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AN EMPIRICAL STUDY OF THE VALUE-AT-RISK OF THE RENEWABLE ENERGY MARKET AND THE IMPACT OF OIL PRICES

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Abstract

Renewable energy is gaining increasing importance in the generation of power due to the finite existence of fossil fuels and concerns about climate change. As its demand grows financial interest from investors' increases, thus it is important to find the most effective way of quantifying the risk of the renewable energy market. Furthermore as renewable energy can be viewed as an economic substitute for other energy sources such as crude oil - a commodity that has been known to have a significant impact on financial markets - an empirical relationship is likely to exist between the two resources. This paper will assess the best way of measuring the risk of the renewable energy market by using one of the most common risk measurement tools Value-at-Risk. Using daily data of the return observations of five renewable energy indices between the 1st of January 2004 and the 12th of June 2015 a total of 2987 observations, the VaR will be estimated for each of these indices. This is achieved using both parametric and non-parametric methods, and then backtesting these using the two-sided Kupiec test to determine which method provides the best estimate of VaR. The non-parametric methods employed in this paper are the Basic Historical Simulation (BHS) and the Exponentially Weighted Moving Average (EWMA) model. The parametric methods applied are the Generalized Autoregressive Conditional Heteroskedasticity, or GARCH (1, 1) model and the Threshold-GARCH, or TGARCH, using both the normal and Student-t distribution. The sample period is split into an in-sample period of 522 days and an out-of-period of 2465 days, where the 522 days will be used as the size of the "rolling-window" which is used to calculate the VaR throughout this paper. After determining which model provides the best estimate of VaR a regression will be run using this VaR estimate as the dependent variable, and the oil price and the three-month rate of a US Treasury bill - taken as the interest rate – as the explanatory variables. The results show that the parametric methods outperform the non-parametric methods with the GARCH (1, 1) model under the Student-t distribution in particular providing the best estimate of VaR. In general they show that the models which can account for heavy-tailed distributions perform better, with all models using the Student-t distribution giving better estimates than the normal distribution. Furthermore a statistically significant relationship between the VaR estimate of any given renewable energy index and the oil price was identified, with a rise in the price of oil causing a decrease in the VaR estimate of the given renewable energy index.

Keywords: Renewable energy, Value-at-Risk (VaR), rolling-window, Basic historical simulation (BHS), Volatility weighted historical simulation (VWHS), Exponentially weighted moving average (EWMA), Generalized Autoregressive Heteroskedasticity (GARCH), Threshold GARCH (TGARCH), Oil, Normal distribution, Student-t distribution, Two-sided Kupiec test

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1. INTRODUCTION

A central characteristic of any modern industrial economy is its reliance on energy resources as inputs to production. Most developed economies are fossil fuel dependent to some degree with petroleum and other liquids being the primary sources of energy consumption at 36% compared to just 8% for renewables between 1990 and 2013 globally (EIA, 2015). However, in the past decade renewable energy investment has increased significantly growing from $45billion in 2004 to $270billion in 2014 (Bloomberg New Energy Finance, 2015) and renewables are expected to account for 10% of energy consumption between 2013 and 2040 (EIA, 2015). This could be due to advances in renewable energy technology that has seen the cost of solar energy, at approximately 13 cents per kilowatt-hour, almost reaching price parity with state-of-the-art coal plants at 12 cents per kilowatt-hour (Helman, 2014). This information is of considerable interest for investors choosing to invest in renewable energy.

Of particular interest in this paper, and for stakeholders is the risk associated with the renewable energy market. Risk management for non-financial firms is said to contribute towards a firm's value: risk management being the process through which various risk exposures are identified, measured, and controlled for (Jorion, 2001). There are two important types of risk: credit risk which is the risk that a firm or individual will default on their loan payment, and market risk which is the risk that market prices may move. The most convenient and common measure of risk, for example, is the standard deviation of returns over one year, however this measure has the tendency to not capture total risk as returns are seldom normally distributed, meaning it assumes equal probabilities of the return being below or above the mean, an unlikely situation. Other measures of market variables that quantify the risk produced daily can be time consuming to interpret due to the sheer quantity of variables to examine. As a result, JPMorgan in 1994 produced a single aggregate risk measure for a 24 hour period across a bank's entire trading portfolio now known as Value-at-Risk (VaR) (Hull, 2012). VaR has become the benchmark measure for quantifying market risk (Manganelli & Engle, 2001) and can be defined as a way of assessing risk using typical statistical techniques. Formally it "measures the worst expected loss over a given horizon under normal market conditions, at a given confidence level." (Jorion, 2001, p.xxii). This interpretation of risk is advantageous due to its simplicity as a means of monetary measurement and risk aggregation providing a summary of market risk; this may explain why it quickly became the standard for financial institutions and some non-financial firms, even becoming required by law as a result of the Basel committee regulation authority in the 1996 amendment (Hull, 2012)

An additional aspect of focus in this thesis, although to a lesser extent, is the impact that the oil price may have on the risk of the renewable energy market. Numerous research studies have indicated a significant relationship between the price of oil and renewable energy companies' share prices, with the general consensus that increases in the price of oil result in a rise in renewable energy share prices (Sadorsky and Henriques, 2008). Further studies have examined the determinants of renewable energy company risk, estimating the impact the oil price has on these companies' risk profile. However, few studies exist that have investigated the VaR of renewable energy indices with none having looked at the effect the oil price has on the VaR of these renewable energy indices: rather the research has measured other forms of risk, such as systematic risk measured by the market beta. Furthermore, to the best of the author's knowledge there has been no analysis regarding finding the best methods of estimating the VaR for renewable energy indices. Thus it is of some interest to analyze the VaR of the renewable energy market and determine whether a relationship between the VaR of renewable energy indices and the oil price exists, with these topics being the main focus of this paper.

This paper looks to build upon the previous literature and to address two key questions:

1) Which method for estimating the VaR of renewable energy indices provides the best estimate?

2) Do fluctuations in the oil price impact on the VaR of these renewable energy indices?

The former is carried out by implementing both parametric and non-parametric methods and subsequently backtesting these to determine which is best. The latter will apply a regression using the VaR estimate of a specific index as the dependent variable, and oil price returns and the risk-free rate as the explanatory variables, so as to determine whether a relationship exists between the VaR of the renewable energy market and the oil price.

1.1 The Renewable Energy Market and Oil Prices

The use of renewable energy existed long before the discovery of fossil fuels, early examples including the sails that powered ships or windmills for crushing grains. However, renewable energy developments tended to stagnate in the wake of the widespread use of fossil fuels through the course of the industrial revolution. The Standard Oil Company was the first energy company to go public on the stock market in the early 1900s, and it wasn't until 1984 that the first renewable energy company, SunEdison Incorporated, did the same. Renewable energy growth has remained fairly steady ever since. It was the arrival of the new millennium that saw real growth in the industry with more companies going public in the first decade of the 21st century than had in all the previous years with renewable energy capacity growing 120% between 2000 and 2014 (IRENA, 2015). The explosion of growth after the year 2000 is likely to be attributable to advances in technologies which helped to increase the efficiency of power generation, lowering costs. It now plays a major role in electricity generation for homes and businesses as efforts to move towards cleaner forms of energy increase and will continue to do so in the future, with some countries such as Scotland targeting to generate 100% of its electricity demand from renewables by 2030 (Nichols, 2015). Due to the increasing role played by renewables in the energy sector it is important to understand how best to measure its risk and examine the relationship it has with oil and other fossil fuels.

Oil prices are subject to significant volatility and the effect these shocks have on the economy are extensively documented, thus it is crucial to analyze these when investigating renewable energy VaR as not only do they derive from a related sector, but they also create risk in the economy as a whole. Increases in the price of oil are held accountable for recessions, periods of excessive inflation, falls in productivity and decreased GDP growth and, in the case of the 1970s oil shock, stagflation (Barsky & Killian, 2004) although whilst increasing oil prices generally affect economic activity negatively, falling oil prices may fail to stimulate the economy. Prior to the 1970's oil crises, oil prices were fairly stable, then they experienced a sharp increase beginning in 1973 when OPEC countries imposed an oil embargo which limited the supply of oil, and raised its price from $3 to $12 per barrel. Since then, oil prices have been considerably volatile with the rise of competition and deregulation creating relatively free energy markets which are subject to high price movements (Sadeghi & Shavvalpour, 2005), and especially to major political events with oil price increases arising in 1979 due to the Iranian Revolution, and similar increases occurring in 1990 and 2003 as a result of both the Gulf war and Iraq war (Barsky & Killian, 2004).

Particularly significant is the relationship between oil prices and the stock market, with Sardosky (1999) finding that positive shocks to oil prices depress real stock returns. Jones & Kaul (1996) identified a similar relationship between aggregate stock returns and oil prices. So, given that oil price volatility contributes to stock market volatility, and previous research has shown a positive relationship between oil prices and renewable energy stock prices, it is interesting to investigate the relationship between oil price changes and VaR in renewable energy.

1.2 MOTIVATION

There appears to be a shortage of literature regarding the VaR of renewable energy indices. Earlier research papers in related areas have tended to focus on the financial risks involved in investing in renewable energy; how the price of oil affects the share price; or the systematic risk associated with renewable energy companies. This paper aims to evaluate the VaR of renewable energy markets and determine the best method for quantifying this risk, as well as investigating whether oil price fluctuations impact the VaR of the renewable energy indices. While there is a significant amount of literature involved in finding the best estimate of VaR by applying a number of different models, few have adopted the Threshold GARCH to estimate VaR that will be used in this paper.

This subject is of considerable significance in the current financial economic environment due to growing concern over climate change, with BP's annual energy outlook forecasting global energy demand to increase by almost 40% and CO2 emissions by 25% by 2035, a demand that BP claim can only be satisfied by use of fossil fuels (BP, 2015).[1] These increases are bound to have negative effects on the environment and with a knock on impact on the economy. This has led to increased financial investment in renewable energy such as the decision made by the Rockefeller Brothers Fund and other global investors to divest $50billion in fossil fuel assets over the next five years, and instead invest in clean energies (BBC, 2014). Thus the current financial significance of renewable energy is evident.

Moreover climate change and renewable energy risk is important for policymakers' decision making processes as political pressures arise from groups wanting to see a reduction in CO2 emissions and fossil fuel dependence. The inability to meet a binding legal contract on climate

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[1] However this report could be subject to bias due to a conflict of interests on behalf of BP one of the largest oil producers in the world.

change at the 2009 United Nations (UN) Copenhagen climate conference was deemed a catastrophic failure by Dubash (2009). Revelations of the US National Security Agency spying on communications between key countries prior to and during the conference has only heightened this pressure (Goldenberg and Vidal, 2014). This has culminated in the 2015 UN Climate Change Conference in Paris being billed as the 'last chance' to limit global warming to below 2 degrees Celsius with the goal of moving to zero carbon emissions by 2050. Any rises above this temperature are expected to have disastrous impacts on the environment (Briggs, 2015). To help address the concerns expressed by pressure groups policymakers need to understand the effect oil prices have on the investment and VaR of the renewable energy industry. Specifically, which policies can help decrease dependence on fossil fuels and encourage additional investment in renewable energy, and which policies have an impact on the VaR within the renewable energy sector.

1.3 Literature review

The first five papers examined here look at cases where risk has been measured for renewable energy firms and whether or not the oil price exhibits any relationship with this, while the remaining papers attempt to find the best VaR estimate for fossil fuels.

Henriques and Sadorsky (2008) using weekly data on the Wednesday closing prices for one clean energy index, one technology index and the West Texas Intermediate crude oil future prices - from January 3rd, 2001 to May 30th, 2007 - implemented a four variable vector auto-regression (VAR) model to determine the empirical relationships between alternative energy stock prices, technology stock prices, oil prices, and interest rates. These VAR models were then used to test Granger causality, whereby the lag of one variable is used to explain the current value of some other variable. Their Granger causality tests indicate that alternative energy stock prices can be explained by past movements in all the previously stated variables. However, despite oil prices having some power in explaining movements in alternative energy stock prices, they unexpectedly found that a one standard deviation oil price shock has no statistically significant, impact on alternative energy stock prices. This implies oil price shocks are not as important as shocks to technology stock prices which are both positive and statistically significant, being felt up to a minimum of ten weeks in the future. Furthermore, in terms of risk, they find that the WilderHill

Clean Energy index of alternative energy companies holds a market beta of approximately 2, thus for a one percentage point change in the U.S. market the index moves by 2%, which is more comparable to technology companies than energy companies, with oil firms exhibiting a beta of around 0.7. However, the general consensus is that renewable energy is sensitive to events in the oil market, with higher oil prices stimulating interest in renewable energy companies, and vice versa, as well as persistently high oil prices manifesting incentives to find substitutes for oil.

