1	1	10	15
Garch-N	1	2	0	0	0	1	0	0	1	0	1	0	1	1	8	22
Garch-t	0	0	0	1	1	2	0	1	0	0	1	1	1	0	8	13
Garch-GED	0	1	1	1	0	1	0	0	1	0	1	0	1	1	8	16
Garch-skew t	0	0	1	1	0	2	0	1	0	0	1	0	1	1	8	13
GJR-Garch-N	1	0	0	0	0	2	2	2	1	0	1	1	0	1	11	20
GJR-Garch-t	0	0	1	2	0	3	0	1	0	0	1	1	1	1	11	15
GJR-Garch-GED	0	0	1	1	1	2	0	0	1	0	1	1	1	0	9	16
GJR-Garch-skew t	0	0	1	2	0	2	0	1	0	0	1	0	1	1	9	14
1 %																
EWQR	0	0	2	2	0	3	0	0	0	0	1	0	0	2	10	
CAViaR1	2	0	0	3	2	2	1	0	0	0	2	0	0	0	12	
CAViaR2	1	0	0	0	1	1	2	0	0	0	0	0	0	0	5	
CAViaR3	1	0	0	3	1	1	0	0	1	0	2	0	0	0	9	
CAViaR4	0	0	0	1	0	0	0	0	0	0	1	0	2	2	6	
CAViaR5	0	0	0	0	3	0	1	0	1	0	0	0	0	0	5	
Garch-N	0	0	1	2	2	2	1	2	2	0	1	1	0	0	14	
Garch-t	0	0	1	1	1	0	0	0	0	0	1	0	0	1	5	
Garch-GED	0	0	0	2	2	1	0	1	0	0	1	1	0	0	8	
Garch-skew t	0	0	1	1	1	0	0	0	0	0	1	1	0	0	5	
GJR-Garch-N	0	0	0	2	2	2	0	0	2	0	1	0	0	0	9	
GJR-Garch-t	0	0	1	1	1	0	0	0	0	0	1	0	0	0	4	
GJR-Garch-GED	0	0	0	2	2	0	0	1	0	0	1	0	0	1	7	
GJR-Garch-skew t	0	0	1	1	1	0	0	0	0	0	1	1	0	0	5	

The tables show number of p-values below 10%, 5% and 1% respectively

Tabel E31: Number of quantiles that pass the conditional coverage test at 5% significance

	CO2 EEX	CO2 Nasdaq	Coal ICE	Coal Nymex	El M EEX	El M ICE	El M Nymex	El Y EEX	Gas ICE	Gas Nymex	Oil ICE	Gasoline	Heating Oil	LC Oil	Total
EWQR	3	3	1	1	3	1	5	5	5	4	2	3	3	1	40
CAViaR1	1	4	1	1	1	0	3	3	2	3	1	2	3	3	28
CAViaR2	1	5	3	4	1	0	3	4	2	3	1	2	3	2	34
CAViaR3	1	3	3	0	0	0	4	2	2	3	1	1	3	3	26
CAViaR4	4	3	4	1	2	3	4	3	3	3	1	3	2	1	37
CAViaR5	0	4	3	2	0	0	3	3	3	3	1	3	3	2	30
Garch-N	3	3	0	3	0	0	2	2	1	3	1	2	3	3	26
Garch-t	4	4	2	3	1	1	3	3	4	4	1	2	3	3	38
Garch-GED	4	4	2	2	1	1	3	3	3	3	1	2	3	3	35
Garch-skew t	4	5	1	3	2	2	3	3	4	3	1	2	3	3	39
GJR-Garch-N	3	5	3	3	0	0	3	2	2	3	1	2	4	3	34
GJR-Garch-t	5	5	1	2	2	1	4	3	4	3	1	2	3	3	39
GJR-Garch-GED	4	5	2	2	0	1	4	3	3	3	1	2	3	3	36
GJR-Garch-skew t	5	5	1	2	2	2	4	3	4	3	1	2	3	3	40

The table gives the number of quantiles for each model and futures series that pass the dynamic quantile test at 5% significanse.

