ERASMUS UNIVERSITEIT ROTTERDAM
ERASMUS SCHOOL OF ECONOMICS

Msc Economics & Business

Master Specialisation Financial Economics

Limiting Risk Exposure for Investments in Clean Energy Stocks

A study on the risk exposure of clean energy stocks, using oil as important risk factor

Abstract: in this thesis I study the risk-return relation of investments in clean energy stock prices. I study the returns of thirteen clean energy indexes and prove that twelve out of thirteen indexes do not underperform the market. I also add oil as a new risk factor to the existing capital asset pricing models. The oil factor appears to be a significant factor but does not add any explanatory power to the existing models. Next, using DCC GARCH models, I show how the correlation between clean energy stock prices and oil is dynamic. Building up on this finding I calculate the time-varying hedge ratios and forecast on-year ahead time-varying hedge ratios to show how investors can limit risks when investing in clean energy stocks.

Keywords: clean energy, asset pricing model, dynamic conditional correlation GARCH, time-varying hedge ratios, forecasting

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Preface

This master thesis is the final piece to graduate from the master's programme Financial Economics. The goal for my thesis was to learn new abilities while writing on two subject in which I am interested; investments and clean energy. During the process of writing my thesis, I found out the hard way that the will to write a thesis using new methodologies and software while working on my career, resulted in lesser focus for at least one of both. Despite finishing a lot later than anticipated, I can say that I am satisfied with the result, I hope that you as reader will as well. In the end, I did learn a lot from writing my thesis; I learned successfully using new quantitative software and new econometric models and learned that time-management is not without its benefits.

I would like to thank my supervisor dr. C.M. Lin for giving me the freedom to write on my own subject and providing me with the necessary guidance and feedback.

Paul van der Veen

Rotterdam, February 2nd, 2016

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1. Introduction

In 2010 the United Nations Framework Convention on Climate Change (UNFCCC) established an agreement in Cancun to limit global warming to a maximum of two degrees compared to the pre-industrial era.[1] To avoid temperatures increasing above the target, human-generated greenhouse gas emissions should be reduced according to the UNFCCC. To reduce greenhouse gas emissions, developed countries should innovate to increase the production of renewables or low carbon alternatives, as well as develop technologies for saving and storing energy and increasing energy efficiency. In order to keep track of developments in the energy sector and to evaluate whether current initiatives are sufficient to prevent the global warming to become irreversible, the International Energy Agency (IEA) records data, publishes findings and provides advice for bodies like the UNFCCC. In 2015, the IEA published a report on the current developments in clean energy (International Energy Agency, 2015). The IEA concludes that all countries are currently off-track for reaching UNFCCC's goal to limit global warming to two degrees Celsius above pre-industrial levels. Current actions taken by bodies like the UNFCCC and governments clearly do not provide enough stimulant for the private sector to reach UNFCCC's targets.

Currently, only 11% of the global energy consumption in 2012 was from renewables (only 4% non-hydropower) (U.S. Energy Information Administration, 2013), while coal accounted for 29% of the total energy production and 44% of the global CO2 emission (International Energy Agency, 2014). Fossil fuels altogether account for 99% of global CO2 emission, these numbers stress the importance of developments in clean energy.

Investments in clean energy carry the stereotype of unprofitable, investors prefer higher pay offs in the short-run and choose less socially responsible investments for their portfolios. In my thesis, I will study the risk-return relationship of investments in clean energy stocks and study how investors can limit risks for investments in clean energy stocks. I will study the correlation of oil prices and clean energy stock prices assuming clean energy to be a direct substitute for oil as energy source.

In the scenario of clean energy being a perfect substitute for oil, scarcity of oil and thus higher oil prices, should lead to higher clean energy stock prices. The plummet of oil prices in 2014 might make investments in clean energy less attractive, considering a positive relationship between oil prices and stock prices of clean energy firms (Managi & Okimoto, 2013). Oil price shocks, such as the one in 2014, may alter the relationship between clean energy stocks and oil prices because of structural changes in

[1] Cancun agreement: http://unfccc.int/key_steps/cancun_agreements/items/6132.php

the markets. When hedging for oil price risks, investors may want to change their portfolio weights following such price shocks. Based on my findings I will answer the following research question:

How are clean energy stock returns influenced by oil as a risk factor and how can investors account for this risk factor in their portfolios?

I will answer the research question by researching the following hypotheses:

1. H_0: Investments in clean energy do not underperform the market
2. H_0: Oil is a significant risk factor for clean energy stocks
3. H_0: The correlation between clean energy stock prices and oil prices is constant overtime
4. H_0: Oil provides efficient hedge opportunities to limit risks for investments in clean energy stocks

By answering the research question I contribute to the literature by increasing insight into the risk-return relationship of clean energy stocks and oil as an important risk factor. Increasing the knowledge on how to forecast and to hedge for clean energy stocks.

This thesis is structured as follows. Next I will discuss the theoretical background for this thesis, after which I will discuss the data and methods used for my empirical research. After discussing the empirical results I will answer the research question in the conclusion.

2. Theoretical Framework

The purpose of my thesis is to narrow the existing gap in the current literature on the understanding of the profitability of investments in clean energy companies. By providing more insight into the risk-return relationship of investments in clean energy and by providing hedge opportunities for investments, I hope to increase the attractiveness of investments in clean energy for constitutional investors as well as private investors. In this chapter I will discuss previous work of academics regarding this subject.

2.1. General

Investing in clean energy generally leads to lower returns than conventional investments. This is the general view on environmentally friendly investments for the previous decades. I approach this subject by using two methods to explain returns and variances in those returns which are academically broadly used.

The first method to focus on finds its origin in the capital asset pricing model (CAPM) from the authors Sharpe (1964) and Lintner (1965). This group of literature focuses on explaining returns based on risk factors to which the assets are exposed to. This group of literature use extended versions of the CAPM, namely either the three-, four- or five-factor model by Fama and French (1993), Carhart (1997) and Fama and French (2015) respectively. There is a large volume of academic articles which focus on the relationship between environmental and financial performance, researching how environmentally friendly assets are exposed differently to conventional risk factors than conventional assets.

For the second method I will focus on the co-movements of clean energy stock prices and oil prices. The method I use comes from a group of literature which starts at the autoregressive conditional heteroscedasticity model (ARCH) proposed by Engle (1982). Bollerslev (1986) improved the ARCH model and proposed the generalized autoregressive conditional heteroscedasticity model (GARCH). After the introduction of the GARCH model, the amount of articles exploded on variations of the GARCH model or practical implications of these methods. In my thesis I will focus on the dynamic conditional correlation GARCH model of Engle (2002). In this chapter, I will discuss the articles which use similar methods and provide practical implications relevant to my thesis. In the next chapter I will explain what the methods I use entail.

2.2. The relationship between environmental and financial performance

Socially responsible investments caught a lot of attention by academics for the last decades. The general view on socially responsible investments is that they tend to perform financially worse than conventional investments.

Stocks are generally screened for a variety of characteristics in order to pass for socially responsible investments (SRI), think of screens on the production of alcohol, tobacco or weapons, environmental screens, screens for human rights and employment equality. A lot of articles have focussed on the performance of SRI's or SRI funds, however, the amount of articles on merely environmentally friendly stocks is limited.

One of the articles in which the performance of SRI funds is studied, is the article of Renneboog et. al. (2008). Renneboog et. al. (2008) use a global database which they examine over the period of 1991 to 2003. To incorporate multiple risk factors, the authors use the three- and four-factor model of Fama and French (1993) and Carhart (1997) respectively. The results show that SRI funds significantly underperform their domestic benchmarks. This effect even exacerbates when looking at risk adjusted returns, in which case funds underperform up to -6.5% per year compared to the domestic benchmark. However, when the authors compare the alpha's, of both the SRI funds and their conventional counterparts, the authors do not find any significant differences. Renneboog et. al. (2008) also construct their own risk factor in order to account for the specific risk which investors are exposed to when investing in SRI funds. The significant and positive coefficient Renneboog et. al. (2008) find for this SRI factor, means that investors are compensated for the risk they face when investing in such funds. Renneboog et. al. (2008) show that SRI funds generally tend to underperform domestic benchmarks and, if controlled for their 'SRI factor', also produce significantly lower alpha's than conventional funds. Without the SRI factor the SRI funds do not perform significantly different from conventional funds.

The combinations of the aforementioned articles reflect my first approach best, but many more academics have studied this subject using similar methodology. Ito et. al. (2013) provide a summary of thirteen articles which have been published up until 2009 on this subject. As the summary in their article shows, most articles using an approach similar to CAPM find that SRI's perform significantly or insignificantly worse than their reference groups. Ito et. al. (2013) themselves find different results when using a dynamic mean-variance model. Ito et. al. (2013) find that SRI funds outperformed conventional funds in the EU and US from 2000 to 2009 , and green funds performed worse than the SRI funds but still equal to or better than conventional funds. Not incorporated in the summary of Ito et. al. (2013) is the articles of Yu (2014). Using the four factor model and monthly data from 1999 up to 2009, Yu (2014) finds that SRI funds have significantly higher alpha's than conventional funds. Thus, newer articles seem to find SRI funds outperforming conventional funds more regularly.

However, these articles have in common that they look at SRI funds in general. Climent and Soriano (2011) study the returns of green funds only using the one factor CAPM and the four factor model. For the period of 1987 – 2001 Climent and Soriano (2011) find that green funds significantly underperform both SRI funds and conventional funds in the US. For the period of 2001 – 2009 the authors find no significant difference in the returns of the different funds. Cai and He (2014) is the only article which finds a significant positive relationship between environmental performance and financial performance. Cai and He (2014) use KLD's database to form portfolios based on environmental performance and study the returns using the four-factor model. Cai and He (2014) find that good environmentally performing firms generally outperform the market. Cai and He (2014) try to prove that environmental performance should be incorporated into stock prices, which according to Cai and He (2014) is wrongfully not the case. This means clean energy firms should generate abnormal returns. Using the CAPM and weekly data on a clean energy index, Henriques and Sadorsky (2008) find that clean energy stocks do not show significantly negative alpha's, showing clean energy stocks deliver market competitive returns. Henriques and Sadorsky (2008) incorporate an oil factor in the basic CAPM. The expanded CAPM shows oil to be a significant risk factor for clean energy stocks and uses this finding to study the dynamic relationship between clean energy stocks and oil.

2.3. The correlation between clean energy stocks and oil prices

In this section I will discuss the literature which focuses on the correlation between clean energy stocks and oil prices. As an alternative energy source to oil, clean energy companies should benefit from higher oil prices. As oil prices rise, the demand for an alternative energy source rises.

Oil is an important driving factor behind the macroeconomic engine, fluctuations in oil prices influence production costs of a large number of industries. Increasing oil prices lowers economic activity because of the higher energy input costs. The influence of oil price fluctuations on stock prices is a popular subject to write about; on an aggregate level ((Apergis & Miller, 2009), (Kilian & Park, 2009), (Cunado & Perez de Garcia, 2014), (Güntner, 2013)) as well as on an industry level ((Elyasiani, Mansur, & Odusami, 2011), (Scholtens & Yurtsever, 2012), (Lee, Yang, & Huang, 2012)).

Apergis and Miller (2009) prove that oil prices play a significant role in explaining stock market returns. Killian and Park (2009) find that oil price shocks can explain up to twenty percent of stock market returns in the U.S., and shows how different kinds of oil demand and supply shocks influence stock prices differently. Cunado and Perez de Garcia (2014) find a significant negative relationship between oil price changes and stock market returns on an aggregate level for most European countries. This effect holds especially for price changes caused by supply shocks, as negative price shocks decrease energy security. Güntner (2013) studies different kinds of oil demand and supply shocks, concluding that unexpected supply shocks do not significantly affect stock returns on an aggregate level.

Elyasiani et. al. (2011) conclude that both returns of oil futures and volatility in the return of oil futures significantly influence stock returns of different industries. The energy sector is significantly influenced by returns of oil futures. Scholtens and Yurtsever (2012) find that the influence of oil prices on stock prices differs among industries, the effect is mostly significant for energy intensive industries. Lee et. al. (2012) also finds a significant effect between oil prices and stock prices of various industries. However, in contract to Elyasiani et. al (2012) and Scholtens and Yurtsever (2012), Lee et. al. (2012) finds no significant influence of oil prices on stock prices in the energy sector.

These studies all have in common that oil is seen as an important risk factor for stock prices in general. The methodology used in these articles differ a lot from one and another, which explains differences in results among these articles. Despite the many different methodologies, academics seem to coincide that the relationship between oil and stock prices may change throughout time or may depend on determinants of oil prices.

Henriques and Sadorsky (2008) were the first to explicitly study the seemingly natural correlation between oil prices and clean energy stocks prices. Using a four-factor vector auto regression, Henriques and Sadorsky (2008) study the correlation between clean energy stocks, technology stocks, oil prices and interest rates. They find that all three variables; oil prices, technology stock prices and interest rates all Granger cause price changes in clean energy stocks. Although all three provide some explanatory power, shocks in technology prices seem to have the strongest effect on clean energy stock prices. The power of shocks in oil prices is hardly significant. Henriques and Sadorsky (2008) conclude that oil price movements may not be as important to clean energy stocks because investors may perceive clean energy stocks as technology stocks, especially because clean energy companies depend on technological breakthroughs when it comes to finding and developing alternative energy sources.