Sadorsky (2012) using data from a sample of renewable energy companies, the closing price of WTI future contracts, and firm level data such as company size, from 2001-2007, constructed a variable beta model to investigate the determinants of renewable energy company risk. The model is an extension of the CAPM which, in this case, incorporates several different factors on systematic risk - the aim being to model the relationship between systematic risk and return for some publicly traded renewable energy companies, accounting for time varying risk. He finds similar results to the Henriques and Sadorsky (2008) study with renewable energy companies having a market beta of approximately 2, implying they are twice as risky as the market standard. Moreover he finds a negative relationship between company sales growth and systematic risk, and a positive relationship between oil price returns and systematic risk, implying risk increases as oil price returns increase, although when oil price returns are positive and moderate, increases in sales growth can offset the effect of oil price returns, resulting in lower systematic risk.

Kumar et al (2012) analyze weekly data from three clean energy indices, the price of technology indices, oil price and the carbon price from April 22nd, 2005 to November 26th 2008 using a five-variable VAR model to study the relationships between clean energy companies' stock prices, technology companies' stock prices, oil prices, carbon prices and interest rates. They find that fluctuations in the three clean energy indices can be explained by past movements in the oil price, stock price of technology firms, and interest rates, but not by the carbon price, with a positive relationship between oil prices and the clean energy indices, in addition to the oil price creating a significant risk factor for these indices. Furthermore, by conducting a forecast error variance for the models used in this study, they find that volatility in oil price, technology stock prices and interest rates, contribute the main source of shock, accounting for 30% of total variability in the clean energy stock price.

Wen et al (2014), using daily samples taken from August 30th 2006 to September 11th 2012, study the return and volatility spillover effects between the stock prices of new energy and fossil fuel firms in China, using a bivariate, asymmetric BEKK model that captures the time-varying volatility of the return series and volatility clustering to model these spillovers. They concluded that new energy and fossil fuel stock spillovers are significant and asymmetric. Furthermore they found that new energy and fossil fuels are perceived as competing assets and positive news about new energy stocks may affect the appeal of fossil fuel stocks, while new energy stock investment is more speculative and riskier than fossil fuel stock investment, showing a distinct interaction between fossil fuels and new energy.

Reboredo (2015) applying daily data for six clean energy stock price indices and Brent oil between December 20th, 2005 and December 12th, 2013 set out to study systematic risk and dependence across the price of oil and renewable energy markets. By implementing copulas to determine the dependence structure between crude oil and clean energy share prices, and then studying the impact the co-movement between crude oil and clean energy share prices has on the systematic risk for these two variables, he was able to calculate the conditional VaR (CoVAR) and measure the systematic risk. The results show that extreme upward or downward oil price movement contributed to around 30% upside or downside risk, meaning an extreme oil price movement increased the VaR of the renewable energy indices by 30% over the VaR when oil prices took normal values. Similar, to some extent, to the analysis in this paper, Roboredo, first has to determine which copula produces the best estimate, before calculating the CoVaR. By the use of parametric and non-parametric methods, as well as an array of distributions for estimating the copulas, he finds, by comparing the AIC specifications of these different copula models, that the time-varying parameter Student-t copula provides the best fit for all the variables, and thus calculates the CoVaR for each series using this copula.

Research that attempts to find the best models for estimating VaR has tended to focus on the energy markets of fossil fuels. One such example, by Sadeghi and Shavvalpour (2005), uses weekly OPEC oil prices from January 1997 to December 2003; they applied Historical Simulation ARMA forecasting (HSAF) and Variance-Covariance models based on GARCH methodologies and found that the HSAF method produced the most efficient results when compared to the Variance-Covariance method. Cabedo and Moya (2003) found comparable results using daily spot Brent prices from January 1992 to December 1999. They reported that the HSAF approach provides a better VaR estimation than the standard HS, as the former allows a more flexible VaR quantification which models continuous price movements more accurately. Furthermore, they found the HSAF delivers a more efficient risk quantification estimate than those given by the GARCH (1, 1) model that overestimated the maximum probable oil price changes.

Fan et al (2008) estimated the upside and downside VaR of returns for WTI and Brent crude spot prices and its spillover effects using GARCH models under the Generalized Error Distribution (GED) over the period 1987 to 2006. Contrary to the findings of previous papers, their results show the GED-GARCH-based VaR method produces better estimates than the HSAF. Aghayeva and Rizvanoghlub (2014) also prefer the GARCH (1,1) with the GED finding it to provide better estimates of the VaR than the TGARCH and EWMA models in their study on the Azeri Light Crude Oil price from the 17th June, 2002 to 18th June 2013. Sadorsky (2006) analyzed different univariate and multivariate ARCH statistical models to assess forecasts of daily volatility in petroleum futures price returns between February 5th 1988 and January 31st 2003 and found that non-parametric methods outperform parametric models in relation to the number of violations in the backtests, concluding that the simple, single equation GARCH outperforms techniques like the moving average and other more complicated models such as the bivariate GARCH. Brooks and Persand (2003) also prefer simpler models such as the autoregressive volatility or historical average models to provide better VaR estimates than their GARCH parametric counterparts.

Andriosopoulos and Nomikos (2012) evaluated data on spot prices from eight energy markets that trade future contracts on NYMEX and the Spot energy index, including propane, natural gas and oil. They assessed several VaR models to capture the dynamics of energy prices and quantify the energy price risk by calculating VaR and ES measures. Comparing a variety of techniques to estimate the VaR such as ARCH models, a Monte Carlo simulation and a Hybrid Monte Carlo Historical Simulation, which they developed by combining the advantages of both the Monte Carlo and Historical Simulation methods, they found this Hybrid method to provide the best VaR estimate. Studies by Huang (2010) indicate that Monte Carlo Simulations provide the most accurate estimates due to its flexibility and its ability to model key aspects of energy markets' behaviour such as seasonality, fat-tails, skewness and kurtotsis.

One issue relating to parametric methods, such as the variance-covariance technique, concerns assumptions about return distributions as these methodologies tend to assume normal or Student-t distributions (Huang, 2010). However, many scholars[2] mention the possibility of fat-tails which are common in return distributions and the normal distribution does not account for this. Symmetry and asymmetry are other prominent features in the literature. Reboredo (2015) identifies positive and symmetric dependence between oil and renewable energy prices, as well as displaying symmetry between the VaR of renewable energy companies and extreme oil price movements for all indices, except the solar index, which was affected asymmetrically. Wen et al (2014) also find significant evidence of asymmetric return spillovers between Chinese new energy and fossil fuel stock prices, with negative (good) news about new energy causing higher (a fall in) returns to spill over into fossil fuel returns, while positive news about fossil fuel stock returns causes a rise in new energy returns the next day. Specifically they find negative news about the stock returns of either of the energy sources results in larger changes in their opposing asset than is the case with positive news, displaying clear asymmetric effects. Regarding their volatility spillovers they also find that both energy sources spill over into the variances of each other, with increases in fossil fuel stock return volatiles being higher for negative fossil fuel return shocks, than for positive ones. Andriosopoulos and Nomikos (2012) note additionally that volatility clustering is another characteristic displayed by energy market returns.

Similar features are likely to be encountered in this study. It is therefore expected that the GARCH (1, 1) model under the Student-t-distribution will provide the best estimate of VaR as it can account for volatility clustering and fat-tails. However it should be noted that, despite most of the literature suggesting the oil prices do have some part in explaining movements in the prices of renewable energy shares, with high oil prices leading investors to look for alternative energy sources, Sardosky (2012) finds the effect is not considerably statistically significant. Nonetheless, one thing the literature does seem consistently to agree upon is that fluctuations in the oil price do impact upon the risk of renewable energy companies. Intuitively it seems likely that fluctuations in the oil price will have a significant impact on the VaR of these indices.

[2] Roberedo (2015), Andriosopoulos & Nomikos (2012), Huang (2010), Sadorsky (2006), Fan et al (2008) and Wen et al (2014) all mention the common occurrence of fat-tails in the return distributions.

This paper follows a similar path to the research outlined above with the first part investigating the risk of the renewable energy companies in the manner of Sadorsky's work, together with an attempt to find the best method of estimating VaR in the manner of Sadeghi and Shavvalpour (2005) and subsequent papers, by using both parametric and non-parametric methods to determine the VaR and backtesting them to determine their accuracy. The latter part of the study aims to determine whether the price of oil impacts on the VaR of renewable energy indices in a manner similar to Reboredo's (2015) work.

2. THEORETICAL FRAMEWORK

This section defines the concept of VaR, the various methods that are used for calculating it, either non-parametric or parametric, the distributions used, and the backtests for determining the VaR estimates' accuracy. It also describes how the regression of the VaR on the oil price and the risk-free rate will be carried out.

2.1 VALUE-AT-RISK

The VaR is an attempt to provide a single value that summarizes the total risk in a portfolio. According to Hull (2012) it is defined as "the smallest loss l such that the probability of a future portfolio loss L that is larger than the loss l, is less than or equal to 1-α" within a specific holding period (Nilsson, 2014, p.2). It can be expressed more formally as:

$$VaR_{\alpha} = \min\{l: \Pr(L > l) \leq 1 - \alpha\} \qquad (1)$$

When perceived statistically VaR is the quantile of the loss distribution, being the distribution of stochastic variable L. The analysis in this paper will use the most common confidence level, $\alpha = 0.99$. The confidence level allows statements to be made regarding the probability of observing a loss, for example, at a 99% confidence level, the probability of observing a loss greater than l is less than or equal to 1%. This confidence level is chosen as it is the standard choice in risk management and is the one required by the Basel regulation for market risk. The analysis will also use a holding period of 1 day, this is because shorter holding periods are better suited for backtesting procedures to determine a model's reliability (Dowd, 2005). This thesis will focus on the probability distribution of the loss where gains are negative losses, meaning positive values are losses, so evaluation will occur in the right tail of the distribution.

There are many advantages of using value-at-risk, the first being that it provides a common reliable measure of risk across different positions and risk factors, meaning it can be applied to all asset classes, allowing for comparisons of risk between different portfolios, improving on the constraints of other traditional risk measures (Dowd, 2005). Secondly, it allows for risk aggregation by adding observed losses from an individual asset, together with other assets to get loss observations for a whole portfolio. Thirdly, VaR is holistic, in the sense it considers all of the influential risk factors and focuses its evaluation on a complete portfolio at a firm-wide level (Dowd, 2005). Furthermore, VaR is probabilistic, giving information about the probability of losses larger than VaR. Finally, it offers a simple interpretation measurable in terms of monetary units, which is clearer than some alternative risk measures. To sum up, "VaR can help provide for a more consistent and more integrated approach to the management of different financial risks, and so lead to better risk management overall" (Dowd, 2005 p13).

However, VaR also has its drawbacks: a key limitation being it only provides evidence of the maximum loss if a tail event does not occur. However, it is silent about the size of loss if a tail-event does occur, meaning that the loss could exceed the VaR. Therefore, there is the potential for traders to manipulate the risk limits imposed by the bank, by constructing a portfolio that meets the bank's requirements of having only a 99% chance of losing $1 million a day, but a 1% chance of losing $100 million a day, pursuing high risks for high returns (Hull, 2012). This has been evident in the media on a number of occasions. Moreover, the VaR is sensitive to incorrect assumptions regarding the loss distribution, as the VaR uses assumptions, such as normality, that applies the central limit theorem showing that, as the number of observations increases, the mean converges to a normal distribution. While appropriate for physical sciences, this is not so applicable to the social science of economics where agents can act irrationally in response to the market environment and can thus cause significant errors in the VaR estimates. VaR also has the potential to destabilize the financial system during a crises because if everyone operates under the same VaR constraints and a crises ensues everyone will simultaneously start trying to sell stock to reduce risk, making uncorrelated risks become correlated (Dowd, 2005). Finally, VaR fails to satisfy the sub-additivity[3] condition that states the risk measure for two portfolios, once combined, should not exceed the sum of their individual risk measures; this condition is one of four principles that a good risk measure should adhere to and was suggested by Artzner et al (1999).

[3] Subadditivity states the risk measure for two portfolios once combined should not exceed the sum of their individual risk measures.