Table E32: Total VaR test results for the dynamic quantile test

10 %	CO2 EEX	CO2 Nasdaq	Coal ICE	Coal Nymex	El M EEX	El M ICE	El M Nymex	El Y EEX	Gas ICE	Gas Nymex	Oil ICE	Gasoline	Heating Oil	LC Oil	Number of breaches	Total
EWQR	0	1	0	0	1	0	0	1	1	0	0	2	0	1	7	46
CAViaR1	0	0	2	0	2	0	1	0	0	1	1	0	0	1	8	30
CAViaR2	0	0	0	0	1	0	0	0	0	1	1	0	0	0	3	20
CAViaR3	0	0	0	0	0	0	1	0	0	0	0	1	1	0	3	25
CAViaR4	2	0	1	1	1	2	0	0	1	0	0	0	0	1	9	44
CAViaR5	1	0	0	0	1	0	1	0	1	1	1	0	2	0	8	22
Garch-N	0	2	2	0	1	0	1	1	0	0	1	1	1	1	11	34
Garch-t	0	2	0	0	0	0	0	1	1	0	1	0	0	0	5	23
Garch-GED	0	1	1	0	0	1	1	0	1	0	1	1	0	0	7	21
Garch-skew t	0	0	0	1	0	1	0	1	1	0	1	0	0	0	5	20
GJR-Garch-N	1	0	0	0	0	0	0	1	0	0	0	0	1	0	3	28
GJR-Garch-t	0	0	2	1	0	1	0	1	1	1	0	0	0	1	8	23
GJR-Garch-GED	0	1	0	0	1	1	0	0	1	1	0	0	0	0	5	21
GJR-Garch-skew t	0	0	2	0	0	1	0	0	2	1	0	0	0	0	6	21
5 %																
EWQR	0	0	0	0	0	1	2	2	1	1	1	0	0	2	10	39
CAViaR1	2	0	0	3	0	1	2	2	2	0	2	1	0	0	15	22
CAViaR2	0	0	2	0	0	0	0	2	0	1	1	0	0	0	6	17
CAViaR3	0	1	0	3	2	1	1	2	1	1	2	0	1	0	15	22
CAViaR4	1	1	1	0	0	1	2	2	0	0	3	1	1	1	14	35
CAViaR5	0	1	1	0	2	0	0	1	0	0	0	0	0	0	5	14
Garch-N	0	0	0	2	1	1	1	0	2	0	0	0	0	0	7	23
Garch-t	0	0	0	1	1	2	1	1	2	0	0	0	1	0	9	18
Garch-GED	0	0	0	0	0	1	0	2	0	0	1	0	1	0	5	14
Garch-skew t	0	0	0	1	0	0	1	1	1	0	1	0	1	0	6	15
GJR-Garch-N	0	0	1	2	0	1	1	0	1	0	1	0	0	0	7	25
GJR-Garch-t	0	1	0	0	0	1	0	1	1	0	1	0	1	0	6	15
GJR-Garch-GED	0	0	1	0	0	1	0	2	0	0	0	0	1	0	5	16
GJR-Garch-skew t	0	0	0	1	0	0	0	1	1	0	1	0	1	0	5	15
1 %																
EWQR	2	3	4	5	5	4	2	2	1	1	0	0	0	0	29	
CAViaR1	1	2	0	0	0	3	1	0	0	0	0	0	0	0	7	
CAViaR2	0	1	1	0	0	4	3	0	2	0	0	0	0	0	11	
CAViaR3	0	1	0	1	0	3	0	1	1	0	0	0	0	0	7	
CAViaR4	3	1	2	3	3	2	2	2	0	1	1	0	1	0	21	
CAViaR5	0	1	1	0	0	4	2	0	1	0	0	0	0	0	9	
Garch-N	1	2	1	2	2	3	1	1	1	0	1	0	1	0	16	
Garch-t	1	1	1	3	1	1	0	0	0	0	1	0	0	0	9	
Garch-GED	1	1	0	4	2	1	0	0	0	0	0	0	0	0	9	
Garch-skew t	1	1	1	2	1	2	0	0	0	0	0	1	0	0	9	
GJR-Garch-N	2	2	2	2	4	2	1	1	2	0	0	0	0	0	18	
GJR-Garch-t	2	1	1	3	1	1	0	0	0	0	0	0	0	0	9	
GJR-Garch-GED	2	1	0	4	2	1	0	0	0	0	1	0	0	0	11	
GJR-Garch-skew t	2	1	1	3	2	1	0	0	0	0	0	0	0	0	10	

The tables show number of p-values below 10%, 5% and 1% respectively

Table E33: Total results for the twosided ES-test dependent on VaR

10 %	CO2 EEX	CO2 Nasdaq	El M Nymex	EL M ICE	El M EEX	El Y EEX	Gas ICE	Gas Nymex	Coal ICE	Coal Nymex	Oil ICE	Gasoline	Heating Oil	LC Oil	Number of breaches	Total
EWQR	0	0	1	0	0	0	0	0	0	1	0	0	1	0	3	4
Garch-N	0	0	0	0	0	0	0	2	1	1	0	1	0	0	5	13
Garch-t	0	0	0	1	0	1	1	0	0	0	2	0	1	0	6	22
Garch-GED	0	0	0	0	1	0	0	0	1	0	0	0	0	0	2	64
Garch-skew t	1	1	0	0	0	1	1	0	0	1	0	0	0	0	5	23
GJR-Garch-N	0	1	0	0	0	0	0	2	1	1	0	1	0	0	6	13
GJR-Garch-t	0	1	0	0	0	2	1	0	1	0	1	0	1	1	8	23
GJR-Garch-GED	0	0	0	0	2	0	0	0	0	0	0	0	0	0	2	67
GJR-Garch-skew t	1	0	0	0	0	0	1	0	0	2	0	0	0	0	4	23
5 %																
EWQR	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1
Garch-N	0	0	4	1	0	2	0	0	0	0	0	0	0	0	7	8
Garch-t	0	2	0	0	0	2	1	1	0	0	0	1	0	2	9	16
Garch-GED	0	1	0	0	2	0	3	0	0	0	0	0	0	1	7	62
Garch-skew t	0	0	1	0	2	0	0	0	0	0	1	0	2	1	7	18
GJR-Garch-N	0	0	2	1	0	2	0	0	0	0	0	0	0	0	5	7
GJR-Garch-t	0	0	0	1	0	1	1	0	0	2	0	1	0	1	7	15
GJR-Garch-GED	0	1	0	0	2	0	3	0	1	0	0	0	0	2	9	65
GJR-Garch-skew t	0	0	0	0	2	0	0	0	0	0	1	1	1	1	6	19
1 %																
EWQR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Garch-N	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	
Garch-t	0	0	1	1	0	0	0	1	0	1	0	0	3	0	7	
Garch-GED	4	4	6	4	0	5	2	5	4	5	4	5	4	3	55	
Garch-skew t	0	0	0	2	1	0	2	2	0	0	0	2	2	0	11	
GJR-Garch-N	0	0	2	0	0	0	0	0	0	0	0	0	0	0	2	
GJR-Garch-t	0	1	1	1	0	0	0	2	0	0	0	0	3	0	8	
GJR-Garch-GED	4	4	6	4	0	5	2	5	5	5	4	5	4	3	56	
GJR-Garch-skew t	0	0	1	2	1	0	2	2	0	0	0	2	3	0	13	