Three articles use the work of Henriques and Sadorsky (2008) as a baseline to continue the research on the dynamic properties of the correlation between clean energy stocks and oil prices. Sadorsky (2012) uses a variety of multivariate GARCH models to examine the correlation and volatility spill overs between oil prices, clean energy stock prices and technology stock prices. With this information, Sadorsky (2012) calculates optimal portfolio weights and how to hedge against risks of clean energy stocks. Using a different statistical approach, Sadorsky (2012) again finds that the clean energy stock prices are influenced more strongly by technology stocks than oil prices as the dynamic conditional correlations are largest between technology stocks and clean energy stocks. However, for hedging the risks of clean energy stocks, Sadorsky (2012) concludes that technology stocks are less suitable than crude oil futures because of the high positive correlation between clean energy stocks and technology stocks. Sadorsky (2012) also finds, when calculating optimal two-asset-portfolio weights, that crude oil futures are more suitable to form a portfolio with than technology stocks as the weights in a portfolio with clean energy stocks and technology stocks would lean more heavily towards technology stocks.

Continuing the work of Henriques and Sadorsky (2008), Kumar et. al. (2012) perform a comparable study by using vector auto regression tests and adding more clean energy indices and carbon prices to the mix. Assuming that high carbon prices increase the demand for low carbon emission substitutes, higher carbon prices should lead to higher clean energy stock prices. Kumar et. al. (2012) find the same results as Henriques and Sadorsky (2008), returns of clean energy stocks behave similar to technology stocks and prices of clean energy stocks are significantly influenced by oil prices. Kumar et. al. (2012) fail to prove that carbon prices significantly influence clean energy stock prices.

Managi and Okimoto (2013) noticed the change in significance in the relationship between clean energy stock prices and oil prices as the data horizon was expanded up until 2008. For this reason, Managi and Okimoto (2013) believed correlation between oil prices and clean energy stock prices may not be constant over time and structural changes in the relationship between the two variables may permanently have shifted the correlation. Managi and Okimoto (2013) study the dynamics of the correlation between oil prices and clean energy stock prices. In the data horizon which Managi and Okimoto (2013) use, the regime assumption of Managi and Okimoto (2013) holds. However, as the economy gradually improves after the downturn of 2008, the markets of oil prices and clean energy may change again and so may the correlation between the two variables. Especially when considering the new technologies which provide both markets with new possibilities for production (e.g. the production of shale-oil, higher efficiency of solar panels, new ways to store energy, etc.).

3. Methodology & Data

In this chapter I will discuss the methodology I use in the thesis. I will start by discussing the data I use in my empirical research, followed by the methods I use. In my thesis I use the article of Sadorsky (2012) as guideline, expanding this article by analysing more indexes and expanding the methodology used in the article.

3.1. Data

I use a variety of clean energy indexes in my research, each index represents a well-diversified portfolio in clean energy stocks with different methods of portfolio formation. Different technologies within the clean energy sector may be exposed differently to certain risks, the same may account for the countries the firms are listed in. Comparing these indexes, reflecting differences in portfolio selection, may explain different views and findings on the performance of clean energy stocks. This is important for my research, one stock may behave differently than another. If clean energy stocks behave differently to the same risk factors, investors may want to account for this when investing in clean energy stocks.

I analyse a total of thirteen different clean energy indexes, all with different selection criteria. Sadorsky (2012) concludes that clean energy stock prices can be used to hedge an investment in clean energy stocks based on the analysis of one clean energy index. In his article, Sadorsky uses the Wilderhill Clean Energy Index to study the dynamic conditional correlation between clean energy stock prices, technology stock prices and oil prices.

The NYSE Euronext (NYSE) and Bloomberg New Energy Finance (BNEF) together launched six clean energy indexes; three global indexes focussing on all areas in the value chain of solar energy (Solar), wind energy (Wind) and advanced transportation, digital energy, energy storage, fuel cells an energy efficiency (EST). The other three indexes from the NYSE Bloomberg series focus on all clean energy companies in the value chain incorporated in the Americas (AMG), Asia-Pacific (APG) and Europe, Middle East and Africa (EMG).

Next, I use six different global clean energy indexes to evaluate whether even diversified portfolios formed from the same sample of stocks to choose from can still show differences in risk exposure to the same risk factors. I choose to use the Wilderhill New Energy Global Innovation Index (NEX) which has the goal to track the entire clean energy sector on a global scale as accurately as possible. Next, the World Alternative Energy Index (WAEX) tracks the twenty largest companies operating in the clean energy sector. The DAX Alternative Energy Index (DAX) tracks the fifteen largest companies operating in the clean energy sector. The S&P Global Clean Energy Index tracks thirty companies in the clean energy sector. The Credit Suisse Global Alternative Energy Index (CSA) tracks the thirty largest and most liquid companies operating in the clean energy sector. The FTSE ET50 index (ET50) tracks the fifty largest companies which derive at least 50% of their revenue from the development of environmentally friendly technologies. Finally, I incorporated the MSCI World Index and the S&P 500 Index as control groups for the second part of my analysis. Graphs of the raw data on all index prices and oil prices are reported in Appendix A.

I collect both daily and monthly data on the indexes using the Bloomberg database from 01-01-2000 onwards, I use the gross total return indexes in order to get the most clean data. Unfortunately, most clean energy indexes are relatively new and the first data on most indexes dates from various starting points after 01-01-2000. This means the amount of observations differ per index, the amount of observations per index are reported in *table 1* and *table 2* for the daily and monthly data respectively. As the sample period is important for results of time series analyses, I take into account that indexes with different sample periods are hard to compare. Despite the different sample periods, I choose to include all of the indexes in my thesis as I believe all indexes provide additional information for the entire view on the risk-return relationship of investments in clean energy as a whole. The amount of observations ranges from 2249 to 4043 for the daily data and 102 to 173 for the monthly data.

For the daily closing prices, I only used weekday data of Bloomberg. As non-trading weekdays are different all over the globe, and because I use indexes from all over the world, I did not omit non-trading weekdays in order to preserve as much daily data as possible.

For building the factor models, I downloaded daily and monthly factors from the website for Kenneth French[2]. For the monthly factors, I downloaded factors formed by Kenneth French for global, U.S., Asia-Pacific (excluding Japan) and European data. The website, unfortunately, has got daily data available for the U.S. only. Forming my own daily factors for global, Asia-Pacific and European data is beyond the scope of my thesis, I therefore only construct factor models with daily data for the U.S. indexes.

Few observations were lost when I combined the data of Bloomberg and Kenneth French's website. For the daily data 123 up to 260 observations per index were lost, depending on the inception date of the index. For the monthly data no observations were lost.

The descriptive statistics for the daily total returns of all indexes can be found in *Table 1.* All of the daily returns have a mean and median close to zero and the standard deviation is higher than the mean for all return series. All series display a low to moderate skewness and high kurtosis. As we can see in the column of the Jarque-Bera test and the probabilities next to the Jarque-Bera coefficients, none of the return series are normally distributed.

[2] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 1 – Descriptive Statistics Daily Data

Panel A shows the descriptive statistics of daily total returns of all indexes and the returns calculated from the daily closing prices of WTI crude oil future contracts. Panel B shows the unconditional correlation matrix.

Panel A: descriptive statistics daily returns

Index	Observations	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Sharpe ratio	Jarque-Bera	Probability	Number of constituents	Region
Credit Suisse Global Alternative Energy Index (CSA)	3782	0.02	0.05	14.91	-10.42	1.35	-0.09	16.05	0.02	26845.08	0.00	30	Global
DAXGlobal® Alternative Energy (DAX)	3782	0.02	0.03	11.86	-10.72	1.42	-0.10	10.48	0.02	8815.27	0.00	15	Global
FTSE ET50 Index (ET50)	4043	0.02	0.06	13.15	-9.67	1.52	0.12	11.76	0.01	12927.18	0.00	50	Global
S&P Global Clean Energy Index (SPG)	3030	0.01	0.08	19.83	-13.91	1.94	-0.11	16.50	0.01	23025.63	0.00	30	Global
The WilderHill New Energy Global Innovation Index (NEX)	3783	0.02	0.05	12.83	-9.95	1.48	-0.18	10.03	0.01	7806.13	0.00	105	Global
World Alternative Energy Index (WAEX)	2249	0.03	0.08	13.70	-9.71	1.62	-0.04	9.35	0.02	5037.46	0.00	20	Global
NYSE Bloomberg Global Energy Smart Technologies Index (EST)	3002	0.04	0.10	7.45	-7.16	1.25	-0.26	6.59	0.04	1360.34	0.00	247	Global
NYSE Bloomberg Global Solar Energy Index (Solar)	2480	0.02	0.04	16.41	-11.86	2.11	-0.23	9.99	0.01	5073.55	0.00	119	Global
NYSE Bloomberg Global Wind Energy Index (Wind)	2480	0.03	0.07	12.96	-13.02	1.55	-0.49	14.04	0.02	12694.83	0.00	77	Global
NYSE Bloomberg Europe Middle East & Africa Clean Energy Index (EMG)	2480	0.04	0.08	13.82	-12.07	1.75	-0.11	11.37	0.02	7242.86	0.00	110	Europe
NYSE Bloomberg Asia Pacific Clean Energy Index (APG)	2480	0.02	0.09	5.82	-7.81	1.30	-0.73	6.55	0.02	1524.24	0.00	352	Asia
NYSE Bloomberg Americas Clean Energy Index (AMG)	2480	0.03	0.09	13.00	-10.49	1.64	-0.19	9.40	0.02	4248.07	0.00	154	U.S.
Clean Edge® Green Energy Index (CEXX)	2480	0.03	0.05	16.33	-13.40	2.22	-0.22	7.82	0.01	2195.77	0.00	48	U.S.
S&P 500 Index (SP)	4043	0.02	0.02	11.58	-9.03	1.25	0.01	11.73	0.01	12832.07	0.00	50	U.S.
MSCI World Index (MWXO)	4043	0.01	0.06	9.52	-7.06	1.04	-0.18	10.75	0.01	10146.36	0.00	1642	Global
Oil	4043	0.04	0.00	14.26	-15.25	2.24	-0.10	6.62	0.02	2219.89	0.00		

Panel B: unconditional correlaton matrix																
	Solar	**Wind**	**EST**	**AMG**	**EMG**	**APG**	**NEX**	**SPG**	**CEXX**	**CSA**	**DAX**	**WAEX**	**ET50**	**Oil**	**MXWO**	**SP500**
Solar	1															
Wind	0.716	1														
EST	0.766	0.73	1													
AMG	0.769	0.547	0.84	1												
EMG	0.699	0.856	0.728	0.626	1											
APG	0.667	0.726	0.684	0.39	0.519	1										
NEX	0.861	0.819	0.866	0.816	0.848	0.647	1									
SPG	0.895	0.753	0.775	0.824	0.79	0.566	0.908	1								
CEXX	0.797	0.506	0.808	0.953	0.572	0.394	0.823	0.822	1							
CSA	0.797	0.782	0.789	0.804	0.868	0.544	0.841	0.877	0.754	1						
DAX	0.76	0.721	0.713	0.733	0.776	0.507	0.753	0.799	0.709	0.829	1					
WAE	0.805	0.77	0.818	0.787	0.815	0.58	0.878	0.855	0.771	0.85	0.781	1				
ET50	0.85	0.806	0.859	0.84	0.859	0.604	0.883	0.906	0.821	0.86	0.779	0.89	1			
Oil	0.344	0.367	0.381	0.374	0.419	0.253	0.291	0.351	0.361	0.368	0.255	0.366	0.261	1		
MXWO	0.701	0.708	0.868	0.844	0.815	0.52	0.838	0.806	0.777	0.84	0.712	0.811	0.779	0.28	1	
SP500	0.607	0.464	0.764	0.89	0.56	0.29	0.694	0.69	0.829	0.699	0.586	0.661	0.642	0.206	0.889	1

Table 2 – Descriptive Statistics Monthly Data
Descriptive statistics of monthly total returns of all indexes and the returns calculated from the closing prices of WTI crude oil future contracts.

Index	Observations	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Sharpe ratio	Jarque-Bera	Probability	Number of constituents	Region
Credit Suisse Global Alternative Energy Index (CSA)	172	0.56	0.94	22.00	-25.33	6.29	-0.66	5.33	0.09	51.40	0.00	30	Global
DAXGlobal® Alternative Energy (DAX)	172	0.47	1.07	25.61	-20.26	6.86	-0.15	4.54	0.07	17.65	0.00	15	Global
FTSE ET50 Index (ET50)	173	0.29	1.22	21.41	-33.58	7.35	-0.94	5.79	0.04	81.41	0.00	50	Global
S&P Global Clean Energy Index (SPG)	138	0.36	1.79	22.56	-39.94	9.04	-1.18	6.27	0.04	93.33	0.00	30	Global
The WilderHill New Energy Global Innovation Index (NEX)	173	0.55	1.79	21.63	-35.00	7.84	-0.85	5.34	0.07	60.50	0.00	105	Global
World Alternative Energy Index (WAEX)	137	0.79	1.45	31.46	-28.53	8.55	-0.20	4.88	0.09	21.12	0.00	20	Global
NYSE Bloomberg Global Energy Smart Technologies Index (EST)	113	1.10	1.97	20.44	-26.55	6.71	-0.56	4.99	0.16	24.48	0.00	247	Global
NYSE Bloomberg Global Solar Energy Index (Solar)	113	0.92	1.56	38.29	-39.46	11.71	-0.41	4.42	0.08	12.57	0.00	119	Global
NYSE Bloomberg Global Wind Energy Index (Wind)	113	0.92	2.06	21.16	-42.46	8.69	-1.21	7.76	0.11	134.38	0.00	77	Global
NYSE Bloomberg Europe Middle East & Africa Clean Energy Index (EMG)	113	0.79	2.02	17.15	-35.34	7.86	-1.12	6.49	0.10	80.95	0.00	110	Europe
NYSE Bloomberg Asia Pacific Clean Energy Index (APG)	113	0.78	1.47	18.71	-30.08	7.51	-0.71	5.25	0.10	33.22	0.00	352	Asia
NYSE Bloomberg Americas Clean Energy Index (AMG)	113	0.67	1.67	20.27	-26.62	6.73	-0.82	5.57	0.10	43.61	0.00	154	U.S.
Clean Edge® Green Energy Index (CEXX)	102	0.50	1.81	20.06	-32.44	9.12	-0.79	4.19	0.06	16.65	0.00	48	U.S.
S&P 500 Index (SP)	173	0.37	1.00	10.77	-16.94	4.33	-0.68	4.20	0.08	23.70	0.00	50	U.S.
MSCI World Index (MWXO)	173	0.32	1.02	10.90	-19.04	4.55	-0.75	4.62	0.07	35.38	0.00	1642	Global
Oil	173	0.48	0.63	28.50	-32.75	9.39	-0.30	3.81	0.05	7.28	0.03		

Panel B of *table 1* shows the unconditional correlation matrix of all indexes and oil. The correlation between oil and all indexes ranges from a low correlation of 0.206 to a moderate correlation of 0.419. The correlation among indexes ranges, naturally, from moderate to high.