2.2 Distributions

Normal Distribution

The normal distribution is a continuous distribution and is paramount to statistical analysis as it has a closed form for the quantile as a function of the mean and volatility, assuming market variables are normal therefore allows for calculation of a confidence interval from daily volatilities. This is key when calculating the models that take account of the weighting of volatilities such as the EWMA, GARCH and TGARCH methodologies employed in this paper. The normal distribution is derived from the mean μ and the standard deviation σ, the probability density function of which is a bell shaped curve (see Figure 1) and is described by:

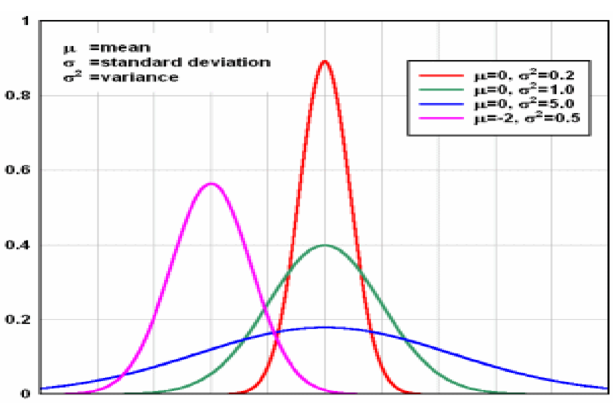
$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2}(\frac{x-\mu}{\sigma})^2\right]$$

where $X \sim N(\mu, \sigma)$, meaning the stochastic variable denoted by X is normally distributed with mean μ and standard deviation σ. The VaR estimate for this type of distribution is calculated from:

$$VaR_\alpha(L) = \mu + \sigma z_\alpha \qquad (2)$$

where z_α is the critical value for the standardized normal distribution at the confidence interval α, which, at the 99% and 95% confidence levels, have the corresponding values of 2.326 and 1.960; here VaR is always estimated one period out of sample (i.e. for the next day).

Figure 1: *Normal Distributions*. (dplot, 2015). Examples of normal distributions are shown here using different means μ which determine the center of the distributions and the standard deviations σ which quantify the amount dispersion over the set of data, the closer σ is to zero the closer the data points will be to the mean, like the red curve, and the higher the standard deviation the more spread out is the curve like the blue curve.



However, it should be kept in mind that financial variables are frequently subject to greater movements than the normal distribution would suggest, with return distributions exhibiting fat-tails, particularly in the energy markets, which the following distribution will look to model.

STUDENT-T DISTRIBUTION

The Student-t distribution is often better suited to financial models than the normal distribution as it can account for excess kurtosis or fat-tails often found in return distributions by placing more probability in its tail ends (see Figure 3). If $Z \sim N(0,1)$ and $\xi \sim \chi_J^2$, then if and Z and ξ are independent the Student-t ratio is:

$$t = \frac{Z}{\sqrt{\xi/J}},$$

meaning it has a Student-t distribution with J degrees of freedom, and as $J \to \infty$ the t-distribution tends to the normal distribution (Verbeek, 2008). Similar to the normal distribution, it is symmetric around 0 but with fatter tails, as depicted on the next page. The probability density function of a Student-t distributed variable with volatility, σ and degress of freedom v can be written in the following way:

$$f(x) = \frac{\Gamma[(v+1)/2]}{\sigma\sqrt{(v-2)\pi}\Gamma(v/2)}\left[1+\frac{1}{v-2}\left(\frac{x-\mu}{\sigma}\right)^2\right]^{-(v+1)/2} \quad for\ x \in (-\infty,\infty)$$

For the Student-t distribution the VaR is calculated by:

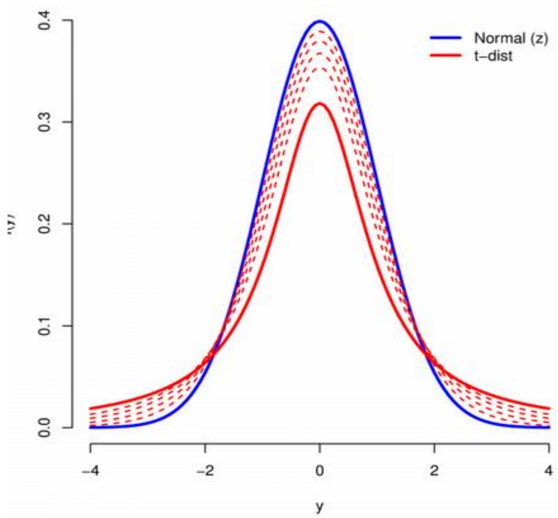
$$VaR_\alpha(L) = \mu + \sqrt{\frac{v-2}{v}}\sigma t_{\alpha,v}\,, \tag{3}$$

where the respective 0.99-quantiles were calculated in Excel[4]

---

[4] Using the function T.INV().

Figure 2: *Student-t distribution.* Source (Otexts, 2015). The blue curve shows the normal distribution and the red curve shows the Student-t distribution, it can be seen that the Student-t distribution places more probability in its tails, which is why it is higher than the normal distribution curve's tails.



2.3 NON-PARAMETRIC METHODS

Non-parametric methods of estimating VaR are exactly those that do not require parameters to be estimated from the sample of observed losses; rather, they rely on the empirical loss distribution, using recently observed loss values to forecast risk in the future. The non-parametric methods adopted in this thesis, are the Basic Historical Simulation and Exponentially Weighted Moving Average methodologies. In this thesis, a sample size of 2987 is used with an in-sample size of 522 and an out-of-sample size of 2465 so a rolling window of 522 days is applied. The rolling window methodology involves calculating the returns from the historical prices of each index, and then converting these into equally weighted losses and gains by multiplying by negative one. This rolling window uses the first 522 days of loss observations to estimate the VaR for the first day in the out-of-sample period then, keeping the window size fixed at 522, it begins at the second loss observation, to find the second day's VaR estimate for the out-of-sample period and so on[5]. It is this rolling window methodology that will be applied to all of the models in this paper

[5] The VaR calculation, in this case, involves using the PERCENTILE.INC() function in Excel that requires inputting the chosen array, 522, and chosen confidence level: in this case, 99%.

BASIC HISTORICAL SIMULATION

This methodology uses the history of past returns to determine the losses and the possible distribution of future returns; it is the simplest tool for evaluating VaR assuming that this historical data can explain the future (Hull, 2012). In this thesis a sample size of 2987 is used with an in-sample size of 522 and an out-of-sample size of 2465. Assuming a sample of N losses and gains it follows that there will be approximately $(1-\alpha)N$ losses that are greater than VaR if the VaR model is correct; here it is the $(1-\alpha)N+1$ largest loss in the sample that will be used as the estimate of VaR. As the rolling window is 522 it is expected, at the 99% confidence level, that there will be 5.22 losses larger than VaR in the sample every two years or 522 days, so the 6.22 or 6th largest lost in the sample will be the chosen estimate of VaR.

VOLATILITY WEIGHTED HISTORICAL SIMULATION

First proposed by Hull and White (1998) it suggests that historical simulation can be improved by considering the volatility changes experienced during the sample period of historical data, as the probability distribution of a market variable, when scaled by its volatility, is discovered to be approximately stationary. The inference being that if volatility is lower (higher) than average in the current period then it is expected to be lower (higher) than average in the next period, as a result of the volatility clustering phenomenon (Nilsson, 2015). Essentially, VWHS involves rescaling the losses by assigning each loss a weight that takes into account current market conditions i.e. volatility. Assume a sample of T[6] losses $l_1, l_2, .., l_T$ is observed these are rescaled by:

$$l_1^* = \frac{\sigma_{T+1}}{\sigma_1} l_1$$

$$l_2^* = \frac{\sigma_{T+1}}{\sigma_2} l_2$$

$$\vdots$$

$$l_T^* = \frac{\sigma_{T+1}}{\sigma_T} l_T \tag{4}$$

[6] Sample size is denoted by T as this is considered a time-series method.

where $\sigma_1, \sigma_2.., \sigma_T$ are the volatilities corresponding to the observed losses and σ_{T+1} is a forecast of the volatility for the next holding period. For the purposes of this paper, rather than calculate σ_{T+1} for every day of the out-of-sample test period, which would take a considerable amount of time, each σ_{T+1} is, instead, updated for the first day of every year in the out-of-sample test period. It should be noted that one implication of this approach is that it can be detrimental to the volatility estimates, as if the volatility is high on the first day of the year it will continue to affect the volatility for the remainder of that year, even if the volatility is actually much lower over this period. A more accurate methodology would therefore be to update the volatility on a monthly basis.

The particular VWHS used in this thesis is the exponentially weighted moving average, or EWMA model which uses the following formula to update volatility estimates:

$$\sigma_t^2 = (1-\lambda)e_{t-1}^2 + \lambda\sigma_{t-1}^2 \text{ for t=1.2,...2987} \qquad (5)$$

where the estimate σ_t^2 for day t is calculated from the previous day's conditional variance σ_{t-1}^2 and e_{t-1}^2 are the residuals constructed by subtracting the mean from the sample of losses. The parameter λ acts as the weight and determines how sensitive the estimate of σ_t^2 is to e_{t-1}^2, a low value of λ results in more weight being given to e_{t-1}^2 when calculating σ_t^2 meaning these volatility estimates are more sensitive, as they decay quicker, while a high value (close to 1) causes the estimates of daily volatility to respond slower to changes in e_{t-1}^2. Here λ is set to equal 0.94 as is commonplace in RiskMetrics database because it was found this value gave forecasts of the variance rate similar to that of the realized variance rate (Hull, 2012).

Once the daily conditional variance has been calculated, the square root is taken to give the standard deviation which is used to rescale the losses as shown in equation 4; these volatility-scaled losses are then calculated for each year of the test period. The basic historical simulation is then implemented on these rescaled losses, using the rolling window of 522 days which is updated every year, so that the corresponding year of estimation coincides with the rolling window for that year, once again using Excel[7]. VaR can then be calculated using equations (2) and (3) for the normal and Student-t distribution.

[7] The PERCENTILE.INC() function as applied previously.

ADVANTAGES & DISADVANTAGES OF NON-PARAMETRIC METHODS

There are a number of advantages and disadvantages that are important to keep in mind when using non-parametric methods. Firstly, they are intuitive and relatively simple to implement as there are no restrictive parametric assumptions that need to be made about the profit / loss distribution, and so they can account for the fat-tails and skewness that raise concerns in parametric techniques. Secondly, they can be applied to accommodate any financial instrument as it directly uses the loss distribution, using data that is readily available. Finally, they are absent from the curse of 'dimensionality' as they automatically take the correlations between portfolio components into account and any problems that are experienced are capable of improvement through semi-parametric methods such as EWMA (Dowd, 2005).

Concerning the disadvantages, their greatest weakness is their results are almost completely dependent on the historical data set. If the dataset is gathered over a fairly calm period there is the potential for the estimates of VaR to be too low, while if the dataset is too volatile it can produce VaR estimates that are too high. Secondly, they are relatively slow in reflecting changing market conditions even despite the aid of volatility weighting. They are also constrained by the largest loss in the sample, unlike their parametric counterparts, meaning that they perform badly during volatile periods. Finally, they are subject to 'ghost effects' whereby a big loss is mistakenly removed that, if included, would have had a large effect on the VaR estimate.

In general, they are useful for the estimation of VaR with a reasonable amount of evidence to support this, often outperforming parametric methods that assume normality. Moreover, they allow for adaptations to the measures that increase performance. However, when market conditions are volatile their accuracy decreases; this could prove to be a problem as the sample size used in this thesis includes the 2007/08 financial crisis.

2.4 PARAMETRIC METHODS

Parametric methods are an alternative way of measuring VaR that require the specification of particular statistical distributions from which data observations are pooled; these distributions include the normal and Student-t outlined earlier (Dowd, 2005). They are deemed parametric as they involve the estimation of parameters such as the standard deviation and tend to provide the most accurate measures of VaR. Some concerns have been raised (Jorion, 2000) over the correct selection of distribution as they do not always fit the data. One example of this being Reboredo's (2015) study that found high values of kurtosis consistent with fat-tails for all of the energy series leading to a rejection of the normal distribution. Dowd (2005) stresses that when implementing parametric methods, assumptions are consistent with the characteristics of the empirical process, such as skewedness or excess kurtosis, which is why the Student-t distribution has been employed as fitting a distribution to data unconditionally – i.e. disregarding information that suggests volatility clustering is present - will lead to excess kurtosis. Thus, to account for volatility clustering, it is important to fit a model that is conditional on the fact that there may be volatility clustering, such as fitting a Student-t distribution conditional on a GARCH volatility process, that would take account of the fat-tails and volatility clustering often found in the return distributions of energy markets. It is the GARCH (1, 1) model and the Threshold GARCH that will be applied here.