The tables show number of p-values below 10%, 5% and 1% respectively

Table E34: Total results for the twosided ES-test independent of VaR

10 %	CO2 EEX	CO2 Nasdaq	El M Nymex	EL M ICE	El M EEX	El Y EEX	Gas ICE	Gas Nymex	Coal ICE	Coal Nymex	Oil ICE	Gasoline	Heating Oil	LC Oil	Number of breaches	Total
EWQR	0	1	1	0	4	1	0	0	0	1	0	1	1	1	11	31
Garch-N	0	2	1	1	0	0	0	2	1	1	0	0	0	0	8	37
Garch-t	1	1	1	3	2	0	1	0	0	0	2	0	0	1	12	46
Garch-GED	1	1	0	0	1	0	0	0	1	0	0	0	0	1	5	80
Garch-skew t	0	1	2	1	2	2	1	0	0	0	1	1	0	1	12	38
GJR-Garch-N	0	2	0	0	1	1	1	1	0	1	0	0	0	1	8	38
GJR-Garch-t	1	2	0	1	1	0	0	0	1	0	2	0	0	1	9	43
GJR-Garch-GED	0	2	0	0	0	0	0	0	1	0	0	0	0	1	4	78
GJR-Garch-skew t	1	0	0	1	1	0	1	0	0	0	0	0	0	0	4	34
5 %																
EWQR	0	0	2	1	0	0	0	0	0	1	2	1	2	2	11	20
Garch-N	1	0	1	0	2	2	1	2	0	1	1	2	4	0	17	29
Garch-t	0	3	1	1	2	2	1	1	0	2	1	2	1	1	18	34
Garch-GED	0	1	2	1	0	0	1	1	1	1	1	0	0	0	9	75
Garch-skew t	1	0	2	2	1	0	1	1	0	1	0	1	1	0	11	26
GJR-Garch-N	1	1	4	1	1	1	0	2	0	1	1	2	5	0	20	30
GJR-Garch-t	1	1	1	3	2	3	1	0	0	2	0	2	1	3	20	34
GJR-Garch-GED	1	0	2	1	1	2	1	1	1	1	1	1	1	1	15	74
GJR-Garch-skew t	0	0	4	2	2	0	2	1	0	2	1	0	2	1	17	30
1 %																
EWQR	0	0	0	2	1	1	0	0	0	1	1	0	2	1	9	
Garch-N	0	0	3	2	1	0	1	0	1	1	1	0	2	0	12	
Garch-t	1	0	0	2	0	1	0	2	0	1	2	0	5	2	16	
Garch-GED	5	4	4	5	4	6	2	5	4	5	5	6	6	5	66	
Garch-skew t	0	0	0	3	2	0	1	2	0	1	0	1	5	0	15	
GJR-Garch-N	0	0	1	2	1	0	1	1	1	1	1	0	1	0	10	
GJR-Garch-t	0	1	0	2	0	0	0	3	0	1	2	0	5	0	14	
GJR-Garch-GED	4	4	4	5	4	4	2	5	3	5	5	5	5	4	59	
GJR-Garch-skew t	0	0	0	3	2	0	0	2	0	0	0	2	4	0	13	

The tables show number of p-values below 10%, 5% and 1% respectively

Table E35: Total results for the onesided ES-test dependent on VaR

10 %	CO2 EEX	CO2 Nasdaq	El M Nymex	EL M ICE	El M EEX	El Y EEX	Gas ICE	Gas Nymex	Coal ICE	Coal Nymex	Oil ICE	Gasoline	Heating Oil	LC Oil	Number of breaches	Total
EWQR	0	0	1	0	0	0	0	1	0	0	0	0	0	0	2	3
Garch-N	1	2	1	1	3	0	0	1	3	0	0	2	0	0	14	35
Garch-t	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	3
Garch-GED	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Garch-skew t	1	0	1	0	0	0	0	0	0	1	0	0	0	0	3	13
GJR-Garch-N	0	1	0	1	2	0	1	1	1	1	0	0	0	0	8	38
GJR-Garch-t	0	0	0	0	0	0	1	0	0	0	0	1	0	0	2	5
GJR-Garch-GED	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GJR-Garch-skew t	0	0	3	0	0	0	0	0	0	1	1	0	0	0	5	12
5 %																
EWQR	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1
Garch-N	0	0	0	0	2	1	3	2	0	3	0	0	0	0	11	21
Garch-t	0	0	0	0	0	2	0	0	0	0	0	0	0	0	2	2
Garch-GED	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Garch-skew t	0	1	1	0	0	2	0	0	0	0	0	1	0	0	5	10
GJR-Garch-N	0	2	2	0	4	1	1	2	4	2	0	2	0	0	20	30
GJR-Garch-t	0	0	0	0	0	2	0	0	0	0	0	1	0	0	3	3
GJR-Garch-GED	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GJR-Garch-skew t	0	0	0	0	0	2	0	0	0	0	0	1	0	0	3	7
1 %																
EWQR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Garch-N	0	0	5	1	0	2	1	0	1	0	0	0	0	0	10	
Garch-t	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Garch-GED	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Garch-skew t	1	0	0	0	0	0	0	0	0	0	1	2	0	1	5	
GJR-Garch-N	0	0	4	1	0	2	2	0	1	0	0	0	0	0	10	
GJR-Garch-t	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
GJR-Garch-GED	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
GJR-Garch-skew t	0	0	0	0	0	0	0	0	0	0	1	2	0	1	4	