3.2. Methodology

In this section I will discuss the methods used in my thesis. I will first address the methods for building the multi factor models, followed by building the dynamic conditional correlation GARCH models. Lastly, I will explain how I use the DCC GARCH models to calculate time-varying hedge ratios and forecast the conditional covariance matrices, dynamic conditional correlations and time varying hedge ratios.

3.2.1. Multi-factor modelling

In this paragraph, I will discuss the method I use to construct multi-factor models for the different indexes. The models are constructed using ordinary least squares (OLS) regressions.

Multifactor modelling started with the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965). Equation (1) shows the equation of the CAPM, in which the market risk premium $\left(R_{m,t} - r_{f,t}\right)$ was the only risk factor incorporated in this model.

$$r_t - r_{f,t} = a + b\left(R_{m,t} - r_{f,t}\right) + \varepsilon_t \quad (1)$$

Fama and French (1993) expand the CAPM with two additional risk factors, namely the book-to-market ratios (or value factor) (HML_t) and the size factor (SMB_t). Equation (2) shows the equation of the three-factor model of Fama and French (1993).

$$r_t - r_{f,t} = a + b_1\left(R_{m,t} - r_{f,t}\right) + b_2(SMB_t) + b_3(HML_t) + \varepsilon_t \quad (2)$$

Carhart (1997) goes a step further and suggests that the three-factor model does not explain all of the returns. He suggests that positive returns in the preceding period may indicate positive returns in the current period. Therefore, Carhart (1997) added his momentum factor (WML_t) to the mix, equation (3) shows the four-factor model of Carhart (1997) .

$$r_t - r_{f,t} = a + b_1\left(R_{m,t} - r_{f,t}\right) + b_2(SMB_t) + b_3(HML_t) + b_4(WML_t) + \varepsilon_t \quad (3)$$

The four-factor model is widely accepted and used for explaining returns and determining risk exposure of stocks. Fama and French (2012) also accept the four-factor model and study its application for various graphical regions. Fama and French (2012) find that the four-factor model outperforms previous models when explaining results and explain how the model can be applied in different situations.

Most recently, Fama and French (2015) came up with their five-factor model. Fama and French (2015) added the profitability (RMW_t) and investment factor (CMA_t) to their three factor model. Equation (4) shows the equation for the five-factor model.

$$r_t - r_{f,t} = a + b_1(R_{m,t} - r_{f,t}) + b_2(SMB_t) + b_3(HML_t) + b_4(RMW_t) + b_5(CMA_t) + \varepsilon_t \quad (4)$$

In addition to the four- and five-factor model, I add an oil factor to incorporate the risk exposure to oil for clean energy stocks just like Henriques and Sadorsky (2008). As clean energy can be seen as a direct substitute for energy generated from fossil fuels, shocks in oil prices may cause larger shocks in clean energy stock prices than the overall market. Thus, the risk exposure may not be fully captured in the market risk premium. Using vector auto regressions I determine whether and how many lags should be used when constructing the Oil factor. The Akaike Information Criteria (AIC) proves one lag to be optimal for both daily and monthly data. I will test the oil factor both without lags and with one lag. For U.S.-based indexes, I use daily data and the five-factor model. For non-U.S.-based indexes, I use monthly data and the four-factor model. Equation (5) through (8) show the models used with the Oil factor.

Without lags:

$$r_t - r_{f,t} = a + b_1(R_{m,t} - r_{f,t}) + b_2(SMB_t) + b_3(HML_t) + b_4(WML_t) + b_5(OIL_t) + \varepsilon_t \quad (5)$$

$$r_t - r_{f,t} = a + b_1(R_{m,t} - r_{f,t}) + b_2(SMB_t) + b_3(HML_t) + b_4(RMW_t) + b_5(CMA_t) + b_5(OIL_t) + \varepsilon_t \quad (6)$$

With one lag:

$$r_t - r_{f,t} = a + b_1(R_{m,t} - r_{f,t}) + b_2(SMB_t) + b_3(HML_t) + b_4(WML_t) + b_5(OIL_{t-1}) + \varepsilon_t \quad (7)$$

$$r_t - r_{f,t} = a + b_1(R_{m,t} - r_{f,t}) + b_2(SMB_t) + b_3(HML_t) + b_4(RMW_t) + b_5(CMA_t) + b_5(OIL_{t-1}) + \varepsilon_t \quad (8)$$

3.1.2. Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroscedasticity Model

The multi factor models using the ordinary least squares regression methods assumed the relationship between variables to be constant overtime. In reality, however, this may not be the case when looking at returns of financial assets. The advantage of GARCH models, is that the GARCH models do not assume the volatility of the variables to be constant over time. GARCH models accept that big shocks in asset prices cause higher volatility in the period(s) following the shock. Therefore, a shock in the oil price because of a sudden increase in oil supply may cause higher volatility in the oil price in the period(s) following the supply shock. In financial markets co-movements of assets are important for asset pricing models, portfolio selection, hedging and Value-at-Risk forecasts. Multivariate GARCH models can model the volatility-spill-over effects between multiple assets while maintaining the ability to let the volatility change over time. I will use the DCC-GARCH model in this thesis to capture the dynamic conditional correlation between oil prices and clean energy indexes.

The DCC-GARCH model is a two-step process. First the GARCH parameters are estimated, followed by the dynamic conditional correlation. Equation (9), (10) and (11) show the model used.

$$r_{it} = \mu_i + \varepsilon_{it} , i = 1{,}2 \ (9)$$

$$\varepsilon_{it} = H_{it}^{1/2} z_{it} \ (10)$$

$$H_t = D_t R_t D_t \ (11)$$

In equation (9), r_{it} stands for the i x 1 vector log returns of return series i and ε_{it} stands for the i x 1 vector of the error term for the returns of asset i at time t. The error matrix ε_{it} from equation (10) is modelled as a univariate GARCH model, where ε_{it} is dependent of the conditional covariance H_t. The conditional covariance H_t is derived from the conditional standard deviation D_t of ε_{it} and the conditional correlation R_t. The conditional standard deviation D_t is the diagonal matrix with standard deviations derived from the univariate GARCH models, see equation (12).

$$D_t = \begin{bmatrix} \sqrt{h_{1t}} & 0 \\ 0 & \sqrt{h_{2t}} \end{bmatrix} \ (12)$$

Equation (13) shows the conditional covariance in a vector form, which forms the elements of the diagonal for equation (12).

$$h_{it} = c_i + \sum_{q=1}^{qi} \alpha_{iq} a_{i,t-q}^2 + \sum_{p=1}^{pi} \beta_{ip} h_{i,t-p}^2 \ (13)$$

The GARCH model in this thesis will have the order of GARCH(1,1), which means both q and p are both equal to one. The conditional correlation matrix R_t of the standardized disturbances ϵ_t is displayed in equation (14) and (15).

$$\epsilon_t = D_t^{-1} a_t \sim N(0, R_t) \ (14)$$

$$R_t = \begin{bmatrix} 1 & \rho_{12,t} \\ \rho_{12,t} & 1 \end{bmatrix} \ (15)$$

Substituting equation (12) and (15) into equation (11) to get the elements of equation (11), see equation (16).

$$[H_t]ij = \sqrt{h_{it} h_{it}} \rho_{ij} \ (16)$$

The DCC-GARCH model is bound to two restrictions. For one, H_t has to be positive and definite. Second, all of the elements in the conditional correlation matrix R_t must have a value of one or less. To ensure these two restrictions, R_t is decomposed in equations (17) and (18).

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \ (17)$$

$$Q_t = (1 - a - b)\bar{Q} + a\epsilon_{t-1}\epsilon_{t-1}^T + bQ_{t-1} \ (18)$$

Where $\bar{Q}$ is the unconditional covariance matrix of the standardized errors ϵ_t. $\bar{Q}$ can be estimated following equation (19). Q_t^* is a diagonal matrix with the square root of the diagonal elements of Q_t at the diagonal, see equation (20).

$$\bar{Q} = \frac{1}{T} \sum_{T=1}^{T} \epsilon_t \epsilon_t^T \ (19)$$

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11t}} & 0 \\ 0 & \sqrt{q_{22t}} \end{bmatrix} \ (20)$$

Q_t^* rescales the elements in Q_t to ensure the second requirement; $|\rho_{ij}| = \left| \frac{q_{ijt}}{\sqrt{q_{ijt} q_{ijt}}} \right| \leq 1$. Next, in order to ensure that the conditional covariance matrix H_t is positive and definite, we can impose restrictions on parameters a and b, namely; $a \geq 0$, $b \geq 0$ and $a + b \leq 1$. In addition, the starting value of Q_t also has to be positive and definite in order for H_t to be positive and definite.

3.1.3. Hedging and out-of-sample forecasting

The next step in my analysis is to define optimal hedge positions between the clean energy indexes and oil, to show how to minimize risk exposure to oil. According to Hsu Ku et. al. (2007) the DCC GARCH model proves to provide the most accurate time-varying hedge ratios. In the research of Chang et. al. (2011) the DCC GARCH model comes in on second place of most effective model to provide time-varying hedge ratios. Basher and Sadorsky (2016), in contract, argue that a combination of GARCH models is the best way to find the optimal hedge ratios. Additionally, Basher and Sadorsky (2016) find oil provides the most effective hedge compared to other options for hedging like gold, CBOE Volatility Index (VIX) and bonds.

Following Sadorsky (2012), I will calculate the time-varying hedge ratios using the method of Kroner and Sultan (1993). By using the conditional covariance matrix H_t and the conditional variance of oil which is retrieved from the diagonal matrix D_t , I will compute the time-varying hedge ratios following equation (21).

$$B_t = \frac{H_{12,t}}{D_{22,t}} \quad (21)$$

GARCH models are effectively ranked by their forecasting ability. Recently, the amount of varieties on the GARCH model has exploded. I have used the DCC GARCH model throughout my thesis and will also do so for forecasting, generally the DCC GARCH model does a good job on forecasting especially in the short-run, though there are newer models that might do slightly better (see for example Boudt et. al. (2013)). For out-of-sample forecasting I will use the method proposed by Engle and Sheppard (2001) for n-step ahead forecast for the DCC GARCH models. Engle and Sheppard (2001) propose two methods; forecasting the conditional covariance matrix Q_{t+n} and directly forecasting the conditional correlation matrix R_{t+n}. Both methods are biased towards their unconditional counterparts, but Engle and Sheppard (2001) found that directly forecasting the conditional correlation matrix leads to the least biased forecasts and is easier to implement, despite both methods not outperforming one and another significantly. I use the method to forecast the conditional covariance matrix Q_{t+n}, using the forecasted conditional variance matrix to calculate the forecasted conditional correlation matrix R_{t+n}. Equation (22) shows the method for forecasting the conditional covariance matrix Q_{t+n}, equation (23) shows how the conditional correlation is computed from the conditional covariance matrix.

$$E_t[Q_{t+n}] = \sum_{i=0}^{n-2}(1-a-b)\bar{Q}(a+b)^i + (a+b)^{n-1}Q_{t+1} \quad (22)$$

$$R_{t+n} = Q_{t+n}^{*-1} Q_{t+n} Q_{t+n}^{*-1} \; (23)$$

I use equation (22) to forecast the 365-step-ahead conditional covariance matrix and equation (23) for compute the 365-step-ahead conditional correlation matrix. I will not reserve any in-sample data for out-of-sample forecasting, which means I will forecast from the end of the data sample up to one year after the end of the data sample. The reason why I choose the slightly more biased method is because I will use the conditional covariance matrix to compute the future time-varying hedge ratios. As it is not optimal for investors to rebalance their portfolios daily, I will calculate the optimal monthly hedge ratios using the daily ones from my analysis.

4. Results

In this section I will discuss the empirical results of my analysis. I will start by discussing the results of the multi-factor modelling, followed by the results of the DCC GARCH models, the hedge ratios and the out of sample forecasts.

4.1. Multi-factor modelling

Table 3 panel A through D and *table 4* panel A and B show the results of the ordinary least squares regressions. *Table 3* shows regression results for monthly data, *Table 4* for daily data.