GARCH (1,1)

The GARCH (1, 1) model proposed by Bollerslev (1986) built on the earlier work of Engle's (1982) ARCH methodology; it aims to model the conditional variance to be dependent upon its own previous lags, placing more weight on recent information, by allowing for past conditional variance to be included in the current conditional variance equation. It is based on a mean equation and a variance equation, the former of which is interpreted as a first-order auto-regression process it can look like:

$$y_t = a + \gamma y_{t-1} + e_t$$

where ε_t is a white noise process with mean zero and variance σ^2, while the conditional mean of y_t is γy_{t-1} and the unconditional mean is zero. The (1, 1) in the GARCH model tells us that the conditional variance σ_t^2 is based on the most recent observation of the error e_{t-1}^2 and the most recent estimate of the variance rate σ_{t-1}^2, it is specified by:

$$\sigma_t^2 = \omega + \alpha e_{t-1}^2 + \beta \sigma_{t-1}^2 \qquad (6)$$

where the conditional variance is a one-period ahead estimate for the variance calculated, and ω, $\alpha$and β are parameters that need to be estimated (Brooks, 2008). For the unconditional variance to be defined $\alpha + \beta < 1$ because $\frac{\omega}{1-\alpha-\beta} > 0$. The GARCH (1, 1) model is useful for our anlaysis as it can account for volatility clustering, where high variance last period results in high variance next period and is leptokurtic meaning it is heavy-tailed, thus allowing to unconditionally account for fat-tails (Bollerslev, 1986).

THRESHOLD-GARCH (1, 1)

Previous ARCH and GARCH models assumed that a shock at $t-1$ whether positive or negative, would have the same effect on present volatility when, in fact, there is evidence of asymmetry in the correlation between present volatility and past volatility (Zakoian, 1994). The Threshold-GARCH or TGARCH, aims to model these asymmetries in volatility by making positive and negative parts of the innovation process have different impacts on the conditional variance (Glosten et al, 1993) it is described by:

$$\sigma_t^2 = \omega + \alpha e_{t-1}^2 + \gamma e_{t-1}^2 \bar{I}_{t-1} + \beta \sigma_{t-1}^2 \qquad (7)$$

where $\bar{I}_{t-1} = 1$ if $e_{t-1}^2 < 0$ and 0 otherwise, this allows good news where $e_{t-1}^2 > 0$, and bad news where $e_{t-1}^2 < 0$ to have different effects on the conditional variance. Good news has an impact of α while bad news has an impact of $\alpha + \gamma$, and if $\gamma > 0$ then bad news increases volatility more than good news, and we say there is a leverage effect (Glosten et al, 1993).

ADVANTAGES & DISADVANTAGES OF PARAMETRIC METHODS

The biggest advantage of parametric methods is they are not dependent on the sample as the distributions are fitted to the data, meaning that the VaR can be calculated at very high confidence levels. For example, with a Student-t-distribution that has higher probability for large losses due to its fat-tails, as well as higher probability for losses close to the mean, it must therefore have lower probability for immediate losses. Therefore, the VaR does not care about the distribution of losses larger than VaR. This means they can account for VaR observations being greater than the largest loss in the sample, by choosing a higher confidence level as the tails stretch to infinity (Nilsson p.5, 2015). Another important advantage is that they are more powerful than their non-parametric counterparts, due to the fact they include additional data within the distribution function (Dowd, 2005). This allows them to model the heavy-tails and skewness found in most return distributions and explains why they often provide more accurate estimates of VaR than non-parametric estimates that are subject to more uncertainty, especially at the 99% confidence level

(Miazhynskaia and Aussenegg, 2006). However, these parametric methods can be subject to considerable error where models are specified incorrectly. They are also much more complex in their calculations than non-parametric methods as certain parameters need to be calculated; this can increase the chances of misspecification as evident in this study.

2.5 BACKTESTING

To determine the accuracy of the VaR estimates produced by each of the outlined models a number of statistical tests can be implemented which can rank a group of models against each other in an attempt to determine which is best.

KUPIEC FREQUENCY TEST

The Kupiec frequency test is the chosen backtesting procedure for this study; it is the standard frequency test used to determine the accuracy of the VaR estimates. Developed by Kupiec (1995) it compares the actual or observed frequency of VaR violations with the expected or predicted frequency of VaR violations over the test period, in order to determine whether the number of violations exceeds the number of expected violations. When the observed frequency of violations deviates significantly from the predicted frequency of violations, the methodology used to evaluate the VaR estimate, is statistically rejected.

A violation occurs when a loss in the sample exceeds the VaR estimate for that specific day, in the event that a violation occurs it is denoted by one (1) and a non-violation by zero (0). Summing all these observations together gives the number of violations over the sample period, it is thus a binomial test, where the cumulative probabilities are calculated by:

$$\Pr(X \leq x) = \sum_{i=0}^{x} \binom{N}{x} p^x (1-p)^{N-x}$$

where x represents the number of observed violations, p is the expected relative frequency of VaR violations derived from $p = 1 - \alpha$, where α is the chosen confidence level, and N is the number of observations in the test period.

A two-sided Kupiec test was chosen for the purpose of this paper. To carry out this test a confidence interval of 99% is used to determine the number of expected VaR violations at the upper and lower bounds, (x_{low}, x_{high}). Using the function in Excel BINOM.INV, this requires the size of the test sample, 2465, the probability p found from $1-\alpha$ in this case 1%. The chosen significance levels here are 99% and 95%. As the distribution looks to the left 0.5% of the probability is to the left of x_{low} and 99.5% of the probability is to the left of x_{high}. The results are shown in Table one below.

Table 1: *Two-sided Kupiec test*

Statistical Significance level	95%	99%
Confidence level	99% VaR	99% VaR
x_{low}	15	13
x_{high}	35	38

For clarification, the first column of the above Table shows the two-sided Kupiec test for the 99% VaR at the 95% statistical significance level, while the last column shows the 99% VaR at the 99% statistical significance level. The first columns was calculated using:

$$x_{low} = BINOM.INV(2465, p, 0.025) \; and \; x_{high} = BINOM.INV(2465, p, 0.975)$$

Where p=1-α corresponds to the chosen VaR confidence level. While the latter column was calculated using:

$$x_{low} = BINOM.INV(2465, p, 0.005) \; and \; x_{high} = BINOM.INV(2465, p, 0.995)$$

2.6 Regressing the Value-at-Risk on the oil price and risk-free rate

After the backtests have determined which model provides the best estimate for VaR a regression of VaR on the oil price returns and the risk-free rate will be carried out in order to determine whether a relationship exists between the VaR and the two explanatory variables. The relationship between the VaR and the oil price returns is of most interest for the purpose of this paper as the nature of the oil price has been proven to influence renewable energy investment because renewable energy and oil are considered to be economic substitutes. Evidence of changes in the oil price affecting the risk of renewable energy markets has also been outlined in the literature review. The interest rate is also included; as this was noted by Managia and Okimotoc (2013) to have an effect on renewable energy risk, as well as the stock price of the renewable energy market, as stated previously by Henriques and Sardosky (2008). The particular risk-free rate chosen is the three-month US Treasury bill rate.

There are five regression models estimated using Ordinary Least Squares (OLS), one for each renewable energy index. These will be specified as follows:

$$VaR_{i,t} = \alpha_i + \delta_1 oil_{t-1} + \delta_2 r_t + \varepsilon_t \quad t = 1 \text{ ....} 2465 \qquad (8)$$

where i, will denote the name of the index, and t is the time parameter.

3. APPLICATION AND RESULTS

This section will begin by describing the data used to carry out the analysis and how it was applied to each of the VaR methodologies and regressions; it will then present the empirical results of the four methods used to calculate VaR from this data, based on the results of the backtests and the finally the results of the regressions.

3.1 DATA

The renewable energy market is to some extent a still emerging one. However, despite renewable sources not being traded on the commodity market there exists a number of renewable energy companies that have been publicly traded over the course of the past three decades. Moreover, there are number of renewable energy indices that began to appear in the late nineties and early noughties that focus on renewable energy companies and clean energy technologies; these can be interpreted as representations of the price of renewable energy for the purpose of this paper. Additionally, there are alternative energy indexes that include renewable energy and natural gas. However, these are excluded from analysis as this paper is concerned only with renewable energy. Most of the indices in question were started in the early noughties and there are now approximately 12 global indices and 10 regional indices. Due to restrictions on the availability of several of the indices and further problems obtaining an appropriate sample size, only five indices have been selected here, four global and one regional.

The four global indices are; the Ardour Global Energy Index which tracks 111 companies that focus only on the renewable energy sector (Ardour Global, 2015); the S&P global clean energy index which track 30 companies whose business is clean energy related, and is a modified capitalization-weighted index (S&P Dow Jones Indices, 2015); the FTSE ET50 index which measures the performance of the 50 biggest companies in the world where 50% of their business is in the development and deployment of environmental technologies (FTSE, 2015); and the WilderHill New Energy Global Innovation Index, which is a modified, dollar-weighted index tracking 86 companies that focus on renewable energy technologies and processes of clean power and energy efficiency (WilderHill New Energy2015). The one regional index that will also be analyzed is the WilderHill Clean Energy Index which is the oldest of the indexes; it focuses on 42 clean energy companies on the U.S exchanges, and is a modified, equal-dollar weighted index that has become a benchmark index for renewable energy (WilderHill Clean Energy Index, 2015).

The West Texas Intermediate spot price measured in U.S Dollars is one of the most referenced commodities and a benchmark for the U.S. As the sample size for this analysis is limited, due to the relatively new emergence of renewable energy indices, the time period considered is a restricted one from the 1st of January 2004 to the 12th of June 2015. There is a significant amount of fluctuation in the oil price to evaluate over this period which includes the impact of the 2007/08 financial crisis and the more recent price decline that started in 2014. WTI crude oil peaked on June 20th at approximately \$107 and has since fallen to approximately \$50 as of the 8th April 2015. This resulted partly from the failure of OPEC to reach an agreement on production curbs on November 27th 2014 (Economist, 2014) but was also due to the fact that China one of the largest consumers of crude oil has reduced its demand for the commodity falling 2.5% in September 2014; this reduction, coinciding with the slowing of growth in its economy, has influenced the falling oil price (Stephen, 2014) which has also been impacted by the increased consumption of shale gas in the US which is an economic substitute for crude oil (Macalister, 2014). The risk-free rate chosen is the three-month rate on a US Treasury bill following Managia and Okimotoc (2013) so as to investigate the relationship between the VaR of renewable energy companies and the interest rate.

This data was sourced from DataStream and totals 2987 daily observations of closing prices, which have been split into an out-of-sample period of 2465 days and an in-sample period of 522 days. Alexander (2008) stated that approximately ten years of daily observations are required for the results to be powerful enough to validate a rejection of any inaccurate VaR models, a condition which has been met in this paper. The daily observations of the WTI crude oil price were also collected from DataStream along with the three-month rate on a US Treasury bill, taken to be the risk-free rate that will be used in the regression analysis. The descriptive statistics of these variables can be found in Table five (see appendix).

3.2 Application

For the non-parametric methods a rolling window of 522 days was used. For the BHS this involves calculating the quantile using Excel[8], beginning on the first trading day of 2006 and using the 522

[8] Applying the PERCENTILE.INC() function in Excel to the column of losses over the sample.

previous daily observations from 1/1/2004 to 12/30/2005, and ending at 12/6/2015 in the manner described in section 2.3. For the EWMA model, this rolling window is instead applied to each individual column of the estimation period using the rescaled losses, this means that of the 2987 rescaled losses for the year 2006, the first 522 are used to estimate the VaR for the year 2006, then for the VaR estimates of 2007 the rolling window continues the same as in the BHS but is switched to the corresponding year of rescaled losses and so forth.

The parameters required for implementation of the GARCH and TGARCH models were estimated in Eviews. The first parameters used for 2006 were estimated from the beginning of 2004 to the end of 2005, with the parameters for 2007 estimated from the beginning of 2005 to 2006 and so on, continuing the rolling window of 522 in the same way as the EWMA model. Different parameters were estimated for the normal and Student-t distribution which were then put into the GARCH or TGARCH equations, updated for every year of the test period, and then estimated in the same manner as the EWMA model.