The tables show number of p-values below 10%, 5% and 1% respectively

Table E36: Total results for the onesided ES-test independent of VaR

10 %	CO2 EEX	CO2 Nasdaq	El M Nymex	EL M ICE	El M EEX	El Y EEX	Gas ICE	Gas Nymex	Coal ICE	Coal Nymex	Oil ICE	Gasoline	Heating Oil	LC Oil	Number of breaches	Total
EWQR	1	0	0	0	1	2	2	2	0	0	0	0	0	0	8	32
Garch-N	0	0	0	1	1	0	1	1	0	1	0	0	0	0	5	16
Garch-t	0	0	1	0	0	1	1	0	1	0	0	0	0	0	4	9
Garch-GED	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Garch-skew t	0	1	1	0	0	1	1	0	0	1	1	0	0	1	7	20
GJR-Garch-N	0	1	0	1	1	0	2	0	0	1	0	0	0	0	6	20
GJR-Garch-t	0	0	2	0	0	1	1	1	0	0	0	1	0	0	6	11
GJR-Garch-GED	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GJR-Garch-skew t	0	1	0	0	0	0	1	1	0	2	0	0	0	1	6	22
5 %																
EWQR	0	1	2	0	1	1	0	1	0	1	0	0	0	0	7	24
Garch-N	0	0	1	0	0	2	1	1	0	1	0	0	0	0	6	11
Garch-t	0	0	1	0	0	2	0	0	0	0	0	0	0	0	3	5
Garch-GED	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Garch-skew t	0	1	0	0	0	2	1	0	1	0	0	1	0	0	6	13
GJR-Garch-N	0	0	1	0	0	2	0	1	1	1	0	1	0	0	7	14
GJR-Garch-t	0	0	0	0	0	2	0	0	1	0	0	0	0	0	3	5
GJR-Garch-GED	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GJR-Garch-skew t	1	0	1	0	0	3	1	0	1	0	1	1	0	1	10	16
1 %																
EWQR	0	0	3	3	4	2	1	0	0	4	0	0	0	0	17	
Garch-N	0	0	4	0	0	1	0	0	0	0	0	0	0	0	5	
Garch-t	0	0	0	0	0	0	2	0	0	0	0	0	0	0	2	
Garch-GED	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Garch-skew t	2	0	2	0	0	0	1	0	0	0	0	2	0	0	7	
GJR-Garch-N	0	0	4	0	0	1	1	1	0	0	0	0	0	0	7	
GJR-Garch-t	0	0	0	0	0	0	2	0	0	0	0	0	0	0	2	
GJR-Garch-GED	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
GJR-Garch-skew t	1	0	2	0	0	0	1	0	0	0	0	2	0	0	6	

The tables show number of p-values below 10%, 5% and 1% respectively

Table E37: Hitpercentage for CO2 on EEX and NASDAQ OMX

CO2 - EEX														
Quantile	**EWQR**	**Symmetric Absolute Value CAViaR**	**Asymmetric Slope CAViaR**	**Indirect GARCH CAViaR**	**Adaptive CAViaR**	**Indirect AR-GARCH CAViaR**	**GARCH Normal**	**GARCH Student t**	**GARCH GED**	**GARCH Skew t**	**GJR Normal**	**GJR Student t**	**GJR GED**	**GJR Skew t**
1 %	0.80	0.40	0.40	0.20	0.80	0.00	1.00	0.40	0.40	0.40	0.80	0.40	0.40	0.40
5 %	3.60	2.00	2.60	2.40	4.40	2.80	3.20	4.00	3.60	3.40	3.20	4.00	3.40	3.40
10 %	8.80	6.60	7.00	6.40	9.40	6.80	7.60	8.80	8.40	8.40	7.20	8.60	8.20	8.20
90 %	11.00	8.00	8.20	8.20	8.60	6.40	6.20	9.00	8.20	9.40	6.40	9.00	8.20	9.00
95 %	4.60	2.00	2.40	2.20	3.80	2.20	3.00	3.20	3.00	3.60	3.00	3.20	3.00	3.60
99 %	0.20	0.80	0.40	0.60	0.00	0.60	0.80	0.60	0.60	0.80	1.00	1.00	0.60	1.00

CO2 - NASDAQ OMX														
Quantile	**EWQR**	**Symmetric Absolute Value CAViaR**	**Asymmetric Slope CAViaR**	**Indirect GARCH CAViaR**	**Adaptive CAViaR**	**Indirect AR-GARCH CAViaR**	**GARCH Normal**	**GARCH Student t**	**GARCH GED**	**GARCH Skew t**	**GJR Normal**	**GJR Student t**	**GJR GED**	**GJR Skew t**
1 %	0.80	0.00	0.60	0.00	0.60	0.00	0.80	0.40	0.40	0.20	0.80	0.20	0.20	0.20
5 %	3.80	2.00	4.00	2.00	4.60	4.20	3.40	4.60	3.40	4.00	3.60	4.80	3.20	4.40
10 %	9.60	10.80	10.00	10.60	7.80	10.00	7.40	10.00	9.40	9.80	8.20	9.20	8.60	9.20
90 %	10.60	9.80	9.80	8.60	8.80	8.60	6.60	8.60	7.80	8.80	7.00	8.20	7.40	8.80
95 %	5.20	4.00	4.60	5.60	4.20	5.60	2.80	3.60	2.80	4.20	3.40	3.60	3.00	4.20
99 %	1.00	0.80	0.80	0.60	0.40	0.80	0.80	0.80	0.80	0.80	1.00	1.00	1.00	1.00

Proportion of losses greater than the forecasted VaR for each of the return quantiles. Ideally 1.00 for 1%, 5.00 for 5%, 10.00 for 10%, 10.00 for 90%, 5.00 for 95% and 1.00 for 99%.