I first consider the different industries within the clean energy sector; Solar, Wind and Technology (*Table 3* panel A). The Solar index has the highest risk exposure to the market, with Wind coming in on second and EST on third with the lowest risk exposure to the market. Solar has the lowest alpha, which indicates the Solar index underperforms compared to the other two industries, however, none of the alpha's differ significantly from zero. The size factor is only significant for both the Wind and EST index. The Wind index has slightly more risk exposure to the size factor than the EST index. Both the value and momentum factors are insignificant for all indexes. When adding a fifth factor to study the risk exposure to Oil, I find no significant risk exposure for any of the industries. The adjusted R-squared is highest for the EST index without the Oil factor, meaning that the four-factor explains the returns of the EST index the best of all three industries. The insignificant alpha's indicate that all three industries do not significantly underperform the market, however, with a risk exposure to the market higher than one, an investment in any of the three industries is more risky than in investment in the market. From the three industries, the EST index is the least risky with a beta of 1.177 in the four factor model.

When considering the returns of clean energy for different continents (*table 3* panel B), differences shrink compared to the differences across the three industries. Note that for modelling the returns of the AMG, APG and EMG indexes different datasets to construct the factors are used to fit the region. The AMG index shows the lowest alpha, indicating underperformance compared to the other regions, however, all of the alphas are insignificant. The EMG index has the highest risk exposure to the market, the APG index has the lowest risk exposure to the market. The size factors are generally lower than the size factors for the Solar, Wind and Technology indexes. The exposure to the size factor is the highest for the AMG index when considering the three regions. Only the AMG index has significant risk exposure to the value factor at a 10% significance level, the momentum factor is again insignificant for all indexes. For the AMG, APG and EMG indexes, the Oil factor is also insignificant in all models.

Lastly, when we look at the remaining indexes (*table 3* panel C and D), we see that for few indexes Oil is a significant risk factor. The NEX is the only index for which the Oil factor is significant at the 1% level, however, when one lag is used the Oil t-1 factor becomes insignificant. For the WAEX and CSA index, the Oil factor without lags is significant at the 5% level and for the CEXX index on the 10% level.

From all of the indexes, the SPG index is the only index with a significant negative alpha, indicating that this index is the only index which underperforms the market. The other indexes provide market competitive returns from a risk-return relation point of view.

Table 3 – Results Monthly Four Factor Models
This table shows the results for the four factor models, without the added oil factor, with the oil factor and with the lagged one period oil factor. Panel A shows the Results for the industry indexes; Solar, Wind and Technology (EST) for the period of 01-01-2006 up to 01-07-2015. Panel B shows the results for the AMG, APG and EMG indexes for the period of 01-01-2006 up to 01-07-2015. Panel C and D show the global indexes (NEX, SPG, WAEX, CSA and DAX) and the CEXX index. For the NEX, CSA and DAX index the results are shown for the period of 01-01-2001 up to 01-07-2015, for the SPG and WAEX from 01-01-2004 up to 01-07-2015 and for the CSA from 01-01-2007 up to 01-07-2015. Robust t-values are reported between parentheses, which are corrected for autocorrelation and heteroscedasticity using the Newey-West estimator. ***, ** and *, denote the significance level of the coefficients on the respectively 1%, 5% and 10% level (two-tailed)

Panel A: four factor models for the Solar, Wind and EST indexes

	Solar Index			Wind Index			EST Index		
Constant	-0.244 (-0.287)	-0.207 (-0.233)	-0.225 (-0.260)	0.085 (0.128)	0.108 (0.161)	0.070 (0.105)	0.388 (1.205)	0.406 (1.245)	0.399 (1.211)
Market	1.785*** (12.746)	1.750*** (11.173)	1.779*** (12.870)	1.403*** (9.768)	1.382*** (7.626)	1.408*** (9.370)	1.177*** (22.612)	1.160*** (19.092)	1.174*** (22.150)
Size	1.110 (1.633)	1.094 (1.588)	1.110 (1.637)	0.995** (2.400)	0.986** (2.277)	0.994*** (2.385)	0.923*** (5.429)	0.916*** (5.362)	0.923*** (5.439)
Value	-0.138 (-0.243)	-0.123 (-0.218)	-0.185 (-0.318)	-0.446 (-0.979)	-0.437 (-0.933)	-0.409 (-0.953)	0.019 (0.107)	0.026 (0.149)	-0.008 (-0.040)
Momentum	0.30 (1.376)	0.290 (1.330)	0.293 (1.359)	-0.047 (-0.390)	-0.053 (-0.462)	-0.041 (-0.352)	-0.041 (-0.360)	-0.046 (-0.402)	-0.045 (-0.401)
Oil		0.032 (0.450)			0.019 (0.247)			0.015 (0.662)	
Oil t-1			0.033 (0.468)			-0.026 (-0.349)			0.018 (0.5466)
Adjusted R-squared	0.522	0.518	0.518	0.635	0.632	0.633	0.804	0.802	0.802
Observations	113	113	113	113	113	113	113	113	113
Region	World			World			World		

Panel B: four factor models for the AMG, APG and EMG indexes									
	AMG Index			APG Index			EMG Index		
Constant	-0.316 (-0.931)	-0.228 (-0.702)	-0.305 (-0.898)	-0.207 (-0.417)	-0.268 (-0.542)	-0.214 (-0.437)	-0.087 (-0.299)	-0.072 (-0.236)	-0.081 (-0.276)
Market	1.216*** (16.470)	1.134*** (13.272)	1.210*** (16.734)	0.882*** (12.915)	0.927*** (11.627)	0.883*** (12.498)	1.256*** (15.872)	1.244*** (10.932)	1.255*** (15.964)
Size	0.676*** (5.154)	0.692*** (5.306)	0.677*** (5.113)	0.540*** (3.604)	0.580*** (3.650)	0.546*** (3.469)	0.460*** (2.777)	0.453*** (2.623)	0.459*** (2.773)
Value	-0.281* (-1.724)	-0.284* (-1.784)	-0.304* (-1.781)	0.203 (1.075)	0.156 (0.835)	0.187 (1.008)	-0.041 (-0.234)	-0.031 (-0.158)	-0.051 (-0.305)
Momentum	0.032 (0.309)	0.001 (0.010)	0.024 (0.243)	0.042 (0.323)	0.052 (0.406)	0.038 (0.295)	0.097 (1.397)	0.094 (1.410)	0.011 (1.435)
Oil		0.073* (1.803)			-0.066 (-1.419)			0.011 (0.226)	
Oil t-1			0.023 (0.763)			-0.036 (-1.148)			0.011 (0.309)
Adjusted R-squared	0.829	0.836	0.832	0.689	0.690	0.688	0.875	0.874	0.874
Observations	113	113	113	113	113	113	113	113	113
Region	North America			Asia-Pacific			Europe		

Panel C: four factor models for the NEX, SPG and WAEX indexes									
	NEX Index			SPG Index			WAEX Index		
Constant	-0.339 (-1.000)	-0.315 (-0.958)	-0.328 (-0.966)	-0.958* (-1.843)	-0.919* (-1.767)	-0.947* (-1.822)	-0.469 (-0.970)	-0.387 (-0.793)	-0.466 (-0.954)
Market	1.457*** (20.494)	1.406*** (19.804)	1.452*** (20.896)	1.666*** (16.570)	1.606*** (14.562)	1.654*** (17.707)	1.488*** (14.742)	1.364*** (13.492)	1.485*** (14.954)
Size	0.812*** (5.372)	0.759*** (4.844)	0.807*** (5.365)	0.622* (1.971)	0.597* (1.841)	0.618* (1.976)	0.842** (2.406)	0.786** (2.306)	0.840** (2.388)
Value	-0.185 (-1.344)	-0.202 (-1.454)	-0.222 (-1.499)	-0.075 (-0.212)	-0.069 (1.841)	-0.162 (-0.463)	0.172 (0.514)	0.184 (0.561)	0.150 (0.427)
Momentum	-0.024 (-0.273)	-0.047 (-0.559)	-0.035 (-0.417)	0.144 (0.954)	0.125 (0.849)	0.129 (0.886)	0.291 (1.489)	0.251 (1.381)	0.288 (1.494)
Oil		0.060*** (2.244)			0.060 (1.419)			0.124** (2.202)	
Oil t-1			0.031 (0.954)			0.058 (1.411)			0.015 (0.372)
Adjusted R-squared	0.795	0.798	0.795	0.681	0.682	0.682	0.627	0.640	0.624
Observations	173	173	173	138	138	138	137	137	137
Region	World			World			World		

Panel D: four factor models for the CEXX, CSA and DAX indexes									
	CEXX Index			CSA Index			DAX Index		
Constant	-0.737 (-1.312)	-0.627 (-1.138)	-0.729 (-1.294)	-0.322 (-1.059)	-0.27 (-0.924)	-0.325 (-1.058)	-0.046 (-0.110)	-0.054 (-0.126)	-0.035 (-0.084)
Market	1.540*** (16.733)	1.427*** (11.724)	1.533*** (16.235)	1.215*** (18.985)	1.137*** (18.055)	1.216*** (19.225)	0.975*** (9.186)	0.987*** (9.033)	0.969*** (9.067)
Size	0.853*** (4.600)	0.890*** (4.702)	0.852*** (4.554)	0.251* (1.703)	0.184 (1.151)	0.253* (1.680)	0.565*** (2.873)	0.576*** (2.850)	0.556*** (2.809)
Value	-0.639** (-2.546)	-0.631*** (-2.618)	-0.663** (-2.502)	0.067 (0.443)	0.034 (0.229)	0.078 (0.527)	-0.487** (-2.051)	-0.482** (-2.037)	-0.536** (-2.145)
Momentum	0.007 (0.059)	-0.025 (-0.237)	-0.001 (-0.009)	0.215*** (2.609)	0.172** (2.306)	0.218*** (2.709)	0.045 (0.392)	0.052 (0.461)	0.033 (0.293)
Oil		0.097* (1.756)			0.088** (2.436)			-0.014 (-0.395)	
Oil t-1			-0.024 (0.588)			-0.009 (-0.262)			0.043 (0.945)
Adjusted R-squared	0.754	0.759	0.752	0.718	0.731	0.716	0.457	0.454	0.457
Observations	102	102	102	172	172	172	172	172	172
Region	North America			World			World		

To test the influence on data frequency, I create a four- and five-factor model with daily data, see *table 4* panel A and B. As daily data on factors is only available for North America on Kenneth Frenchs' website, I only test the AMG and CEXX indexes. Note that the AMG index is mostly but not solely comprised out of companies incorporated in North America, 80% of the companies is incorporated in the U.S.. For the AMG and CEXX indexes, the Oil factor is significant for both the four- and five-factor model either with or without one lag. The models improve only slightly with the use of the Oil factor, as the adjusted R-squared only increases by 0.005 and 0.002 for the Americas and Clean Edge index respectively. The factor models with daily data show that Oil is a significant risk factor but does not add power to the explaining factor of the models.

Table 4 - Results Daily Four and Five Factor Models

This table shows the results for the four and five factor models with daily returns data, without the added oil factor, with the oil factor and with the lagged one period oil factor. Panel A shows the results for the four factor models and Panel B for the five factor models. Only data indexes with a majority of U.S. listed firms in their portfolio have been used, as there is only U.S. data available for the daily factors. The sample period for the AMG index is 01-01-2006 up to 01-07-2015, for the CEXX index the sample period is 01-01-2007 up to 01-07-2015. Robust t-values are reported between parentheses, which are corrected for autocorrelation and heteroscedasticity using the Newey-West estimator. ***, ** and *, denote the significance level of the coefficients on the respectively 1%, 5% and 10% level (two-tailed)

Panel A: four factor models with daily data						
	AMG Index			**CEXX Index**		
Constant	-0.012 (-0.878)	-0.010 (-0.763)	-0.012 (-0.880)	-0.025 (-1.026)	-0.023 (-0.971)	-0.025 (-1.034)
Market	1.148*** (56.945)	1.113*** (57.288)	1.152*** (56.390)	1.378*** (38.111)	1.333*** (36.099)	1.381*** (37.807)
Size	0.273*** (6.509)	0.286*** (7.314)	0.271*** (6.547)	0.664*** (8.963)	0.680*** (9.618)	0.662*** (8.997)
Value	-0.183*** (-3.976)	-0.189*** (-4.472)	-0.187*** (-4.115)	-0.341*** (-4.847)	-0.341*** (-5.094)	-0.344*** (-4.931)
Momentum	0.001 (0.022)	0.001 (0.105)	-0.001 (-0.026)	-0.105** (-2.011)	-0.098** (-2.036)	-0.107** (-2.053)
Oil		0.060*** (7.224)			0.075*** (5.128)	
Oil T-1			-0.023*** (2.894)			0.022* (1.889)
Observations	2350	2350	2350	2126	2126	2126
Adjusted R-squared	0.827	0.832	0.827	0.754	0.759	0.754
Region	North America			North America		
Panel B: five factor models with daily data						
	AMG Index			**CEXX Index**		
Constant	-0.004 (-0.290)	-0.003 (-0.221)	-0.004 (-0.291)	-0.009 (-0.385)	-0.008 (-0.360)	-0.009 (-0.391)
Market	1.097*** (53.787)	1.073*** (54.108)	1.102*** (53.302)	1.277*** (34.614)	1.252*** (33.178)	1.281*** (34.323)
Size	0.239*** (5.920)	0.249*** (6.536)	0.239*** (5.945)	0.590*** (10.108)	0.601*** (10.532)	0.59*** (10.142)
Value	-0.231*** (-5.164)	-0.247*** (-6.014)	-0.230*** (-5.189)	-0.359*** (-5.308)	-0.370*** (-5.768)	-0.359*** (-5.281)
Profit	-0.381*** (-5.035)	-0.372*** (-5.122)	-0.370*** (-4.963)	-0.845*** (-7.768)	-0.831*** (-7.698)	-0.837*** (-7.722)
Investment	-0.452*** (-5.769)	-0.383*** (-5.025)	-0.453*** (-5.845)	-1.016*** (-8.709)	-0.953*** (-8.342)	-1.017*** (-8.768)
Oil		0.049*** (6.345)			0.049*** (3.848)	
Oil T-1			0.020*** (2.870)			0.016 (1.440)
Observations	2350	2350	2350	2126	2126	2126
Adjusted R-squared	0.836	0.84	0.837	0.781	0.783	0.781
Region	North America			North America		

4.2. DCC-GARCH

In this paragraph I will discuss the results from the DCC-GARCH models. The table 5 panel A and B show the parameters resulting from the DCC-GARCH models for all indexes.