3.3 NON- PARAMETRIC RESULTS

Table two shows the results of the non-parametric methods for estimating VaR at the 99% confidence level. Observing these results it can be clearly seen that the EWMA model with the Student-t distribution gives the best estimates of VaR out of the three models, with the number of violations lying between the expected number at both the 95% and 99% statistical significance level. The results, highlighted in bold, indicate they have passed the two-sided Kupiec test. As the EWMA model with the Student-t distribution produces the least violations[9] it could be implied that there is evidence of fat-tails in the empirical return's distributions that the normal distribution was unable to model for; this may explain the normal distributions higher number of violations. The exception in the Student-t distribution model is the Wilderhill clean energy index, this is due to problems with the data that resulted in very large and sometimes negative estimates of the degrees of freedom, making it impossible to calculate the VaR for the t-distribution. Instead, the degrees of freedom was set to 100 to assume a normal distribution which may explain why the

[9] While the best estimates are those that fall between the lower and upper bounds of the two-sided Kupiec test, it can be taken as a general rule of thumb, that a lower number of violations is better when both fail the test following Sardosky (2006).

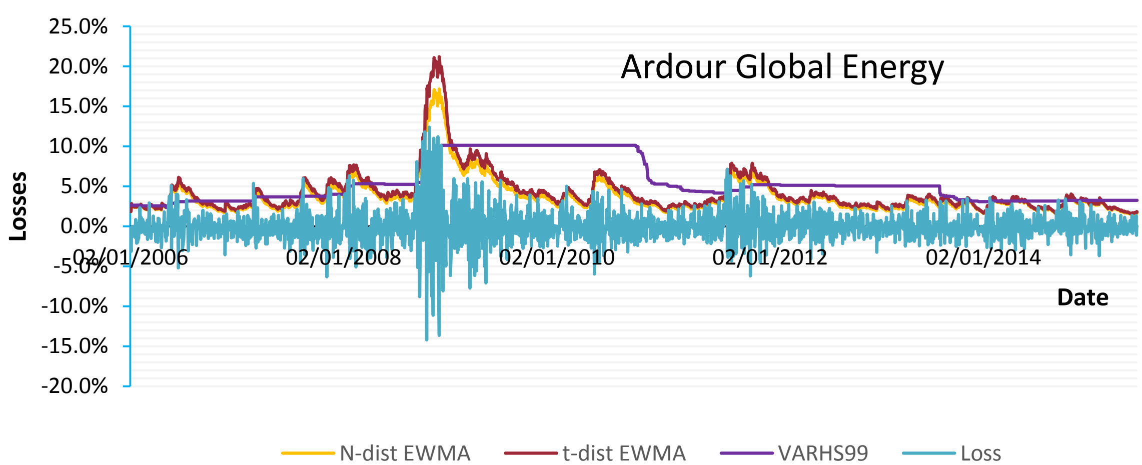
EWMA N-dist and EWMA t-dist have the same number of violations. This assumption is held throughout the rest of the paper.

Table 2: *Non-parametric VaR violations at 99% confidence level*

99% Confidence Level	BHS	EWMA N-dist	EWMA t-dist
Ardour global energy	43	53	**35**
FTSE ET50	41	47	**33**
S&P global clean energy	43	45	**31**
Wilderhill clean energy	43	59	59
Wilderhill global energy	40	58	**38**

Figure three illustrates the non-parametric methods of VaR estimation for the Ardour Global Energy index; it can be clearly seen that the EWMA t-dist outperforms the other models as it consistently lies above the losses to a greater extent than the other models. The HS method with VaR at the 99% confidence level is clearly the worst performer persistently passing through the loss distribution. Perhaps the most evident feature in the graph is the HS curve which is flat due to the lack of volatility updating involved in this procedure, this is highlighted during the financial crisis where volatility was high and the HS curve barely adjusts to account for this, whereas the EWMA models experience shifts.

Figure 3: *Non-parametric VaR estimates*



3.4 PARAMETRIC RESULTS

It was expected that the parametric methods would outperform most of the non-parametric models as most of the literature suggests, with Carbedo and Moya finding the GARCH (1, 1) model to outperform the BHS. However, Ding and Meade (2010)[10] found that the EWMA models provided more accurate forecasts of the VaR than the GARCH (1, 1) model, and Sardosky (2006) found evidence of non-parametric methods outperforming parametric methods in relation to the number of violations in the backtests, as noted in section one. This evidence could explain why, when observing Table three and two, the GARCH N-dist has more violations than the EWMA N-dist, furthermore this is in line with earlier theory that implied non-parametric methods tend to outperform parametric methods when the latter assume normality.

Observing Table three the TGARCH N-dist clearly produces the worst estimates in comparison to all of the models; this might suggest that there is no asymmetry in the renewable energy market, or simply that accounting for asymmetries has little effect on the model's accuracy. This contradicts studies by Kumar et al (2008) and other researchers which suggest an asymmetric effect is present between renewable energy markets and the oil price, however Kumar et al (2008) use an asymmetric BEKK model that included the oil price to measure this. Furthermore, estimation of the TGARCH in Eviews produced a number of negative α parameters[11] for some of the periods, which resulted in a negative variance, thus meaning the VaR could not be calculated. This negative α problem has been noted by Goldman and Wang (2013), and to overcome this, the negative α parameters were replaced with their corresponding GARCH (1, 1) α parameters in the periods of concern[12]. This parameter replacement could help explain why the Wilderhill Clean energy index has such a high number of violations, although the other indexes that had their parameters replaced[13] actually produced less violations in some cases, and the S&P and FTSE ET50 TGARCH t-dist models both passed the Kupiec two-sided frequency test producing better results than the GARCH N-dist in terms of less violations. Nonetheless, it should be noted that these models may not be as reliable due to their parameter replacement.

[10] Although it should be noted this paper was not based on the energy market.
[11] All parameter estimates and their corresponding significance values can be found in the appendix.
[12] These negative α parameters can be seen in the Appendix along with the other parameters estimated for each models index and period.
[13] FTSE ET50 t-dist; Wilderhill clean energy N-dist and t-dist; Wilderhill global energy N-dist and t-dist.

The GARCH (1,1) t-dist model clearly produces the best estimates with almost all indices passing the two-sided Kupiec test with the exception of Wilderhill clean energy index; this is due to the earlier assumption made regarding the degrees of freedom, although it does still produce a lower number of violations than the GARCH (1, 1) N-dist, perhaps because it was estimated using the t-distribution. Nonetheless, it once again supports evidence of a heavy-tailed distribution, as violations decrease significantly when using the t-distribution that models this. Most of the literature regarding the models selected for this study would support this result. However it does run contrary to the conclusions of Aghayev and Rizvanoghlu (2014) who found the TGARCH estimation to produce the least violations. As the GARCH t-dist clearly produces the best estimates of VaR in relation to the two-sided Kupiec test, these are the VaR estimates that will be used to run the regression of VaR on the oil price and risk-free rate.

Table 3: *Parametric VaR violations at the 99% confidence level*

	GARCH N-dist	GARCH t-dist	TGARCH N-dist	TGARCH t-dist
Ardour global energy	57	**37**	66	43
FTSE ET50	57	**32**	43	**25**
S&P global clean energy	50	**30**	58	**38**
Wilderhill clean energy	55	51	205	53
Wilderhill global energy	53	**32**	50	39

Figure four displays the models estimated using the normal distribution for the S&P Global energy index, here it looks as if the TGARCH and GARCH models perform the best as they closely replicate the trend of the losses; this is because they can accommodate for volatility clustering. The EWMA model produces a relatively flat volatility forecast in comparison to the other two models as it ignores recent adjustments in the data, which explains the lag in adjustment at the start of the financial crisis the smoothed downward trend during the financial crisis, even though it does produce the least violations. The GARCH model appears to marginally outperform the TGARCH, with the latter passing through the losses more often than the former, especially during the financial crisis. Similar arguments hold for Figure five which shows the same models but this time using a t-distribution.

Figure 4: *Parametric and Non-parametric VaR estimates using the Normal distribution*

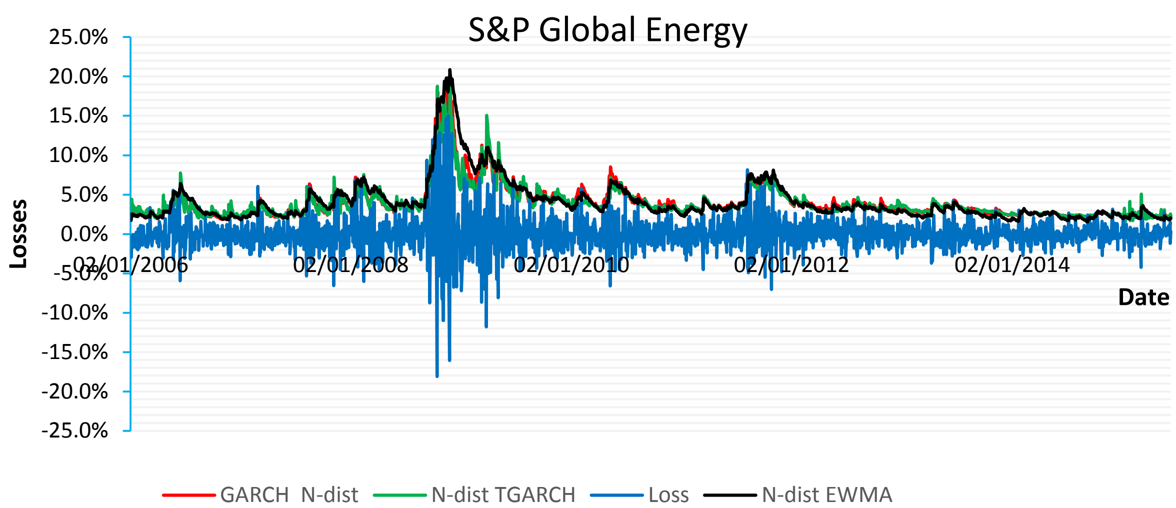


Figure 5: *Parametric and Non-parametric VaR estimates using Student-t distribution*

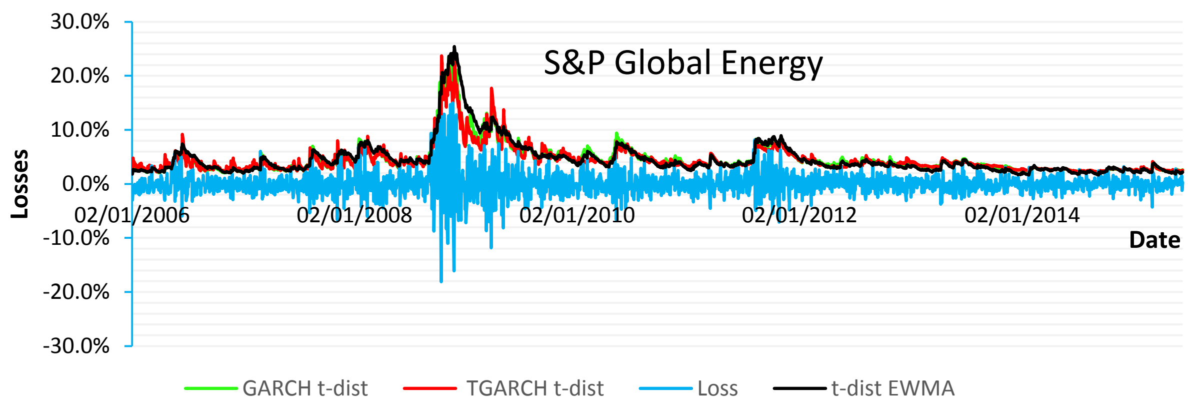


Figure six produces the ARCH family models for the S&P Global Energy index. All of these models capture the volatility well especially the GARCH t-dist and TGARCH t-dist, with the former performing slightly better. Figure seven produces the same set of models but for the Ardour Global Energy index; this illustration gives a clearer picture than the previous figures of the GARCH t-dist modelling volatility better than the other models, consistently lying above the other models' curves, with less movement inside the loss distribution and thus fewer violations.

Most noticeable in this figure is the random jump at around 2013; this is likely to have been caused by the parameter replacement producing inefficient estimates.