Table E38: Hitpercentage for Coal on ICE and NYMEX

Coal - ICE														
Quantile	**EWQR**	**Symmetric Absolute Value CAViaR**	**Asymmetric Slope CAViaR**	**Indirect GARCH CAViaR**	**Adaptive CAViaR**	**Indirect AR-GARCH CAViaR**	**GARCH Normal**	**GARCH Student t**	**GARCH GED**	**GARCH Skew t**	**GJR Normal**	**GJR Student t**	**GJR GED**	**GJR Skew t**
1 %	0.40	0.80	0.80	1.00	0.40	1.00	0.80	1.00	1.20	1.00	0.80	1.00	1.00	1.00
5 %	5.60	3.80	3.60	3.40	4.60	3.60	2.40	4.20	3.00	3.60	2.20	4.00	3.00	3.20
10 %	9.80	9.40	8.80	10.00	9.60	10.40	2.60	9.00	6.40	8.40	2.80	9.00	6.80	8.60
90 %	9.00	7.40	7.40	7.60	8.80	9.40	6.40	13.80	10.40	14.00	7.20	13.20	10.80	13.20
95 %	4.20	4.00	4.40	4.80	3.40	4.80	2.00	7.00	5.80	7.00	4.00	7.20	5.60	7.20
99 %	0.40	0.60	1.00	1.00	0.40	1.00	0.60	1.20	1.20	1.20	1.20	1.20	1.20	1.20

Coal - NYMEX														
Quantile	**EWQR**	**Symmetric Absolute Value CAViaR**	**Asymmetric Slope CAViaR**	**Indirect GARCH CAViaR**	**Adaptive CAViaR**	**Indirect AR-GARCH CAViaR**	**GARCH Normal**	**GARCH Student t**	**GARCH GED**	**GARCH Skew t**	**GJR Normal**	**GJR Student t**	**GJR GED**	**GJR Skew t**
1 %	0.60	0.20	0.20	0.40	0.80	0.60	0.60	0.40	0.40	0.40	0.60	0.40	0.40	0.40
5 %	6.20	1.80	3.20	1.80	4.60	2.20	3.20	4.40	3.40	3.80	3.20	4.40	3.60	4.20
10 %	11.60	6.20	7.80	7.20	9.00	7.00	6.20	9.40	7.60	9.00	6.40	9.40	7.60	9.20
90 %	11.40	9.20	9.00	10.40	10.20	11.40	8.20	11.00	10.40	11.40	8.80	11.60	10.20	11.80
95 %	7.60	4.40	4.60	5.60	4.80	5.60	4.80	5.80	5.20	5.80	5.00	6.20	5.20	6.40
99 %	2.20	0.40	0.40	0.40	0.20	0.40	1.40	1.00	1.00	1.00	1.20	1.00	1.00	1.00

Proportion of losses greater than the forecasted VaR for each of the return quantiles. Ideally 1.00 for 1%, 5.00 for 5%, 10.00 for 10%, 10.00 for 90%, 5.00 for 95% and 1.00 for 99%.

Table E39: Hitpercentage for Gas on ICE and NYMEX

Gas - ICE														
Quantile	**EWQR**	**Symmetric Absolute Value CAViaR**	**Asymmetric Slope CAViaR**	**Indirect GARCH CAViaR**	**Adaptive CAViaR**	**Indirect AR-GARCH CAViaR**	**GARCH Normal**	**GARCH Student t**	**GARCH GED**	**GARCH Skew t**	**GJR Normal**	**GJR Student t**	**GJR GED**	**GJR Skew t**
1 %	1.00	0.60	0.80	1.00	0.00	1.00	1.00	1.00	0.80	1.00	1.00	1.00	0.80	1.00
5 %	5.00	3.20	3.20	3.80	3.80	3.80	2.20	4.60	3.40	5.00	2.40	4.40	3.40	4.80
10 %	9.60	9.40	10.00	10.40	9.00	10.20	4.40	11.60	10.00	11.60	5.00	11.60	10.40	11.60
90 %	10.40	13.80	13.40	15.00	9.20	15.20	6.80	12.40	11.40	12.20	7.20	12.60	11.40	12.60
95 %	5.80	7.00	8.40	7.20	4.60	7.20	4.60	7.20	5.60	7.20	5.00	7.20	6.00	7.20
99 %	1.60	1.20	1.60	1.20	0.80	1.20	1.60	1.60	1.20	1.40	2.00	1.60	1.20	1.40

Gas - NYMEX														
Quantile	**EWQR**	**Symmetric Absolute Value CAViaR**	**Asymmetric Slope CAViaR**	**Indirect GARCH CAViaR**	**Adaptive CAViaR**	**Indirect AR-GARCH CAViaR**	**GARCH Normal**	**GARCH Student t**	**GARCH GED**	**GARCH Skew t**	**GJR Normal**	**GJR Student t**	**GJR GED**	**GJR Skew t**
1 %	0.80	0.60	0.60	0.40	1.00	0.40	0.60	0.40	0.20	0.40	0.60	0.40	0.40	0.40
5 %	5.20	3.80	3.80	4.20	4.00	4.00	4.20	4.20	4.20	4.40	3.60	4.40	3.60	4.60
10 %	10.00	9.20	8.80	10.60	9.40	10.20	8.80	10.80	10.40	11.20	8.60	10.40	9.60	10.60
90 %	10.00	10.20	10.80	10.40	9.80	10.80	9.20	10.40	10.20	10.40	9.40	10.00	10.00	10.00
95 %	4.20	4.20	5.40	4.80	4.80	5.40	4.40	5.20	4.60	5.00	4.80	4.80	4.80	4.80
99 %	1.20	1.20	1.40	1.20	1.60	1.20	1.40	1.20	1.20	1.20	1.40	1.20	1.20	1.20

Proportion of losses greater than the forecasted VaR for each of the return quantiles. Ideally 1.00 for 1%, 5.00 for 5%, 10.00 for 10%, 10.00 for 90%, 5.00 for 95% and 1.00 for 99%.