The mean variable μ_i represents the dependence of current returns on their one period lag returns. As we can see from the tables, all indexes are significantly dependent on their one period lag return. For the Oil returns this is only the case for the models with the longest data horizon (NEX, CSA, ET50, MXWO, SP), and even for those models only on the 10% level.

The term c_i stands for the constant term of conditional variance function (equation (13)). The terms α_i and β_i stand for the ARCH and GARCH terms respectively and are important for explaining the conditional variance. The ARCH term reflects short term persistence, whereas the GARCH term represents long term persistence. All of the terms across the different indexes are highly significant and the coefficients are similar. The GARCH terms are close to one, whereas the ARCH terms are much smaller, meaning that the long-term persistence is higher for all returns series than the short-term persistence.

Terms a_i and b_i represent the conditional correlation terms from equation (18), all of the terms are significant at the one percent level. For all models the coefficients of the conditional correlation terms sum up to a value of slightly less than one, meaning that the values in the conditional covariance matrix are positive and finite. The sum of the terms close to one, means that the conditional correlation between all indexes and oil is very dynamic.

Table 5 – DCC-GARCH Parameters

Table 5 shows the parameters of the univariate GARH models, followed by the parameters for the dynamic conditional correlation (a and b). The mean variables (μ_1 and μ_2) stand for the effect of last period returns on current returns. The ARCH terms (α_{11} and α_{21}) measure the short-term persistence, the GARCH terms (β_{11} and β_{21}) measure the long-term persistence. The t-values are reported between parentheses. ***, ** and *, denote the significance level of the coefficients on the respectively 1%, 5% and 10% level (two-tailed)

Panel A: DCC-GARCH parameters

	NEX	Solar	Wind	EST	AMG	EMG	APG
Mean_Index (μ_1)	0.087*** (4.763)	0.081** (2.174)	0.097*** (3.888)	0.099*** (4.697)	0.076*** (3.237)	0.109*** (4.240)	0.077*** (3.680)
Mean_Oil (μ_2)	0.051* (1.710)	0.019 (0.579)	0.019 (0.577)	0.019 (0.576)	0.019 (0.577)	0.019 (0.577)	0.019 (0.577)
Constant_Index (c_1)	0.020*** (3.470)	0.073*** (2.891)	0.057*** (3.656)	0.027*** (3.144)	0.034*** (3.624)	0.038*** (3.493)	0.029*** (3.329)
Constant_Oil (c_2)	0.026** (2.314)	0.024** (2.181)	0.024** (2.185)	0.024** (2.187)	0.024** (2.183)	0.024** (2.184)	0.024** (2.186)
ARCH_Index (α_{11})	0.079*** (7.285)	0.076*** (4.844)	0.089*** (5.926)	0.085*** (6.413)	0.088*** (7.149)	0.096*** (7.078)	0.094*** (7.479)
ARCH_Oil (α_{21})	0.051*** (5.047)	0.058*** (5.374)	0.058*** (5.379)	0.058*** (5.385)	0.058*** (5.363)	0.058*** (5.376)	0.058*** (5.374)
GARCH_Index (β_{11})	0.911*** (75.150)	0.905*** (45.941)	0.882*** (47.799)	0.896*** (54.425)	0.896*** (65.803)	0.890*** (62.511)	0.889*** (61.278)
GARCH_Oil (β_{21})	0.945*** (90.759)	0.938*** (82.427)	0.938*** (82.495)	0.938*** (82.475)	0.938*** (82.382)	0.938*** (82.390)	0.938*** (82.398)
DCC1 (a)	0.020** (3.209)	0.014** (2.208)	0.012*** (3.827)	0.026*** (3.490)	0.024*** (3.501)	0.017*** (3.211)	0.006** (2.521)
DCC2 (b)	0.976*** (116.638)	0.984 (116.896)	0.986*** (249.504)	0.969*** (98.093)	0.972*** (108.537)	0.979*** (137.885)	0.992*** (254.911)
$a + b$	0.997	0.998	0.998	0.995	0.996	0.997	0.998
Log L	-13853	-9898	-9083	-8579	-9052	-9225	-8826
AIC	7.330	7.991	7.334	6.928	7.310	7.449	7.127
Observations	3783	2480	2480	2480	2480	2480	2480

Panel B: DCC-GARCH parameters continued								
	CEXX	**SPG**	**CSA**	**DAX**	**WAEX**	**ET50**	**MXWO**	**SP500**
Mean_Index (μ_1)	0.078** (2.181)	0.079*** (3.273)	0.082*** (5.095)	0.067*** (3.656)	0.080*** (3.493)	0.076*** (4.364)	0.048*** (4.051)	0.049*** (3.726)
Mean_Oil (μ_2)	0.032 (0.908)	0.038 (1.200)	0.052* (1.737)	0.048 (1.629)	0.038 (1.202)	0.056* (1.938)	0.056* (1.936)	0.056* (1.935)
Constant_Index (c_1)	0.066*** (3.030)	0.033*** (3.285)	0.017*** (2.828)	0.027*** (2.699)	0.031*** (2.930)	0.021*** (3.339)	0.009*** (3.556)	0.015*** (3.499)
Constant_Oil (c_2)	0.023** (2.181)	0.023** (2.316)	0.024** (2.489)	0.026** (2.269)	0.023** (2.317)	0.025** (2.289)	0.025** (2.291)	0.025** (2.288)
ARCH_Index (α_{11})	0.083*** (6.090)	0.085*** (6.590)	0.078*** (5.633)	0.088*** (5.331)	0.081*** (5.638)	0.090*** (6.189)	0.084*** (7.698)	0.085*** (7.974)
ARCH_Oil (α_{21})	0.058*** (5.430)	0.053*** (6.276)	0.049*** (7.203)	0.052*** (4.928)	0.053*** (6.266)	0.050*** (5.094)	0.05*** (5.108)	0.050*** (5.098)
GARCH_Index (β_{11})	0.901*** (56.285)	0.903*** (63.346)	0.911*** (57.472)	0.898*** (44.538)	0.905*** (52.679)	0.900*** (58.167)	0.907*** (78.863)	0.903*** (79.258)
GARCH_Oil (β_{21})	0.938*** (85.387)	0.943*** (106.373)	0.946*** (130.621)	0.944*** (86.914)	0.943*** (106.136)	0.946*** (92.992)	0.946*** (93.120)	0.946*** (93.089)
DCC1 (a)	0.023*** (3.702)	0.017*** (3.295)	0.014*** (3.492)	0.019** (2.206)	0.018*** (3.762)	0.017** (2.551)	0.023*** (3.631)	0.022*** (3.132)
DCC2 (b)	0.970*** (110.462)	0.978*** (128.893)	0.983*** (187.528)	0.975*** (67.674)	0.978*** (153.223)	0.981*** (116.053)	0.974*** (124.452)	0.975*** (110.787)
$a + b$	0.993	0.996	0.998	0.994	0.996	0.998	0.997	0.997
Log L	-8949	-11432	-12282	-13764	-11149	-14882	-13355	-14054
AIC	8.072	7.621	6.977	7.325	7.435	7.368	6.612	6.958
Observations	2220	3003	3524	3761	3002	4043	4043	4043

Using the results from the DCC GARCH models, I plotted the covariance matrices needed for calculating the conditional correlation, hedge ratios and for forecasting. The plots for the conditional covariance matrices can be found in Appendix B, a summary of the conditional covariance's can be found in Appendix C. For all of the indexes the conditional covariance does not part a lot from the unconditional covariance, with the financial crisis as major exception. The financial crisis brought along a major spike in the conditional covariance for all indexes, after 2012 the conditional covariance seems have restored to pre-financial crisis levels.

In Appendix D graph 3 we can see the dynamic correlation between the indexes and oil. The mean of the dynamic correlations differs from 0.218 to 0.395, the pattern in the conditional correlation is very similar across the different indexes with the APG index as exception. For most indexes we can observe a volatile period with a constant mean up until the start of the financial crisis in 2008. During 2008 the conditional correlations drop significantly before jumping to record high levels after which the conditional correlation keeps climbing until it plummets again in 2011. After the even most dramatic plummet in 2011, the conditional correlation forms one final peak until declining towards pre-credit-crisis levels. For the dynamic conditional correlation between the NEX index and oil, the correlation ranges from -0.241 to 0.693 with a mean and median of 0.227 and 0.184 respectively.

4.3. Hedging

Appendix E shows the graphs of the time-varying hedge ratios. As we can see from the graphs, just like the conditional correlations, the dynamic hedge ratios are very volatile, showing exactly why computing dynamic hedge ratios are important. Portfolios constructed based on time-invariant hedge ratios would be inefficient for investors most of the time.

As we can see from in the graphs, the hedge ratios appear lower than the mean in the pre-crisis years. During the financial crisis the hedge ratios follow a similar trend as the conditional covariance, gradually decreasing towards the pre-crisis levels after the initial shock. In the upwards shocks during and after the financial crisis, hedge ratios reach up to 2 to 3 for all indexes, meaning a 1 dollar investment in the index should be hedged with a short position of 2 to 3 dollars.

Table 6 shows the summary of the time-varying hedge ratios for all indexes. Investments in clean energy stocks can be hedged with short positions in oil with averages ranging from 45 cents for the DAX index up to 75 cents for the EMG index.

Table 6 – Summary Time-Varying Hedge Ratios This table shows the summary of the time-varying hedge ratios for all indexes.				
	Average	**Minimum**	**Maximum**	**Standard deviation**
NEX	0.491	-0.795	2.982	0.569
Solar	0.582	-0.094	3.855	0.472
Wind	0.650	-0.003	2.794	0.522
EST	0.653	-0.459	3.056	0.602
AMG	0.681	-0.448	2.788	0.561
EMG	0.750	-0.024	3.117	0.568
APG	0.467	0.022	2.199	0.374
SPG	0.580	-0.244	2.768	0.505
CEXX	0.684	-0.368	2.799	0.533
WAEX	0.639	-0.139	2.833	0.511
CSA	0.704	-0.579	3.138	0.548
DAX	0.447	-1.004	2.853	0.511
ET50	0.478	-0.716	2.889	0.553
MXWO	0.453	-1.143	2.962	0.621
SP	0.324	-1.035	2.329	0.583

From the different industries, Solar provides the cheapest hedge with a ratio of 0.582 and has the least volatile dynamic hedge ratio. Wind and EST have almost equal hedge ratios but EST is more volatile. From the industries the Solar index provides the best hedge, it is the on average the cheapest hedge and needs the least rebalancing.

From the AMG, APG and EMG indexes, the APG provides the cheapest hedge on average. A one dollar investment in the APG index can be hedged with a short position in oil of 46,7 cents. The APG has also got the least volatile dynamic hedge ratio.

When considering the six global indexes (NEX, SPG, WAEX, CSA, DAX, ET50), the DAX index provides cheapest hedge and the SPG has the least volatile dynamic hedge ratio. Interestingly, although all six indexes globally track clean energy stocks and attempt to provide a well-diversified portfolios, the different ways for constructing the portfolios obviously cause dissimilarities between the hedge ratios of the indexes. This stresses the importance to analyse the specific investment investors are interested in, to form an optimal portfolio for that specific investment.

4.4. Out-of-sample forecasting

Appendix F shows the graphs of the one year ahead forecasts of the covariance matrices. As we remember from the previous chapter, using the n-ahead forecast of Engle (2001) leads to biased forecasts towards their unconditional counterpart especially for longer forecasts. The patterns in the graphs show how the method of Engle (2001) puts more weight on more recent data than on older data, but eventually the covariance will grow to the mean conditional covariance.

The forecasts of the dynamic conditional correlation are shown in appendix G. In the forecast, all correlations are rising except for the correlation between the SP index and oil. For the forecast of the conditional correlation also holds the convergence towards the unconditional correlation in the long-run.

Appendix H shows the graphs of the calculated time-varying hedge ratios from July 2015 until July 2016. As we can see, the hedge ratios are very volatile and overall lower than the mean of the sample period. In July 2015 investors can hedge investments in the clean energy indexes ranging from short positions in oil of 12 for the DAX index up to 35 cents for the CEXX index. In July 2016 this is 17,5 cents of the APG index up to 64 cents for the CEXX index. Judging from these hedge ratios, hedging clean energy indexes with oil provides efficient hedge opportunities, however as we see highly dynamic ratios it is important to rebalance the investors' portfolios regularly. Of course, when considering transaction costs rebalancing portfolios daily is not efficient.

Table 7 shows the average monthly hedge ratios from the one-year ahead forecast. Just like the graphs in Appendix H, the table shows that the all forecasted hedge ratios are lower than the average hedge ratios of the sample period. As we can see from the table, the EST and APG index need the least rebalancing from all clean energy indexes. Also note that the control group, the MSCI world index and the S&P500 index, are cheaper to hedge than twelve out of thirteen clean energy indexes.