Figure 6: *Parametric VaR estimates using both the Normal and Student-t distributions*

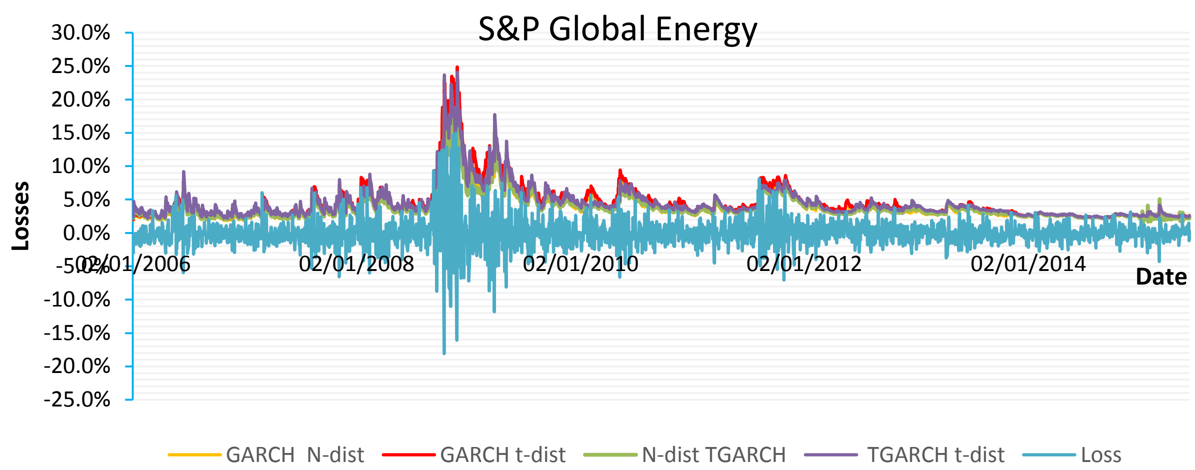
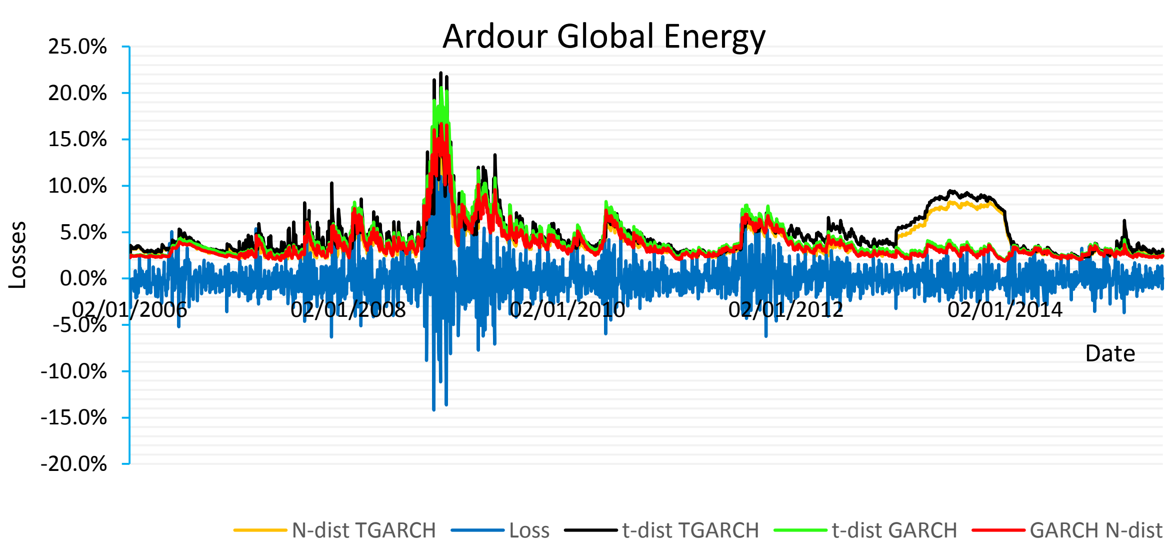


Figure 7: *Parametric VaR estimates using both the Normal and Student-t distributions*



3.5 Regression Application

After determining that the GARCH model with Student-t distribution produced the best VaR estimates these estimates were imported into Eviews. Augmented Dickey-Fuller tests for a unit root were first carried out to determine whether the explanatory variables were stationary. While the Oil price returns were stationary they identified the Treasury bill as not stationary so this variable was first differenced. Then, using equation (8), regressions were run for each of the five renewable energy indices. The results can be seen in Table four. The estimated coefficients are marked with one, two or three stars to determine their statistical significance at the 0.01, 0.05 and 0.1 levels and their corresponding standard errors are the values in brackets. Once the regressions had been estimated a number of tests were applied to determine the results.

3.6 Regression results

Observing Table four (on the next page) the results suggest that explanatory variables, Oil_{t-1} and the risk-free rate have a statistically significant effect on the VaR estimates of all the renewable energy indices. Thus, an increase in the price of oil or the risk-free rate causes a decrease in the VaR estimate of the renewable energy indices, in the case of the Ardour index, for example, in percentage terms an increase in the price of oil by 1% will decrease the VaR estimate by -0.067851%. The F-statistic is also important to note as this explains whether the two explanatory variables can jointly explain the dependent variable, as all are significant it could be said that the two explanatory variables may have some influence on the dependent variable. The fact that the oil price and risk-free rate are able to explain VaR to an extent implies that these three markets are interrelated, and so the two explanatory variables may contain some information about the risk in the renewable market as the regression shows. Thus it could be argued that both the explanatory variables should be included in a VaR model for renewable energy indices as conditioning information i.e. the VaR model for renewable energy indices could possibly be improved by including the oil price and risk-free rate in the VaR model directly, for example, by including them as explanatory variables in the GARCH (1, 1) model.

The first five regressions run were then tested for heteroskedasticity as this results in the error terms of these models not being independently and identically distributed. They are therefore mutually uncorrelated, with the error terms no longer having identical variances over observations, meaning the diagonal elements of the covariance matrix are not the same.

Therefore, the variance it computes will be based on the wrong expression, and although the OLS estimator is still unbiased it is no longer the best under the BLUE statement of the Gauss-Markov assumptions (Verbeek, 2008). Table 25 (see appendix) shows the results of White's test for hetereoskedasticity, where the null hypothesis states that the error terms are homoskedastic, as the p-values are lower than the 5% significant level the null is rejected and the alternative hypothesis of heteroskedasticity is not rejected meaning the models have heteroskedastic error terms.

Table 4: *Regression Results, * p<0.1; ** p<0.05; *** p<0.01*

	_cons	Oil_{t-1}	**Risk-free rate**	**F-statistic**
Ardour	0.043531*** (0.000553)	-0.067839*** (0.020003)	-0.002081*** (0.000255)	39.56487***
FTSE ET50	0.036400*** (0.000487)	-0.054303*** (0.017637)	-0.001072*** (0.000225)	16.37157***
S&P	0.049659*** (0.000681)	-0.080154*** (0.024651)	-0.003161*** (0.000314)	56.49289***
Wilderhill Clean	0.049928*** (0.000496)	-0.051335*** (0.017942)	-0.003116*** (0.000229)	97.62798***
Wilderhill Global	0.039133*** (0.000485)	-0.047856*** (0.017565)	-0.001907*** (0.000224)	40.39472***
Ardour NWSE	0.043531*** (0.001750)	-0.067839* (0.036829)	-0.002081*** (0.000417)	39.56487***
FTSE ET50 NWSE	0.036400*** (0.001515)	-0.054303* (0.031980)	-0.001072*** (0.000413)	16.37157***
S&P RSE	0.049659*** (0.002183)	-0.080154* (0.047356)	-0.003161*** (0.000534)	56.49289***
Wilderhill Clean NWSE	0.049928*** (0.001598)	-0.051335* (0.032323)	-0.003116*** (0.000398)	97.62798***
Wilderhill Global NWSE	0.039133*** (0.001512)	-0.047856* (0.031041)	-0.001907*** (0.000437)	40.39472***

Testing for autocorrelation is also important as the presence of this can cause the covariance matrix to be non-diagonal meaning different error terms are correlated so they are no longer independent (Verbeek, 2008). Similar to heteorskedasticity the OLS estimator is still unbiased. However, it is no longer BLUE as the standard errors are estimated in the wrong way. Applying Breusch-Godfrey's test for Serial Correlation to each index and observing the p-values of the results in Table 26 (see appendix) it can be seen that the null hypothesis of no serial correlation is rejected, meaning the alternative hypothesis of serial correlation is not rejected and thus autocorrelation is present in regression outputs of these indices.

To account for the heteroskedasticity and autocorrelation that is present in the original regressions it is recommended that the regression is estimated again but this time using the Newey-West Standard Errors (NWSE) specification; this particular specification is preferred to White's Robust Standard Errors as the former is more appropriate when using time series data, as is the case here. NWSE accounts for this by adjusting the variance-covariance matrix to produce a consistent OLS estimator in the presence of heteroskedasticity and autocorrelation, this is why the coefficients do not change as OLS does not use any covariances to estimate its parameters. The results of these can be seen in the lower half of Table four denoted NWSE. It can be noticed that the statistical significance of these estimated coefficients has decreased and they are now only significant at the 10% level. Nevertheless, their statistical significance still implies that a valid relationship between the VaR of the renewable energy market and the oil price exists. It is also noticeable that the standard errors of these NWSE regressions have changed to account for the heteroskedasticity and autocorrelation that was found to be present in the original regressions.

Interpreting the economic intuition behind the relationship that, when the oil price rises, VaR decreases, supports the theory in the literature review because to an extent higher oil prices are said to lead to higher share prices of renewable energy companies, creating more interest and investment in these companies. This increased investment increases the value of renewable energy companies and reduces the risk associated with investing in them as it can be expected that companies increased revenue streams allow them to increase their capital, so for example in the case of a potential default on a loan, they would have more capital to cover any costs. A similar relationship is backed by Kumar et al (2012) who find that increases in the oil price increase renewable energy companies' share prices as well as Managi and Okimoto (2013) after a structural break in 2007.

There is also evidence to support the relationship that when the oil price falls VaR increases, as renewable investment will decrease as demand for oil increases because the two energy sources are perfect substitutes. Governments, in particular, will continue to buy cheaper oil to power the grid rather than invest in expensive renewable energy development, especially in developing Asian countries like Indonesia (GBG Indonesia, 2013) and the Philippines (KPMG, 2013) where oil is the second largest fuel type used for electricity generation. This fall in renewable energy investment will lead to share prices of renewable energy companies to fall and thus their risk will increase. Reboredo (p.33, 2015) supports these argument stating “incentives to encourage development of the renewable energy sector are effective when oil prices are high, as the economic viability of renewable energy projects is enhanced; however, low oil prices discourage renewable energy investments and reduce the value of renewable energy companies”.

However the empirical relationship between the risk of renewable energy companies and oil price are mixed with Henriques and Sardosky (2008) finding that while oil price can explain past movements in renewable energy companies’ share prices, an oil price shock has no statistically significant impact on renewable energy companies’ share prices suggesting there is no impact on risk. Furthermore, Sardosky (2012) finds a positive relationship between rises in the oil price and renewable energy companies’ risk contradicting the findings in this study. Also, it should be noted that while some developing countries still rely on oil for electricity generation, the vast majority of countries use of coal, natural gas, and even renewable energy for electricity generation, outweighing that of oil which only makes up 5% of world electricity generation in 2012 in comparison to hydropower alone contributing 16.2% (IEA*, 2014). In reality the markets for renewable energy and oil are rather different, with the former used mostly for powering the grid while the latter is used for transportation and the manufacturing industry. The demand for these energy sources comes from two different markets and it can be argued that the two are not perfect substitutes, as when the price of one decreases the demand for the other does not also decrease. Rather the demand for renewable energy has kept growing in light of the 2014 fall in oil prices (Rojas and Stinson, 2015), so it is reasonable to assume there is no relationship between the two.

The relationship between the interest rate and the VaR of renewable energy indices is harder to explain. Economic intuition would suggest that a rise in the interest rate will reduce investment as the cost of borrowing increases meaning projects become more expensive to fund, and so more investors choose to save their money. This results in a fall in investment for renewable energy companies’ and thus a fall in their share price and firm value both of which are likely to increase the risk of these indices. Henriques and Sardosky (2008) and Kumar et al (2012) argue that the interest rate does have some effect on renewable energy share prices and risk, although they do not state explicitly whether this relationship is positive or negative only that they use impulse response functions to simulate standard deviation shocks of the interest rates. Arguments to justify this negative relationship between the VaR of renewable energy indices and the oil price found in this paper are difficult to find.

4. CONCLUSION

This paper looked to answer two questions:

1) Which method for estimating the VaR of renewable energy indices provides the best estimate?