Table E40: Hitpercentage for Monthly Electricity on ICE and NYMEX

Monthly Electricity - ICE														
Quantile	**EWQR**	**Symmetric Absolute Value CAViaR**	**Asymmetric Slope CAViaR**	**Indirect GARCH CAViaR**	**Adaptive CAViaR**	**Indirect AR-GARCH CAViaR**	**GARCH Normal**	**GARCH Student t**	**GARCH GED**	**GARCH Skew t**	**GJR Normal**	**GJR Student t**	**GJR GED**	**GJR Skew t**
1 %	0.20	0.40	0.40	0.20	0.00	0.00	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
5 %	8.60	0.60	0.60	1.00	4.20	1.00	2.00	2.60	2.40	3.00	2.60	2.80	2.40	3.00
10 %	12.20	3.80	3.80	2.40	9.60	2.60	4.80	7.60	6.60	7.60	5.20	7.60	7.20	7.60
90 %	10.60	3.60	3.20	3.00	9.60	2.20	5.80	8.40	7.60	7.60	6.00	7.80	7.60	7.60
95 %	4.20	1.00	0.80	1.00	0.00	0.80	2.60	4.00	3.00	3.80	2.80	3.80	3.20	3.60
99 %	1.60	0.00	0.00	0.00	1.00	0.00	1.40	0.60	0.60	0.60	1.20	0.60	0.60	0.60

Monthly Electricity - NYMEX														
Quantile	**EWQR**	**Symmetric Absolute Value CAViaR**	**Asymmetric Slope CAViaR**	**Indirect GARCH CAViaR**	**Adaptive CAViaR**	**Indirect AR-GARCH CAViaR**	**GARCH Normal**	**GARCH Student t**	**GARCH GED**	**GARCH Skew t**	**GJR Normal**	**GJR Student t**	**GJR GED**	**GJR Skew t**
1 %	1.60	91.00	88.00	0.00	1.20	2.80	2.60	1.60	1.80	1.60	2.40	1.60	1.60	1.20
5 %	5.20	4.40	4.00	4.20	4.80	4.40	5.80	6.40	6.00	6.20	5.60	6.40	5.80	6.20
10 %	10.20	6.60	1.40	8.40	9.20	8.00	9.00	11.20	10.80	11.00	9.00	11.20	10.60	11.20
90 %	12.60	9.40	8.60	9.40	7.20	9.60	5.80	9.20	8.00	9.40	6.40	8.40	7.80	8.40
95 %	5.40	5.00	5.20	5.60	5.60	4.60	4.40	5.00	4.60	5.20	4.60	5.00	4.60	5.00
99 %	1.80	2.20	2.40	2.00	0.80	2.40	1.80	1.00	1.20	1.20	2.20	1.40	1.60	1.60

Proportion of losses greater than the forecasted VaR for each of the return quantiles. Ideally 1.00 for 1%, 5.00 for 5%, 10.00 for 10%, 10.00 for 90%, 5.00 for 95% and 1.00 for 99%.

Table E41: Hitpercentage for Monthly and Yearly Electricity on EEX

Yearly Electricity - EEX														
Quantile	**EWQR**	**Symmetric Absolute Value CAViaR**	**Asymmetric Slope CAViaR**	**Indirect GARCH CAViaR**	**Adaptive CAViaR**	**Indirect AR-GARCH CAViaR**	**GARCH Normal**	**GARCH Student t**	**GARCH GED**	**GARCH Skew t**	**GJR Normal**	**GJR Student t**	**GJR GED**	**GJR Skew t**
1 %	0.60	0.20	0.00	0.20	0.20	0.40	0.60	0.60	0.60	0.40	0.60	0.60	0.60	0.40
5 %	6.60	4.00	3.60	5.20	3.20	4.40	3.80	4.20	3.80	4.20	3.80	4.20	3.80	4.20
10 %	9.60	11.20	8.20	13.80	8.80	11.00	7.60	9.80	9.20	9.80	8.00	10.20	9.60	10.40
90 %	10.80	9.00	9.60	8.80	9.40	9.20	8.20	9.00	8.80	9.20	8.00	9.00	8.60	9.40
95 %	5.80	5.00	5.80	5.60	4.20	5.20	5.20	5.40	5.20	5.60	5.20	5.40	5.20	5.60
99 %	1.20	2.00	1.80	2.20	0.80	2.20	2.60	1.80	2.00	1.80	2.40	1.80	1.80	1.80

Monthly Electricity - EEX														
Quantile	**EWQR**	**Symmetric Absolute Value CAViaR**	**Asymmetric Slope CAViaR**	**Indirect GARCH CAViaR**	**Adaptive CAViaR**	**Indirect AR-GARCH CAViaR**	**GARCH Normal**	**GARCH Student t**	**GARCH GED**	**GARCH Skew t**	**GJR Normal**	**GJR Student t**	**GJR GED**	**GJR Skew t**
1 %	1.80	1.80	1.00	0.20	0.80	0.60	0.80	0.60	0.80	0.80	1.00	0.60	1.00	1.00
5 %	7.40	2.80	2.40	2.40	4.80	2.40	1.80	4.00	3.00	4.40	1.40	4.20	3.00	4.60
10 %	10.40	6.00	6.20	5.80	10.00	5.80	3.00	7.20	5.80	7.60	2.80	7.40	5.60	7.80
90 %	11.40	8.00	6.00	6.60	10.20	5.60	3.00	6.40	5.20	6.20	3.20	5.80	4.60	5.80
95 %	6.80	2.80	3.00	3.20	5.40	2.40	2.00	3.40	3.00	3.20	1.80	3.40	2.80	3.20
99 %	1.20	0.20	0.40	0.60	1.00	0.40	0.80	0.80	1.00	0.80	0.80	0.60	0.80	0.60

Proportion of losses greater than the forecasted VaR for each of the return quantiles. Ideally 1.00 for 1%, 5.00 for 5%, 10.00 for 10%, 10.00 for 90%, 5.00 for 95% and 1.00 for 99%.