Table 7 – Monthly One-Year ahead Forecasted Hedge Ratios

This table shows

	NEX	Solar	Wind	EST	EMG	APG	AMG	SPG	CEXX	WAEX	CSA	DAX	ET50	MXWO	SP
1-7-2015	0.184	0.340	0.225	0.335	0.228	0.177	0.278	0.234	0.405	0.228	0.309	0.133	0.171	0.161	0.151
1-8-2015	0.203	0.335	0.227	0.324	0.278	0.164	0.330	0.274	0.484	0.264	0.328	0.160	0.200	0.173	0.168
1-9-2015	0.219	0.336	0.235	0.318	0.321	0.154	0.365	0.308	0.538	0.293	0.342	0.184	0.223	0.183	0.179
1-10-2015	0.233	0.342	0.245	0.318	0.355	0.148	0.389	0.334	0.572	0.316	0.353	0.202	0.239	0.190	0.186
1-11-2015	0.244	0.351	0.255	0.320	0.384	0.145	0.405	0.354	0.595	0.334	0.362	0.218	0.252	0.196	0.190
1-12-2015	0.254	0.361	0.265	0.325	0.407	0.146	0.417	0.370	0.610	0.349	0.368	0.230	0.261	0.200	0.192
1-1-2016	0.262	0.373	0.275	0.329	0.428	0.148	0.426	0.384	0.621	0.362	0.374	0.240	0.269	0.204	0.192
1-2-2016	0.269	0.384	0.284	0.334	0.445	0.152	0.433	0.394	0.629	0.372	0.378	0.248	0.275	0.206	0.193
1-3-2016	0.275	0.395	0.293	0.338	0.460	0.156	0.438	0.403	0.634	0.381	0.381	0.254	0.280	0.209	0.192
1-4-2016	0.280	0.406	0.301	0.342	0.473	0.161	0.443	0.411	0.638	0.389	0.384	0.259	0.284	0.210	0.192
1-5-2016	0.284	0.416	0.309	0.346	0.485	0.166	0.447	0.417	0.641	0.396	0.386	0.264	0.287	0.212	0.191
1-6-2016	0.288	0.425	0.316	0.349	0.495	0.170	0.450	0.422	0.644	0.402	0.389	0.267	0.290	0.213	0.190
1-7-2016	0.290	0.431	0.320	0.350	0.501	0.173	0.451	0.425	0.645	0.405	0.390	0.269	0.292	0.213	0.190
Mean real data	0.491	0.582	0.650	0.653	0.750	0.467	0.681	0.580	0.684	0.639	0.704	0.447	0.478	0.453	0.324

5. Conclusion

In 2012 only 11% of the global energy consumption was from low-carbon alternatives. In order to keep global warming within two degrees Celsius compared to the pre-industrial era, the transition to clean energy needs to speed up. My thesis focussed on providing more insight into the risk-return relationship of investments in clean energy companies and showing how investors can limit risk when investing in such relatively risky investments.

Factor modelling thirteen different clean energy indexes showed that twelve out of thirteen indexes did not significantly underperform the market. I therefore accept my first hypothesis, investments in clean energy stocks do not underperform the market. Though, investments in clean energy stocks are riskier than investments in the market. Twelve out of thirteen indexes have a risk exposure to the market larger than one, which shows the importance of research on the risk dynamics of investments in clean energy. These findings are consistent with a lot of articles (see Ito. et. al. (2013) and Henriques and Sadorsky (2008))

The factor models showed different results for monthly and daily data. For monthly data oil turned out not to be a significant risk factor for the majority of the clean energy indexes, only five out of the thirteen indexes were significantly exposed to the oil factor. The oil factor was significant in all cases for the factor models built with daily data, though the factor hardly added any explanatory power to the models. Oil is a significant risk factor for a part of the models I have shown in my thesis and oil turned out to be efficient for hedging purposes. Therefore, oil cannot be ignored as a risk factor for investments in clean energy companies, making this commodity a significant risk factor for clean energy stocks. However, for factor modelling the oil factor does not add power to the existing capital asset pricing models for explaining returns.

The results of the dynamic conditional correlation GARCH models showed conditional correlation estimators to be significant and added up very close to one for all clean energy indexes. This means the conditional correlation between the indexes and oil is very volatile, which is also clearly visible in the graphs of the conditional correlation. I therefore reject the hypothesis of the correlation between clean energy stocks and oil to be constant overtime. This means that the risk exposure of clean energy stocks to oil is dynamic, which investors may want to account for.

Consistent with Sadorsky (2012), I find that oil can be an efficient hedge for investments in clean energy stocks. On average, investors can hedge a one dollar investment in clean energy stocks with a short position between 45 and 75 cents. As we have seen though, the time-varying hedge ratios are very dynamic just like the dynamic conditional correlation. Investors' portfolios would have to be rebalanced regularly in order to maintain an optimal hedge.

Forecasts of the conditional covariance, conditional correlation and time-varying hedge ratios show how investors can use the analysis of my thesis to limit risk exposure of their investments in clean energy stocks. The forecasts are all mean reverting, which means the future hedge ratios will also be dynamic and thus portfolios may need to be rebalanced regularly for an optimal hedge. Considering transaction costs, I show how investors can adjust their short positions in oil on a monthly basis for each index. From July 2015 up to July 2016 investors can hedge their investments in clean energy stocks with short positions ranging from 12 to 64 cents a dollar.

Though, limitations in my thesis should be recognized before making use of my forecasted hedge ratios. As most indexes are relatively new, the sample period in my research differs for several indexes making it hard to compare results among the different indexes. Further, multivariate GARCH modelling with the factor models may offer more information than the OLS regressions which I have used. For multivariate GARCH factor modelling, daily factors have to be constructed in order to match data from outside the U.S..

From the introduction of the GARCH model by Bollerslev (1986) the amount of varieties on GARCH models has exploded and there is discussion among econometricians about which models are best to use. In the end, the quality of GARCH models is measured by its ability to forecast. The method I used from Engle and Sheppard (2001) is biased towards the unconditional counterparts. The question remains whether the DCC GARCH model is the best model to use for forecasting and if so, better methods to forecast are available like rolling forecasts. Rolling forecasts are harder to implement but are certainly worth for future research.

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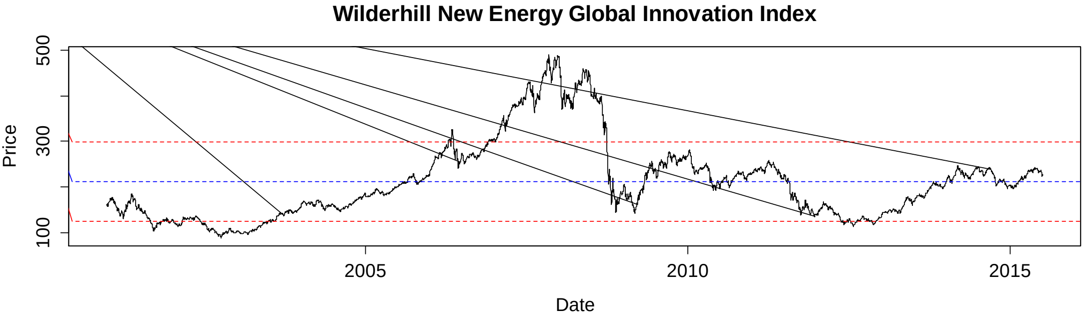
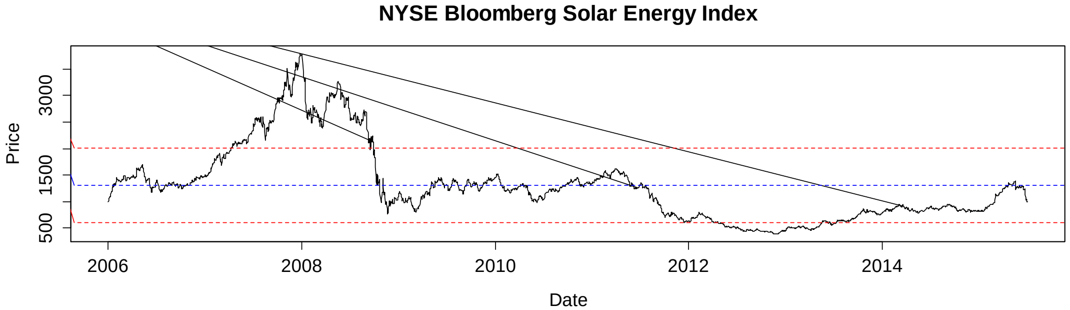
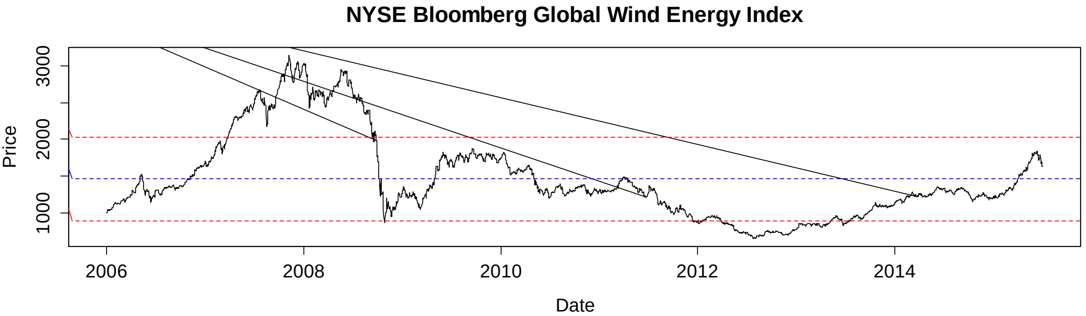
Appendix A – Time Series plots

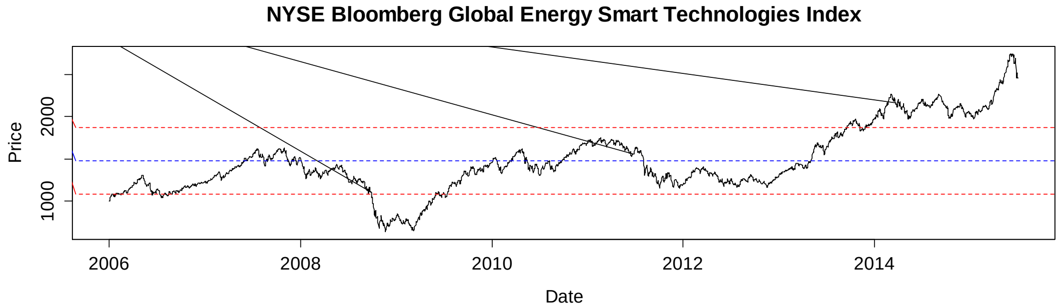
Figure 1 – Time Series plots

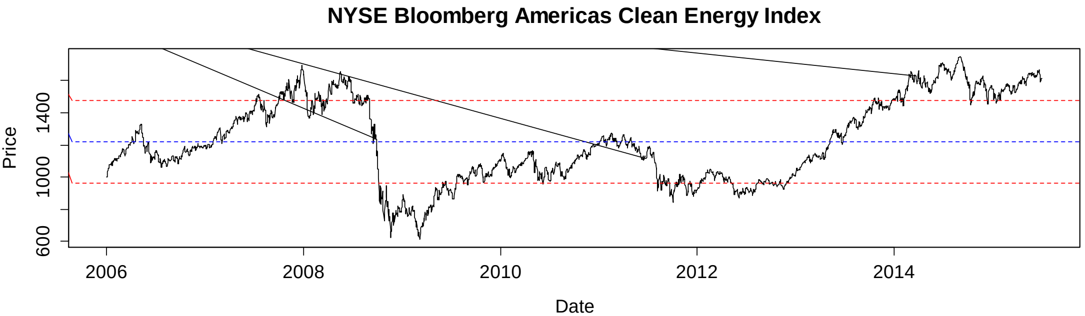
Figure 1 shows all plots for the raw gross total return index prices and oil prices. The blue dotted line represents the mean, the red dotted lines the mean plus and minus the standard deviation.