The answer to this involved implementing a number of parametric and non-parametric methods to estimate the VaR, and then backtesting these using Kupiec's two-sided test to determine which model provided the best estimate. This paper found that the GARCH (1, 1) Student-t distribution model provided the best estimates as it had four of the five indices number of violations fall between Kupiecs x_{low} and x_{high} bands, while this equals the number that the EWMA Student-t distribution found, the former model was chosen as it is taken as a proxy that less violations are better which applied to the Wilderhill Clean Energy index. The results are consistent with findings that suggest return distributions of the energy market tend to be fat-tailed, this explains why the models that use Student-t distributions provide the best estimates of VaR. Furthermore, it could be argued the parametric methods outperform the non-parametric methods with the GARCH and TGARCH models passing the Kupiec test more so than the BHS and EWMA models, however this is subject to criticism due to the negative α parameters in the TGARCH model that had to be replaced, creating bias estimates. Asymmetry in the renewable energy market is also present to an extent but this can also be discredited using the parameter replacement argument. The second question asked:

2) Do fluctuations in the oil price impact on the VaR of these renewable energy indices?

This paper found that the oil price does impact the VaR of these renewable energy indices. More specifically, it found that a negative relationship between the oil price and the VaR of the renewable energy indices existed that was significant at the 10% level suggesting that a rise in the price of oil causes a fall in the VaR of the renewable energy indices. While this is supported by some studies others have found either a positive relationship, or that no relationship exists whatsoever. It is important to question this effect as studies tend to contradict the findings of others and the fact that renewable energy demand and oil demand essentially apply to two different markets raises the question: Why does a relationship between the two variables exist at all? One argument made by Rojas and Stinson (2015) suggests that it is a problem of perception, whereby the public believe that the price of oil represents the price of energy in general, and it is this belief that energy is cheap because oil is cheap that manifests disincentives for investors, policymakers and customers to back renewable energy. This in turn impacts upon the financial markets and may play a part in creating the negative correlation between the price of oil and the VaR of renewable energy indices as found in this study.

Future research regarding the VaR of the renewable energy market could be improved in a number of ways, first of all the study could evaluate the VaR at the 95% confidence level as this is the second most popular confidence level, and allows for the analysis of more losses. Second, additional models could be used that may better capture the VaR such as the wide range of ARMA models or the Exponential-GARCH model. Third, these models could be estimated using other distributions that may be able to account for more than just fat-tails. Fourth, different backtesting approaches could be used to determine the accuracy of VaR such as the Christoffersen frequency test. Fifth, as the two explanatory variables do play some part in explaining the VaR an improvement of the VaR model for renewable energy indices is possible, future research could include these variables directly in some of the other ARCH family models. Finally, whilst this research has yielded some evidence that the price of oil does have an impact on the VaR of the renewable energy indices in the current research sample, and is supported by the results of some other studies, it is recommended that further research would need to be carried out to help determine that a relationship between the two does exist and to clarify, more precisely, the nature of any such relationship. To reach a more definitive set of conclusions the research would require to take account of additional variables and perhaps to use a wider set of regression models.

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8. APPENDIX

Table 5: *Descriptive Statistics for Renewable energy indices*

Descriptive Statistics	Ardour	FTSE 50	S&P	Wilderhill Clean	Wilderhill Global	Oil Price	Treasury Bill
Mean	-3.06E-06	0.000195	-0.000128	-0.000303	9.92E-05	0.000205	1.353217
Median	0.000804	0.000843	0.000743	0.000303	0.000684	0.000000	0.160000
Maximum	0.142012	0.123529	0.180929	0.145195	0.120705	0.164137	5.050000
Minimum	-0.124123	-0.126472	-0.149728	-0.144673	-0.104854	-0.128267	0.000000
Std. Dev.	0.017679	0.014705	0.019589	0.020987	0.015025	0.023133	1.764691
Skewness	-0.442817	-0.614668	-0.535385	-0.365226	-0.498392	-0.032762	1.012776
Kurtosis	12.07383	12.72500	15.73905	8.140906	10.89450	8.226797	2.434785
Jarque-Bera	10344.82	11958.81	20340.22	3355.704	7880.284	3400.662	550.3961
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	-0.009149	0.581170	-0.383761	-0.906213	0.296313	0.612128	4042.060
Sum of Sq. Dev.	0.933220	0.645689	1.145828	1.315203	0.674108	1.597915	9298.804
Observations	2987	2987	2987	2987	2987	2987	2987

Table 6: *Ardour Global Energy Index GARCH Normal Distribution*, * p<0.1; ** p<0.05; *** p<0.01

Parameters	20042005	20052006	20062007	20072008	20082009	20092010	20102011	20112012	20122013	20132014	20142015
Mean	0.000313	0.001556***	0.002517***	0.002012***	0.000357	0.000238	-0.000436	-0.000380	0.000967**	0.001009*	0.000340
Omega	0.000001	0.000014***	0.000014***	0.000015***	0.000005	0.000003	0.000004	0.000002	0.000006	0.000018*	0.000004
Alpha	0.016787*	0.115897***	0.137595***	0.162588***	0.106029***	0.068481***	0.090856***	0.069405***	0.051511**	0.078154**	0.058779**
Beta	0.976589***	0.778702***	0.794180***	0.814567***	0.888573***	0.919771***	0.898149***	0.920749***	0.901287***	0.797067***	0.911721***

Table 7: *FTSE ET50 Index GARCH Normal Distribution*

Parameters	20042005	20052006	20062007	20072008	20082009	20092010	20102011	20112012	20122013	20132014	20142015
Mean	0.000664*	0.001245***	0.002483***	0.001551**	0.000268	0.000668	0.000136	0.000052	0.000912**	0.000770**	0.000314
Omega	3.75E-06*	3.78E-06**	0.000009***	0.000011***	0.000003	0.000003*	0.000004*	0.000003	0.000002	0.000014**	0.000010
Alpha	0.059132***	0.104797***	0.123411***	0.142725***	0.095510***	0.066346***	0.099907***	0.077336***	0.031494*	0.100437**	0.079614*
Beta	0.881063***	0.854000***	0.829324***	0.834183***	0.899935***	0.918536***	0.884682***	0.908120***	0.944378***	0.709232***	0.777438***

Table 8: *S&P Global Clean Energy Index GARCH Normal Distribution*

Parameters	20042005	20052006	20062007	20072008	20082009	20092010	20102011	20112012	20122013	20132014	20142015
Mean	0.000986	0.001711***	0.002387***	0.001601*	-0.000420	-0.000311	-0.000490	-0.000983	0.000307	0.000607	0.000724
Omega	4.90E-06*	8.25E-06**	0.000012**	0.000016***	0.000009*	0.000004	0.000010**	0.000007**	0.000003	0.000018	0.000128***
Alpha	0.069884***	0.115883***	0.107078***	0.140667***	0.112132***	0.067060***	0.102287***	0.070434***	0.029052**	0.053293*	0.216009***
Beta	0.877496***	0.819130***	0.842609***	0.838676***	0.881790***	0.920484***	0.869905***	0.904452***	0.948808***	0.794448***	-0.386760***

Table 9: *WilderHill Clean Energy Index GARCH Normal Distribution*

Parameters	20042005	20052006	20062007	20072008	20082009	20092010	20102011	20112012	20122013	20132014	20142015
Mean	0.000672	0.000884	0.001228*	0.000339	-0.000321	0.000585	-0.000388	-0.001242	0.000338	0.000542	-0.000253
Omega	0.000012	0.000020**	0.000018***	0.000016***	0.000011*	0.000005	0.000010**	0.000007*	0.000040	0.000034*	0.000003
Alpha	0.060570*	0.115530***	0.117843***	0.137811***	0.097893***	0.071552***	0.114289***	0.088717***	0.103465*	0.094820**	0.053917***
Beta	0.867666***	0.782663***	0.822170***	0.842431***	0.891688***	0.916910***	0.867234***	0.893643***	0.739015***	0.786029***	0.932762***

Table 10: *WilderHill New Energy Global Innovation Index GARCH Normal Distribution*

Parameters	20042005	20052006	20062007	20072008	20082009	20092010	20102011	20112012	20122013	20132014	20142015
Mean	0.000938***	0.001538***	0.001987***	0.001182**	-0.000005	0.000319	-0.000181	-0.000323	0.000868*	0.000810*	0.000480
Omega	0.000002	0.000003**	0.000007***	0.000008**	0.000005	0.000002	0.000004***	0.000003***	0.000001	0.000015	0.000012
Alpha	0.049513***	0.124435***	0.153592***	0.171717***	0.105652***	0.062891***	0.091313***	0.060887***	0.020313**	0.058323*	0.044716
Beta	0.920407***	0.835038***	0.805078***	0.816479***	0.887338***	0.925645***	0.894566***	0.925911***	0.969307***	0.773701***	0.818333***

Table 11: *Ardour Global Energy Index GARCH Student-t distribution parameters*

Parameters	20042005	20052006	20062007	20072008	20082009	20092010	20102011	20112012	20122013	20132014	20142015
Mean	0.000312	0.00134***	0.002427***	0.002012***	0.000374	0.000489	-0.00031	-0.000378	0.001128**	0.00156***	0.000757
Omega	7.15E-07	7.54E-06	1.12E-05*	1.30E-05*	4.94E-06	2.36E-06	4.36E-06	2.47E-06	5.40E-06	1.28E-05	2.99E-06
Alpha	0.016746	0.078464***	0.121372***	0.166848***	0.103517***	0.070979***	0.088461***	0.064322***	0.055126*	0.105417**	0.068693**
Beta	0.976640***	0.861935***	0.82549***	0.817238***	0.89207***	0.919146***	0.898586***	0.924958***	0.904666***	0.816044***	0.912571***

Table 12: *FTSE ET 50 Index GARCH Student-t distribution parameters*

Parameters	20042005	20052006	20062007	20072008	20082009	20092010	20102011	20112012	20122013	20132014	20142015
Mean	0.000691**	0.001153***	0.002529***	0.001795***	0.000421	0.000785	0.000199	7.25E-05	0.001117***	0.001060***	0.000487
Omega	3.37E-06	3.12E-06*	8.92E-06**	9.51E-06*	3.61E-06	2.59E-06	3.90E-06	2.48E-06	1.89E-06	1.09E-05	8.50E-06
Alpha	0.049915*	0.082341***	0.138942***	0.153875***	0.095770***	0.067887***	0.097371***	0.074398***	0.040924**	0.112877**	0.091836*
Beta	0.896632***	0.884584***	0.819337***	0.833895***	0.899913***	0.918158***	0.886820***	0.911081***	0.936784***	0.740304***	0.788649***

Table 13: *S&P Global Clean Energy Index GARCH Student-t distribution parameters*

Parameters	20042005	20052006	20062007	20072008	20082009	20092010	20102011	20112012	20122013	20132014	20142015
Mean	0.001053	0.001666***	0.002572***	0.001948***	-0.000222	-9.73E-05	-0.000533	-0.001071	0.000450	0.000877*	0.000756
Omega	4.87E-06	7.83E-06**	1.10E-05*	1.33E-05*	8.08E-06	3.66E-06	9.85E-06	6.46E-06	1.63E-06	1.34E-05	0.000131***
Alpha	0.073212	0.110218***	0.118908***	0.152756***	0.104581***	0.063987***	0.094127***	0.059097***	0.027372*	0.046525	0.199438***
Beta	0.875861***	0.827759***	0.834016***	0.837434***	0.890397***	0.923692***	0.878790***	0.917521***	0.960511***	0.842485***	-0.379797**

Table 14: *WilderHill Clean Energy Index GARCH Student-t distribution parameters*

Parameters	20042005	20052006	20062007	20072008	20082009	20092010	20102011	20112012	20122013	20132014	20142015
Mean	0.000672	0.000890	0.001624	0.000838	-0.000149	0.001271	0.000120	-0.001100	0.000387	0.000990	0.000466
Omega	1.22E-05	1.88E-05*	1.47E-05	1.34E-05**	8.06E-06	3.88E-06	9.24E-06	6.31E-06	3.88E-05	3.09E-05	3.94E-06
Alpha	0.060584*	0.112316***	0.119034***	0.142226***	0.099238***	0.084823***	0.106559***	0.073789***	0.105309*	0.100095**	0.059164**
Beta	0.867688***	0.793259***	0.835365***	0.845957***	0.895430***	0.909422***	0.877559***	0.909471***	0.740841***	0.792359***	0.925681***

Table 15: *WilderHill New Energy Global Innovation Index GARCH Student-t distribution parameters*