Table E42: Hitpercentage for Brent Crude Oil on ICE and Light Crude Oil on NYMEX

Brent Crude Oil - ICE														
Quantile	**EWQR**	**Symmetric Absolute Value CAViaR**	**Asymmetric Slope CAViaR**	**Indirect GARCH CAViaR**	**Adaptive CAViaR**	**Indirect AR-GARCH CAViaR**	**GARCH Normal**	**GARCH Student t**	**GARCH GED**	**GARCH Skew t**	**GJR Normal**	**GJR Student t**	**GJR GED**	**GJR Skew t**
1 %	1.00	0.00	0.20	0.00	0.00	0.00	0.80	0.40	0.40	0.40	0.80	0.40	0.40	0.40
5 %	2.20	3.80	4.00	3.80	2.40	3.60	3.40	3.40	3.40	3.40	3.60	3.80	3.60	3.60
10 %	9.60	8.20	8.60	8.20	7.60	7.60	6.80	7.40	7.00	7.20	6.60	7.40	7.00	7.00
90 %	6.80	10.40	11.20	9.80	7.60	9.00	9.20	10.20	9.80	10.60	9.20	10.00	9.60	10.40
95 %	4.40	4.80	5.00	4.40	3.00	4.40	5.00	4.80	4.80	5.20	4.80	5.00	4.80	5.00
99 %	0.40	0.40	0.60	0.40	0.20	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40

Light Crude Oil - NYMEX														
Quantile	**EWQR**	**Symmetric Absolute Value CAViaR**	**Asymmetric Slope CAViaR**	**Indirect GARCH CAViaR**	**Adaptive CAViaR**	**Indirect AR-GARCH CAViaR**	**GARCH Normal**	**GARCH Student t**	**GARCH GED**	**GARCH Skew t**	**GJR Normal**	**GJR Student t**	**GJR GED**	**GJR Skew t**
1 %	0.40	0.40	0.60	0.40	0.00	0.40	0.80	0.60	0.60	0.40	0.80	0.60	0.80	0.40
5 %	3.20	3.80	3.20	4.20	2.80	3.20	4.60	4.20	4.20	3.60	4.20	4.40	4.20	3.60
10 %	7.00	9.20	8.80	9.80	6.80	9.00	7.80	9.20	8.40	8.40	8.00	8.20	8.20	8.20
90 %	7.20	9.60	10.40	8.80	7.00	8.40	9.00	10.00	10.00	10.40	9.40	10.80	10.20	11.00
95 %	2.60	3.00	2.60	3.20	2.60	3.00	2.80	2.80	2.60	3.20	2.60	3.00	2.40	3.00
99 %	0.40	0.60	0.20	0.40	0.20	0.40	0.60	0.40	0.40	0.60	0.60	0.20	0.20	0.40

Proportion of losses greater than the forecasted VaR for each of the return quantiles. Ideally 1.00 for 1%, 5.00 for 5%, 10.00 for 10%, 10.00 for 90%, 5.00 for 95% and 1.00 for 99%.

Table E43: Hitpercentage for Gasoline and Heating Oil on NYMEX

Gasoline - NYMEX														
Quantile	**EWQR**	**Symmetric Absolute Value CAViaR**	**Asymmetric Slope CAViaR**	**Indirect GARCH CAViaR**	**Adaptive CAViaR**	**Indirect AR-GARCH CAViaR**	**GARCH Normal**	**GARCH Student t**	**GARCH GED**	**GARCH Skew t**	**GJR Normal**	**GJR Student t**	**GJR GED**	**GJR Skew t**
1 %	1.00	0.60	0.60	0.80	0.80	0.20	1.00	1.00	1.00	0.80	1.00	1.00	1.00	0.80
5 %	3.80	3.60	3.80	3.40	3.40	3.80	3.80	3.80	3.80	3.60	4.00	4.00	4.00	3.20
10 %	8.60	7.60	7.20	7.60	8.00	8.00	7.00	7.40	7.00	7.00	6.60	6.80	6.60	6.20
90 %	9.20	9.00	9.60	7.40	8.40	8.60	9.40	9.60	9.60	9.60	8.80	9.20	9.00	9.80
95 %	3.20	3.20	3.60	3.00	3.60	3.00	3.60	3.60	3.40	4.80	3.20	3.60	3.20	4.20
99 %	0.80	1.80	1.20	1.00	0.20	1.40	0.60	0.20	0.20	0.80	0.40	0.40	0.40	0.40

Heating Oil - NYMEX														
Quantile	**EWQR**	**Symmetric Absolute Value CAViaR**	**Asymmetric Slope CAViaR**	**Indirect GARCH CAViaR**	**Adaptive CAViaR**	**Indirect AR-GARCH CAViaR**	**GARCH Normal**	**GARCH Student t**	**GARCH GED**	**GARCH Skew t**	**GJR Normal**	**GJR Student t**	**GJR GED**	**GJR Skew t**
1 %	0.40	0.20	0.60	0.20	0.00	0.40	0.20	0.00	0.00	0.00	0.20	0.00	0.00	0.00
5 %	3.40	4.00	4.00	4.60	2.20	4.40	4.00	4.20	4.00	4.40	3.80	4.20	4.00	4.40
10 %	8.20	9.00	9.00	9.00	6.40	8.60	8.40	9.00	9.00	9.00	8.40	9.00	9.00	9.00
90 %	8.20	7.40	7.80	8.60	7.80	8.20	8.20	9.20	8.80	8.80	8.00	9.20	8.80	9.00
95 %	3.80	3.60	3.60	3.20	3.40	3.20	3.80	4.00	3.80	3.80	3.80	4.00	3.80	3.80
99 %	0.80	0.00	0.00	0.00	0.20	0.40	0.20	0.00	0.00	0.00	0.20	0.00	0.00	0.00

Proportion of losses greater than the forecasted VaR for each of the return quantiles. Ideally 1.00 for 1%, 5.00 for 5%, 10.00 for 10%, 10.00 for 90%, 5.00 for 95% and 1.00 for 99%.

Appendix F: Source Codes

F.1 Overview

The source codes for calculating the different VaR and ES models and tests are left in the attached zip-file. EWQR is programmed in EViews since it is relatively easy to perform this kind of quantile regression with it. The other models are implemented in MATLAB. The VaR tests have been implemented in both EViews and MATLAB, for easier VaR testing, while the ES tests have been written only in MATLAB.