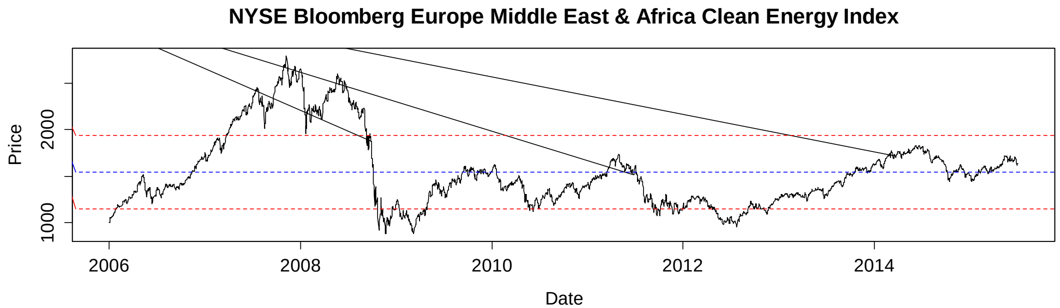




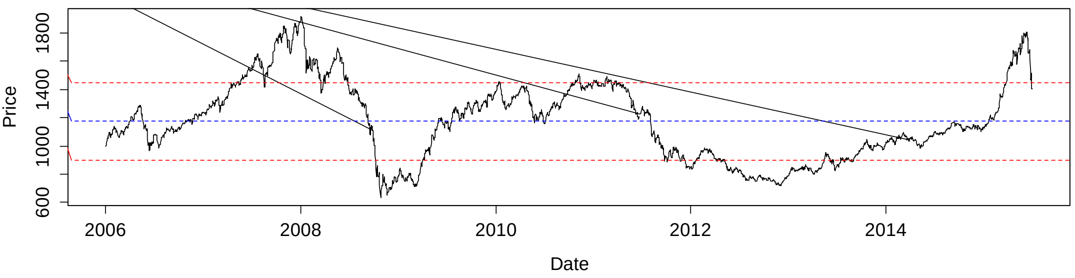




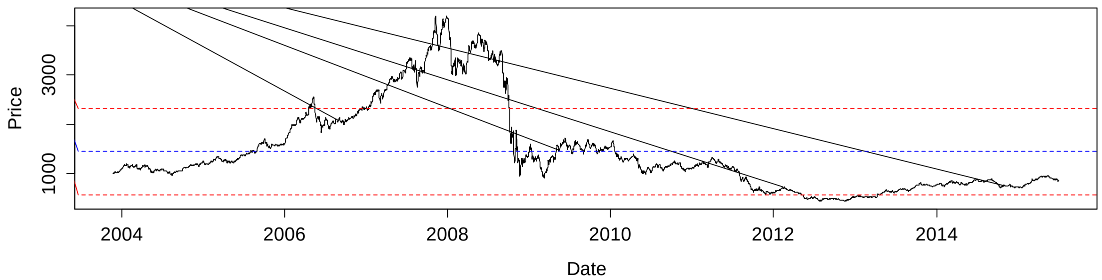




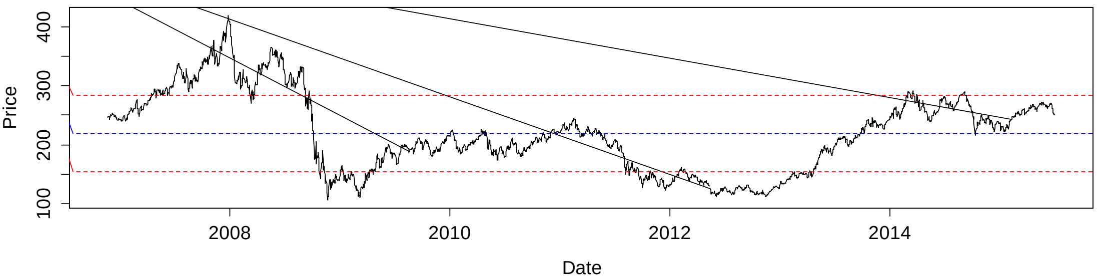
NYSE Bloomberg Asia Pacific Clean Energy Index



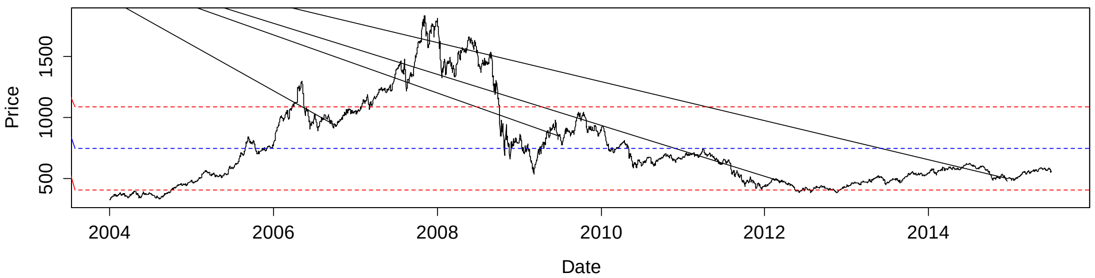
S&P Global Clean Energy Index



Nasdaq Clean Edge Green Energy Index

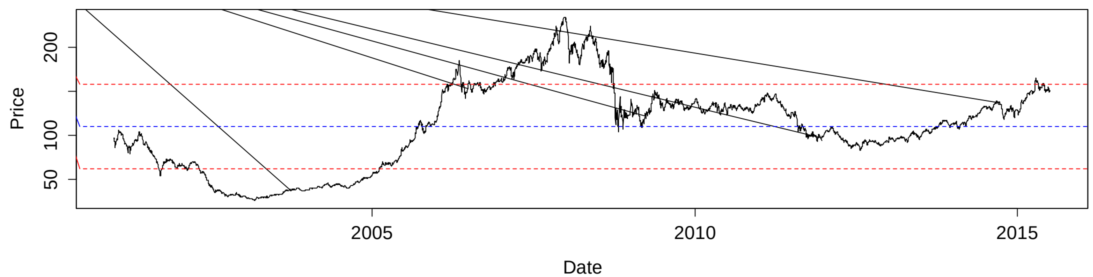


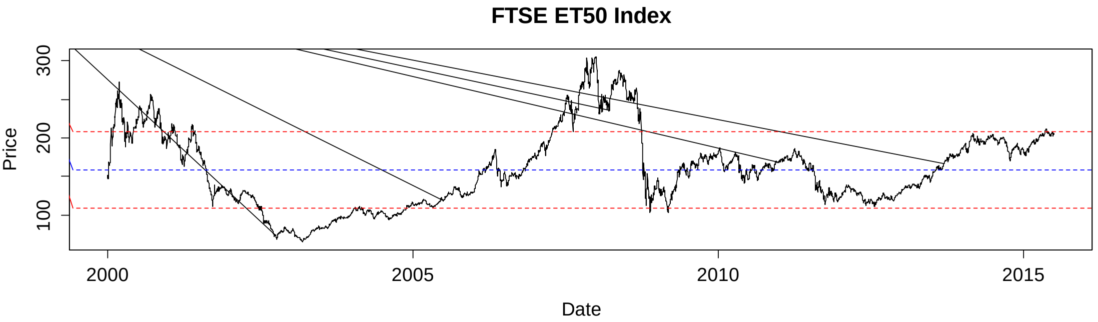
World Alternative Energy Index

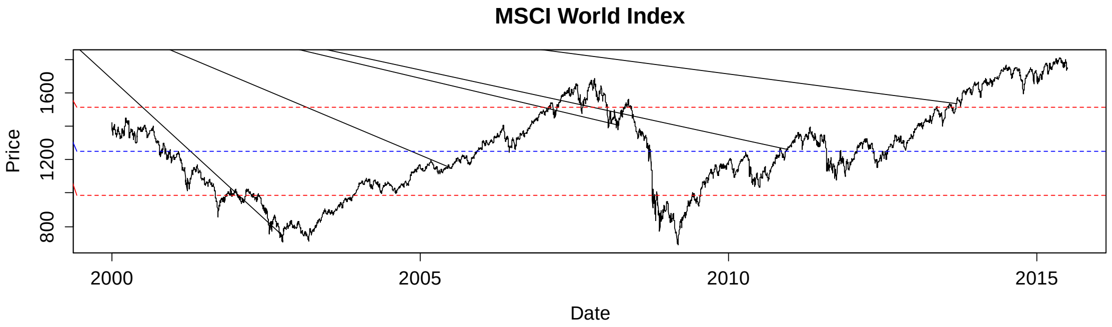


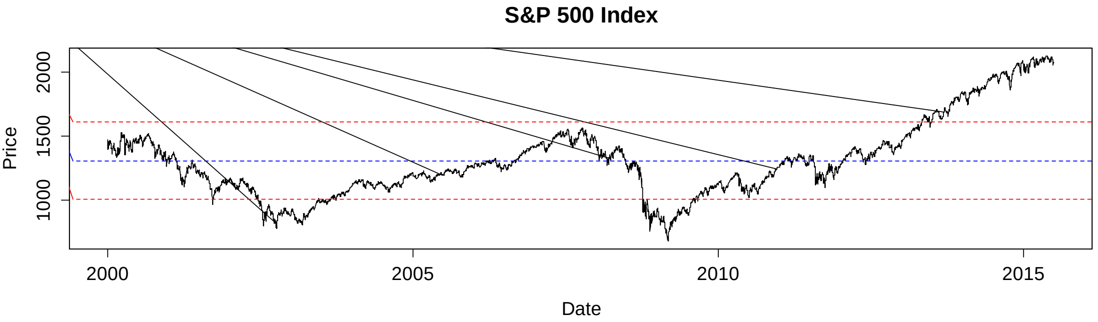
Credit Suisse Global Alternative Energy Index

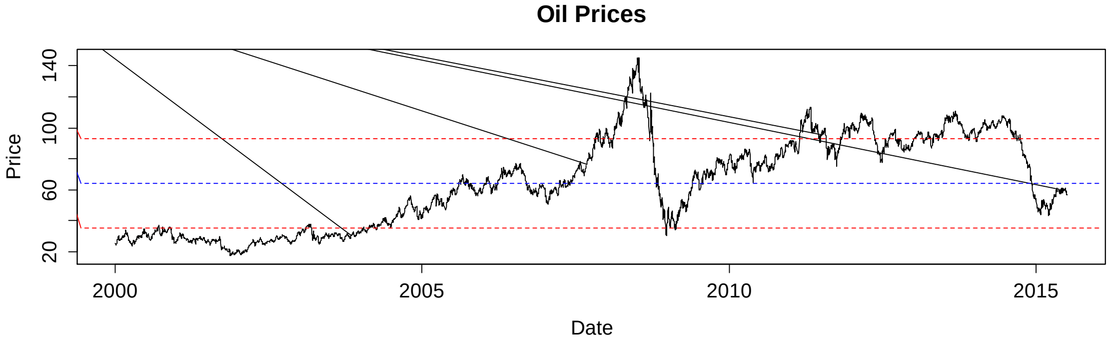
DAX Global Alternative Energy Index




FTSE ET50 Index
Price
100
200
300
2000
2005
2010
2015
Date


MSCI World Index
Price
800
1200
1600
2000
2005
2010
2015
Date

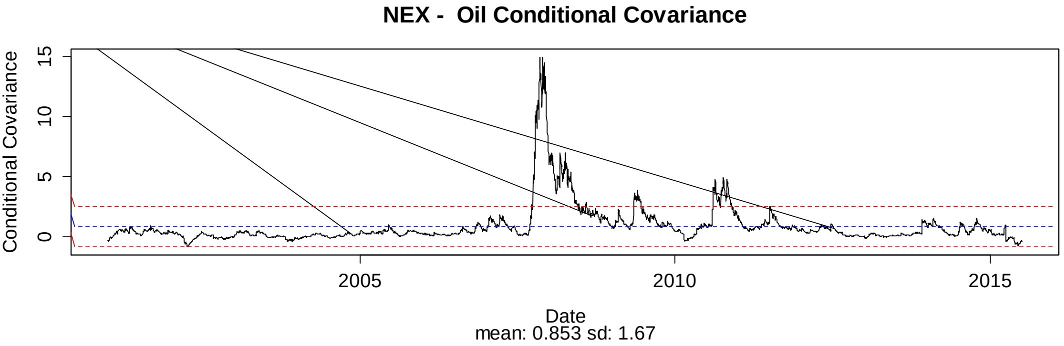

S&P 500 Index
Price
1000
1500
2000
2000
2005
2010
2015
Date

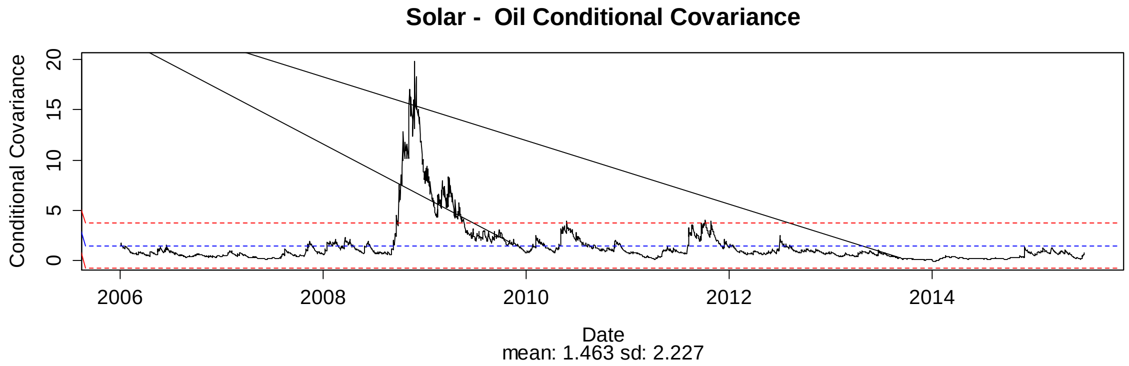

Oil Prices
Price
20
60
100
140
2000
2005
2010
2015
Date

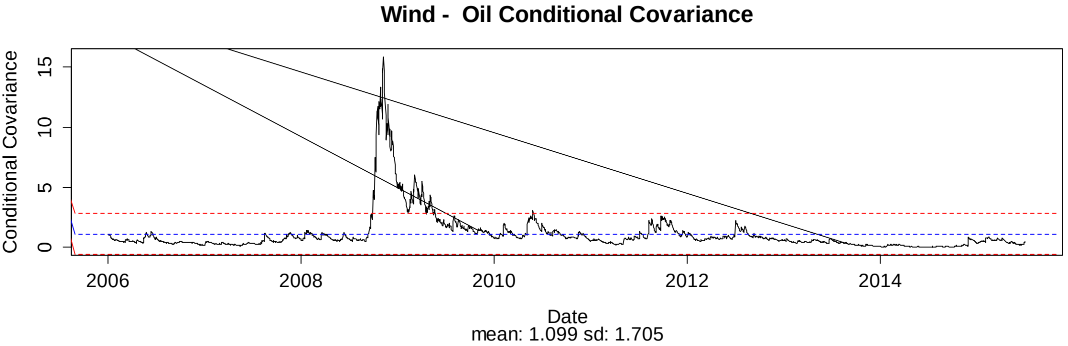
Appendix B – Conditional Covariance plots