Parameters	20042005	20052006	20062007	20072008	20082009	20092010	20102011	20112012	20122013	20132014	20142015
Mean	0.000935***	0.001400***	0.002234***	0.001481**	4.12E-05	0.000581	3.18E-05	-0.000310	0.001045**	0.001172***	0.000546
Omega	1.82E-06	3.53E-06**	7.08E-06**	8.51E-06**	5.64E-06	1.83E-06	4.03E-06	2.56E-06	6.21E-07	1.20E-05	5.30E-06
Alpha	0.048353**	0.111967***	0.146638***	0.172833***	0.102642***	0.065447***	0.094455***	0.056218***	0.023477*	0.083432*	0.046829
Beta	0.919521***	0.843596***	0.811298***	0.813284***	0.889044***	0.925465***	0.893442***	0.932039***	0.968793***	0.790511***	0.891582***

Table 16: *Ardour Global Energy Index TGARCH Normal Distribution*

Parameters	20042005	20052006	20062007	20072008	20082009	20092010	20102011	20112012	20122013	20132014	20142015
Mean	0.000306	0.001392***	0.002378***	0.001477**	-0.000358	-0.000119	-0.000962	-0.001380***	0.000864*	0.000939*	0.000176
Omega	4.81E-06*	3.17E-05***	2.56E-05***	1.90E-05***	6.56E-06**	2.48E-06	6.57E-06***	3.34E-06***	8.67E-06	2.08E-05***	6.42E-06**
Alpha	-0.004159	0.002477	0.049102	0.023680	0.019212	0.025439	0.004491	-0.059551***	0.017303	-0.039444	-0.025944
Resid(-1)^2*(Resid(-1)<0)	0.061072**	0.268585***	0.238486***	0.219631***	0.124366***	0.061234**	0.124908***	0.119708***	0.057534	0.172092***	0.146665***
Beta	0.934210***	0.605162***	0.698919***	0.819370***	0.906767***	0.931353***	0.904086***	0.982063***	0.886832***	0.799445***	0.902320***

Table 17: *FTSE ET50 Index TGARCH Normal Distribution*

Parameters	20042005	20052006	20062007	20072008	20082009	20092010	20102011	20112012	20122013	20132014	20142015
Mean	0.000596*	0.001134***	0.002276***	0.001079*	-0.000384	7.57E-05	-0.000422	-0.000418	0.000690*	0.000666*	0.000245
Omega	7.49E-06**	5.30E-06***	1.55E-05***	1.40E-05***	4.01E-06**	1.24E-06	4.48E-06***	2.31E-06***	1.10E-06	1.11E-05***	7.31E-06***
Alpha	-0.008239	0.063662**	0.039503	0.010819	0.000717	-0.004267	-0.013027	-0.013936	-0.016305*	-0.082563***	-0.086712***
Resid(-1)^2*(Resid(-1)<0)	0.117847***	0.079586**	0.183259***	0.190457***	0.120999***	0.094533***	0.153286***	0.097815***	0.048785***	0.257847***	0.251559***
Beta	0.823669***	0.835194***	0.776334***	0.848328***	0.927160***	0.947868***	0.910674***	0.947133***	0.976469***	0.790358***	0.852191***

Table 18: *S&P Global Clean Energy Index TGARCH Normal Distribution*

Parameters	20042005	20052006	20062007	20072008	20082009	20092010	20102011	20112012	20122013	20132014	20142015
Mean	0.000876**	0.001530***	0.002283***	0.001049	-0.001257	-0.000621	-0.001087	-0.001192*	0.000311	0.000608	0.000611
Omega	1.69E-05***	1.40E-05***	1.59E-05**	2.00E-05***	6.55E-06*	3.53E-06	1.35E-05***	7.08E-06***	3.84E-06	1.71E-05	0.000126***
Alpha	-0.001299	0.050530	0.061180**	0.029433	0.016623	0.033731	0.011488	0.020098	0.036874*	0.043831	0.119854**
Resid(-1)^2*(Resid(-1)<0)	0.179074***	0.135104**	0.091113**	0.170141***	0.119399***	0.041395	0.128512***	0.059357***	-0.010332	0.021879	0.133945
Beta	0.725326***	0.767017***	0.818659***	0.843377***	0.915936***	0.932382***	0.879603***	0.922970***	0.941464***	0.797094***	-0.364985**

Table 19: *WilderHill Clean Energy Index TGARCH Normal Distribution*

Parameters	20042005	20052006	20062007	20072008	20082009	20092010	20102011	20112012	20122013	20132014	20142015
Mean	0.000610	0.000699	0.001153**	-0.000160	-0.001363	0.000092	-0.001159	-0.002723***	0.000378	0.000444	-0.000459
Omega	1.61E-05	3.28E-05**	2.14E-05***	1.91E-05***	7.51E-06	0.000005*	1.73E-05***	0.000002***	4.19E-05	3.63E-05*	4.02E-06
Alpha	0.028785	0.057958	0.105099***	0.055654	0.003891	-0.036155	-0.009689	-0.043507***	0.125515*	0.050981	0.025105
Resid(-1)^2*(Resid(-1)<0)	0.056593	0.137953**	0.036386	0.116722***	0.132336***	0.070592***	0.187071***	0.102314***	-0.035969	0.062376	0.039614
Beta	0.845737***	0.704013***	0.804016***	0.852181***	0.919367***	0.927123***	0.867584***	0.988451***	0.726563***	0.784751***	0.935533***

Table 20: *WilderHill New Energy Global Innovation Index TGARCH Normal distribution*

Parameters	20042005	20052006	20062007	20072008	20082009	20092010	20102011	20112012	20122013	20132014	20142015
Mean	0.000753**	0.001286***	0.001831***	0.000758	-0.000631	-0.000137	-0.000816	-0.000873	0.000855*	0.000894*	0.000904**
Omega	4.72E-06***	7.26E-06***	1.05E-05***	1.18E-05***	4.85E-06*	7.97E-07	4.35E-06***	2.70E-06***	1.05E-06	1.88E-05*	6.40E-05***
Alpha	-0.042018*	0.035960	0.095851**	0.037887	0.017402	0.009573	-0.009621	-0.012119	0.020313	-2.68E-05	-0.078415*
Resid(-1)^2*(Resid(-1)<0)	0.156092***	0.250560***	0.119316**	0.171540***	0.116113***	0.064110***	0.128039***	0.080648***	0.004062	0.081559*	0.413723***
Beta	0.877295***	0.752110***	0.774188***	0.833060***	0.914498***	0.951226***	0.921764***	0.955876***	0.968323***	0.749449***	0.094380

Table 21: *Ardour Global Energy Index TGARCH Student-t distribution*

Parameters	20042005	20052006	20062007	20072008	20082009	20092010	20102011	20112012	20122013	20132014	20142015
Mean	0.000306	0.001317***	0.002281***	0.001512**	-0.000253	0.000200	-0.000724	-0.001154**	0.001050**	0.001391***	0.000526
Omega	4.81E-06*	3.09E-05***	2.04E-05***	1.67E-05***	6.66E-06*	2.22E-06	7.23E-06**	3.30E-06***	7.66E-06	1.70E-05**	5.82E-06*
Alpha	-0.004161	-0.016034	0.043211	0.022067	0.014381	0.024848	-0.000622	-0.061677***	0.017423	-0.018780	-0.024131
Resid(-1)^2*(Resid(-1)<0)	0.061082**	0.282924***	0.203507***	0.229653***	0.126691***	0.063164**	0.134494***	0.119686***	0.063325	0.176806**	0.157190***
Beta	0.934204***	0.626604***	0.747921***	0.824020***	0.909699***	0.931350***	0.900059***	0.983161***	0.890861***	0.805477***	0.898518***

Table 22: *FTSE ET50 Index TGARCH Student-t distribution*

Parameters	20042005	20052006	20062007	20072008	20082009	20092010	20102011	20112012	20122013	20132014	20142015
Mean	0.000669**	0.001112***	0.002341***	0.001413**	-0.000110	0.000301	-0.000313	-0.000360	0.000939**	0.000937***	0.000370
Omega	7.12E-06**	5.11E-06**	1.40E-05***	1.20E-05***	4.29E-06*	1.26E-06	4.67E-06***	2.30E-06***	1.19E-06	9.56E-06***	6.32E-06***
Alpha	-0.013640	0.054654	0.060927	0.015832	-0.002744	-0.004715	-0.016710	-0.016764	-0.010654	-0.076762**	-0.086372***
Resid(-1)^2*(Resid(-1)<0)	0.117086**	0.072622	0.174676**	0.197453***	0.124274***	0.096103***	0.157776***	0.100111***	0.054808**	0.258332***	0.245587***
Beta	0.835584***	0.851340***	0.773759***	0.847655***	0.927230***	0.946644***	0.910067***	0.948601***	0.965592***	0.802383***	0.866733***

Table 23: *S&P Global Clean Energy Index TGARCH Student-t distribution*

Parameters	20042005	20052006	20062007	20072008	20082009	20092010	20102011	20112012	20122013	20132014	20142015
Mean	0.000948**	0.001517***	0.002402***	0.001414*	-0.000919	-0.000358	-0.000982	-0.001238*	0.000456	0.000893**	0.000777
Omega	1.62E-05**	1.39E-05***	1.47E-05**	1.64E-05***	6.61E-06	3.48E-06	1.40E-05***	6.54E-06**	1.87E-06	1.40E-05	0.000117***
Alpha	-0.003147	0.050118	0.062774	0.032284	0.009414	0.028333	0.004278	0.015418	0.031971*	0.032776	0.057973
Resid(-1)^2*(Resid(-1)<0)	0.186782***	0.135164**	0.110485*	0.185252***	0.121691***	0.047330	0.137156***	0.054870***	-0.006056	0.032496	0.282176
Beta	0.730975***	0.768194***	0.812834***	0.843767***	0.920576***	0.934378***	0.880152***	0.931734***	0.957564***	0.832935***	-0.242130*

Table 24: *WilderHill Clean Energy Index TGARCH Student-t distribution*

Parameters	20042005	20052006	20062007	20072008	20082009	20092010	20102011	20112012	20122013	20132014	20142015
Mean	0.000617	0.000712	0.001558**	0.000432	-0.001101	0.000980	-0.000474	-0.002462***	0.000404	0.000900	0.000274
Omega	1.62E-05	3.04E-05**	1.75E-05**	1.58E-05**	7.18E-06	4.39E-06	1.53E-05***	1.71E-06**	4.09E-05	3.40E-05*	5.86E-06
Alpha	0.028083	0.055984	0.104661**	0.061575	0.004309	0.031730	-0.006766	-0.039233***	0.122760*	0.041353	0.018300
Resid(-1)^2*(Resid(-1)<0)	0.059307	0.137600*	0.040325	0.119014	0.131879***	0.079370*	0.181015***	0.098541***	-0.029439	0.082297	0.059227
Beta	0.844579***	0.718950***	0.818359***	0.852854***	0.919051***	0.915790***	0.870460***	0.985299***	0.730006***	0.792222***	0.923507***

Table 25: *WilderHill New Energy Global Innovation Index TGARCH Student-t distribution*

Parameters	20042005	20052006	20062007	20072008	20082009	20092010	20102011	20112012	20122013	20132014	20142015
Mean	0.000754**	0.001195***	0.002047***	0.001072*	-0.000501	0.000215	-0.000362	-0.000737	0.001029**	0.001207***	0.000909**
Omega	4.72E-06***	7.93E-06***	1.07E-05***	1.22E-05***	5.40E-06*	7.22E-07	5.88E-06**	2.60E-06***	7.73E-07	1.46E-05*	6.47E-05***
Alpha	-0.042067*	0.027022	0.054983	0.009529	0.011522	0.011560	-0.003571	-0.010540	0.020142	0.024599	-0.070890
Resid(-1)^2*(Resid(-1)<0)	0.156101***	0.254993***	0.174338**	0.220869***	0.123421***	0.069326**	0.156007***	0.077322***	0.005695	0.090739	0.444660***
Beta	0.877222***	0.750329***	0.781923***	0.832641***	0.914849***	0.946433***	0.893492***	0.956040***	0.967643***	0.770158***	0.072476

Table 26: *The White test for Heteroskedastiscity*

	F-statistic	Probability
Ardour	129.8239	0.0000
FTSE	109.7052	0.0000
S&P	145.5397	0.0000
Wilderhill Clean	171.7394	0.0000
Wilderhill Global	111.7517	0.0000

Table 27: *Breusch-Godfrey test for Autocorrelation*

	F-statistic	Probability
Ardour	30200.00	0.0000
FTSE	30817.88	0.0000
S&P	35758.49	0.0000
Wilderhill Clean	27274.55	0.0000
Wilderhill Global	27368.61	0.0000