The parameters of GARCH and GJR-GARCH are estimated using Kevin Sheppard's "Oxford MFEToolbox", which can be downloaded together with program documentation at http://www.kevinsheppard.com/wiki/MFE_Toolbox. We found a bug in the file "gedinv.m", which made it produce wrong answers when the input quantiles were all above or below 0.5. We have therefore changed the file to make sure that it works properly. When the input contains quantiles both above and below 0.5, there is no problem using the original file. Another bug was found and corrected for "skewtinv.m". Input values for degrees of freedom that were too high led to the answer NaN, since the function then divided two terms that were infinity. We avoided this by implementing an if-statement that inserts the following limit value when this problem occurs.

$$c = \lim_{v\to\infty} \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{\pi(v-2)}\Gamma\left(\frac{v}{2}\right)} = \frac{1}{\sqrt{2\pi}}$$

The implementation of CAViaR has been based on the public codes of Engle and Manganelli, found at http://www.simonemanganelli.org/Simone/Research.html, which have been simplified and tailored to this paper. Among the changes made are the exclusion of in-sample testing and the inclusion of the indirect AR-GARCH CAViaR model.

In all programs "theta" refers to the quantiles considered of the return distribution. In this paper the 1%, 5%, 10%, 90%, 95% and 99% quantiles are considered. Values of theta greater than 50% have been assumed to correspond to short trading position, while values below 50% correspond to long trading position. This is because VaR and ES are risk measures that consider extreme losses. For short trading positions these are found in the right tail of the returns distribution, since a loss occur when the price change is positive, while for long trading positions these are in the left tail, since losses occur for negative price changes. The 1%, 5%, 10%, 90%, 95% and 99% quantiles in the return distribution therefore correspond to the 90%, 95% and 99% quantiles in the loss distribution for long and short trading positions, respectively.

In some of the programs random functions ("rand" and "randi") have been used. To ensure reproducibility of our results, we have let the seed to the random functions be constant. In this paper the number 50 is used.

F.2 How to Run the Programs

Each of the programs calculates VaR and ES for one return series at the time. This is to provide the user the flexibility to easily apply the models to other time series by changing input, and to allow the results to be stored in separate files if desired. When working in

MATLAB it is important to add all the relevant folders and subfolders to the path in order to make all functions available. In addition to the programs provided in the attached zip-file, the Statistics Toolbox for MATLAB needs to be added to use the GARCH program, since it calls some probability distribution functions from the toolbox. For the CAViaR program, some functions are written in C, to make the programs up to a hundred times quicker. In order to call them from MATLAB, they must be converted to MEX files with a C compiler. Our MEX files are found in the attached zip file.

F.2.1 EWQR

First, a work file containing the relevant return series needs to be open in EViews. This series needs to be named “r” for the program to run. Open the file “ewqr. prg” and click run. Among the variables created in the work file are then “var” and “es”, which are matrices containing the VaR and ES forecasts respectively. The vector “theta” contains the considered quantiles, and the columns of “var” and “es” correspond to the elements for “theta”.

Regarding the VaR tests, the program “coverage tests” needs to be run before the “dqtest”. The p-values from the tests are displayed in pop-up windows, but can also be found in the work file as “ucpvalue” (p-value for the unconditional coverage test), “ccpvalue” (p-value for the conditional coverage test) and “dqpvalue” (p-value for the dynamic quantile test). Each row correspond to the test result for a quantile in “theta”.

The ES tests are written in MATLAB. Thus, to perform them some variables need to be exported from EViews and imported to MATLAB. Export the return series “r” and the VaR and ES forecasts “var” and “es”. Import them to MATLAB and run “estest”. This test considers only one quantile at the time, and is done by writing the following command in MATLAB, where r is the out-of-sample period of the returns, THETA is the quantile to consider, VaR and ES are the column of “var” and “es”, respectively, that correspond to THETA, and nb is the number of bootstraped samples to consider (e.g. 10000).

```
[DV1 DV2 IV1 IV2] = estest(r,THETA,VaR,ES,nb)
```

The test results are then put in the variables: “DV1” (one-sided DV test), “DV2” (two- sided DV test), “IV1” (one-sided IV test) and “IV2” (two-sided DV test).

F.2.2 GARCH

To run the GARCH program in MATLAB, simply type one of the following two commands, where r is replaced by the name of a return series that is imported as a variable in MATLAB.

```
rungarch(r,1)

rungarch(r,2)
```

Use the first line to use GARCH(1,1) to estimate VaR and ES, and the second line to use GJR-GARCH(1,1,1). Both of them automatically estimate VaR and ES for all of the six quantiles (1%, 5%, 10%, 90%, 95% and 99%) and the four distributions (normal, student t, GED and skewed student t) and perform the VaR and ES tests. The test results for VaR are saved in the variables “UCpvalue” (unconditional coverage test), “CCpvalue” (conditional coverage test), “DQpvalue” (dynamic quantile test), while the ES test results are names as for EWQR.

F.2.3 CAViaR

A difference between the CAViaR program and the others is that the return series is not imported to MATLAB before running the program. Instead, the program imports it from a .txt file. In order to do so, it is important to change the saving path in line 39 of “CAViaR.m” and the loading path with corresponding variable in lines 34 and 35 of “CAViaROptimisation.m”. When this is done, run the program by typing:

```
CAViaR
```

The program automatically estimates VaR for each quantile for each of the following five CAViaR specifications:

1: Symmetric Absolute Value
2: Asymmetric Slope
3: Indirect GARCH
4: Adaptive
5: Indirect AR-GARCH

The name of the test result variables are the same as for GARCH. In addition more information about each model and quantile is saved in structures such as “output(x)_(y)”, where x refers to the CAViaR specification and y to the quantile. For example does the structure “output1_5” contain among other things VaR forecasts, the hit percentage, volatility forecasts and parameters for the first CAViaR model at the 5% quantile.