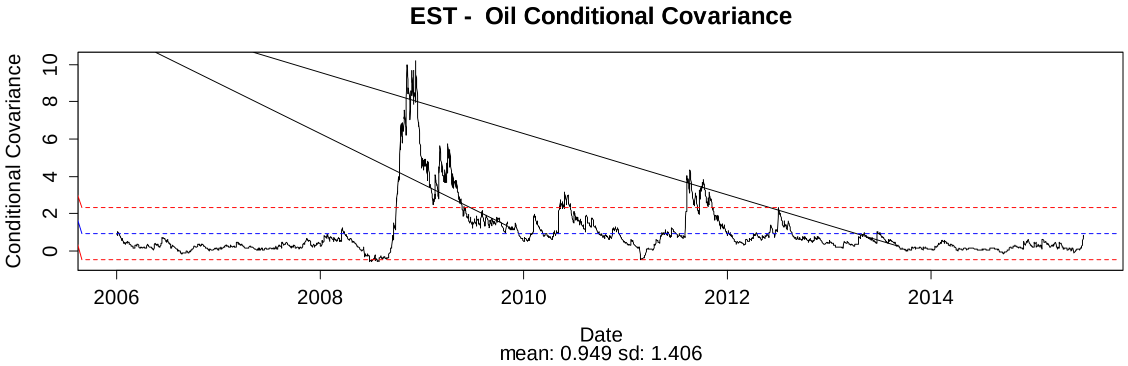
Figure 2 – Conditional Covariance plots

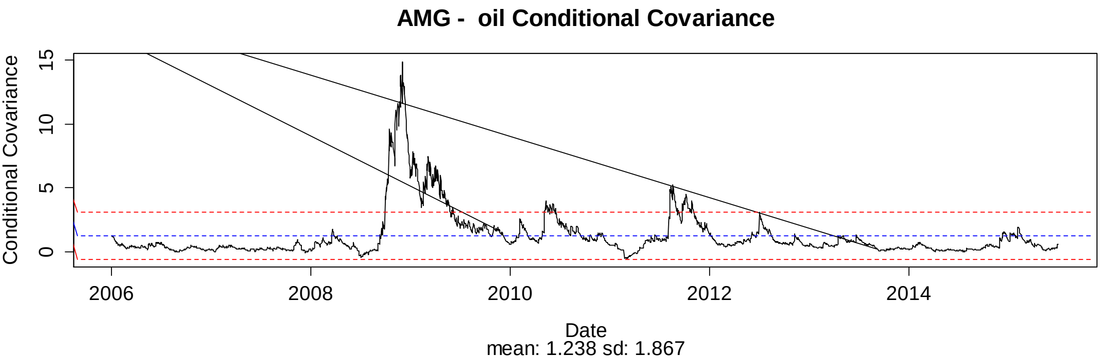
Figure 2 shows the plots of the conditional covariance for all indexes. The blue dotted line represents the mean, the red dotted lines the mean plus and minus the standard deviation.



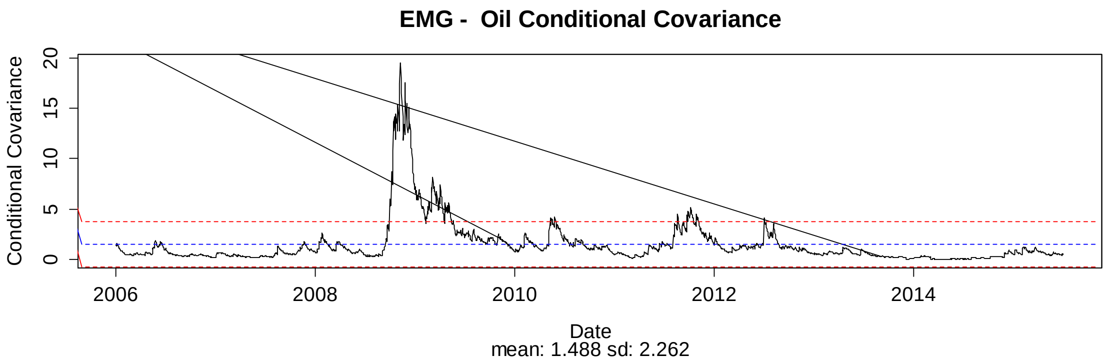




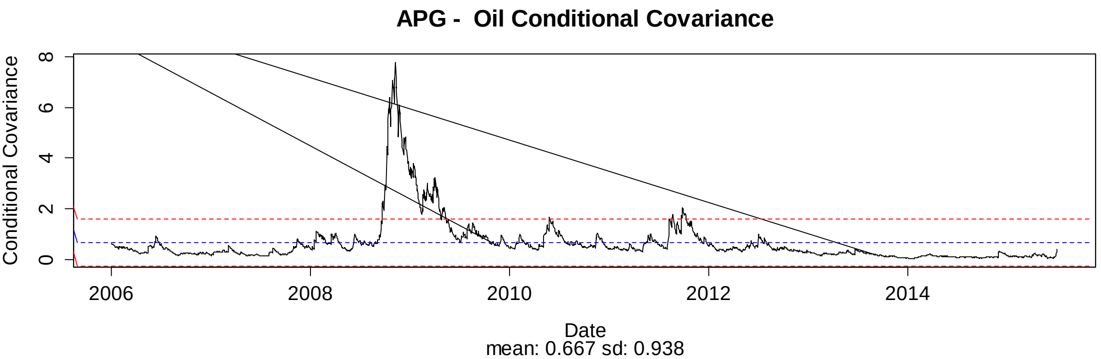




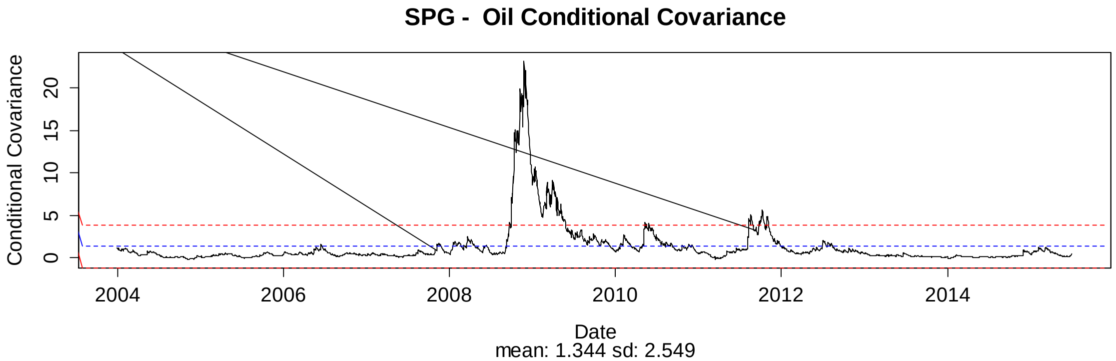
AMG - oil Conditional Covariance
Conditional Covariance
0
5
10
15
2006
2008
2010
2012
2014
Date
mean: 1.238 sd: 1.867



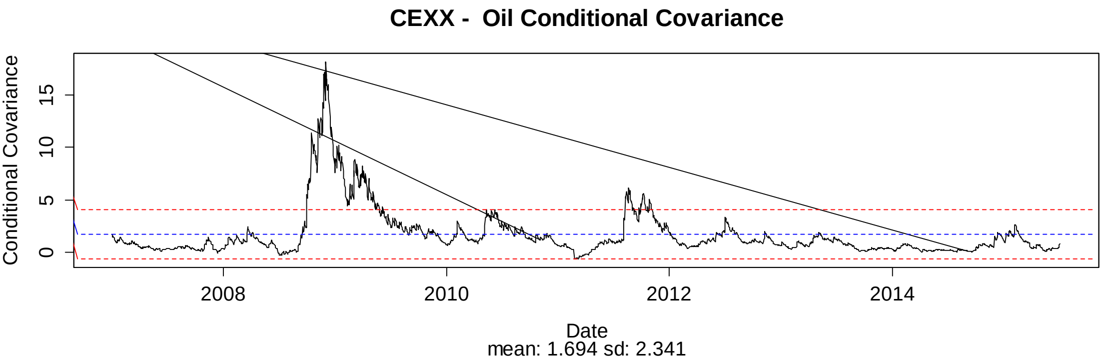
EMG - Oil Conditional Covariance
Conditional Covariance
0
5
10
15
20
2006
2008
2010
2012
2014
Date
mean: 1.488 sd: 2.262



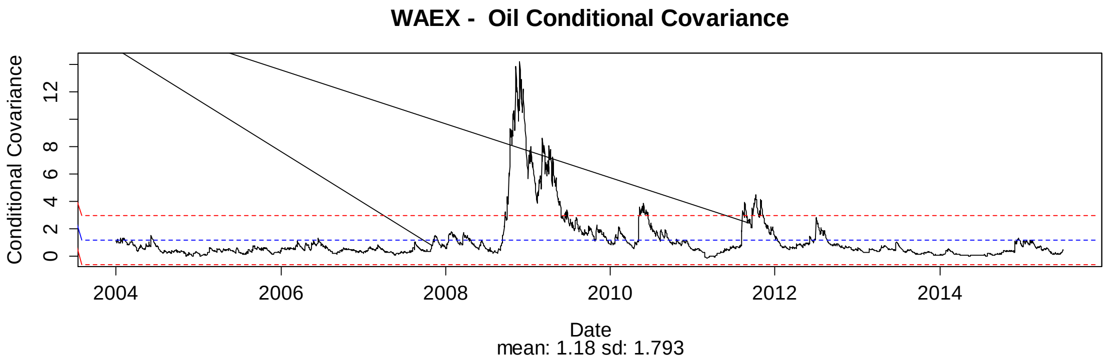
APG - Oil Conditional Covariance
Conditional Covariance
0
2
4
6
8
2006
2008
2010
2012
2014
Date
mean: 0.667 sd: 0.938



SPG - Oil Conditional Covariance
Conditional Covariance
0
5
10
15
20
2004
2006
2008
2010
2012
2014
Date
mean: 1.344 sd: 2.549

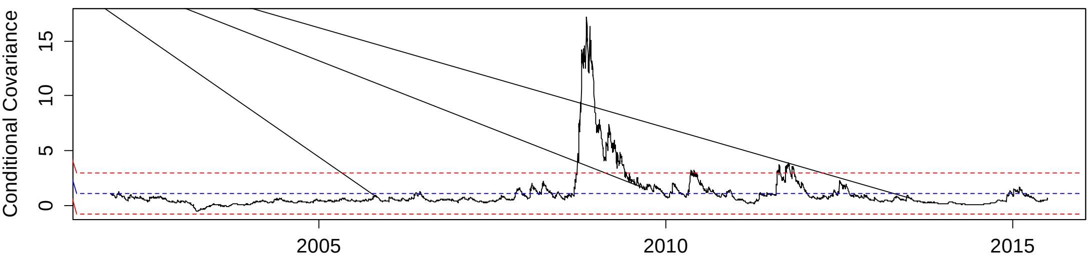


CEXX - Oil Conditional Covariance
Conditional Covariance
0
5
10
15
2008
2010
2012
2014
Date
mean: 1.694 sd: 2.341



WAEX - Oil Conditional Covariance
Conditional Covariance
0
2
4
6
8
12
2004
2006
2008
2010
2012
2014
Date
mean: 1.18 sd: 1.793

CSA - Oil Conditional Covariance

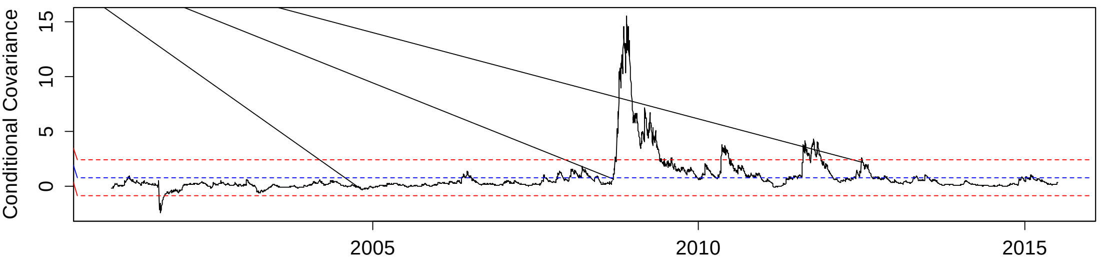


Date
mean: 1.086 sd: 1.89

DAX - Oil Conditional Covariance

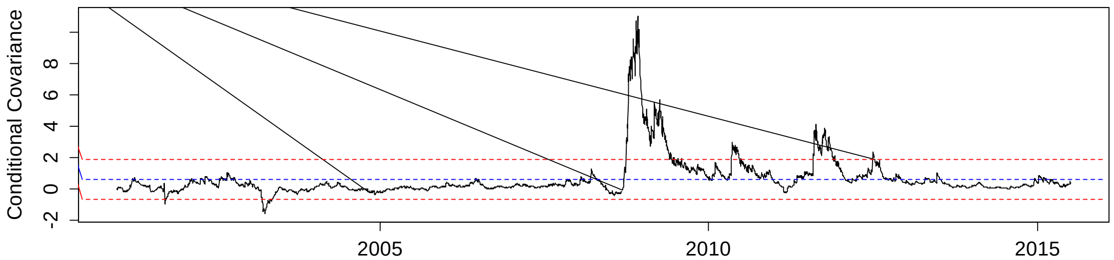
Date
mean: 0.726 sd: 1.508

ET50 - Oil Conditional Covariance



Date
mean: 0.819 sd: 1.644

MXWO - Oil Conditional Covariance



Date
mean: 0.587 sd: 1.252

SP - Oil Conditional Covariance

Date
mean: 0.486 sd: 1.154

Appendix C – Summary Conditional Covariance

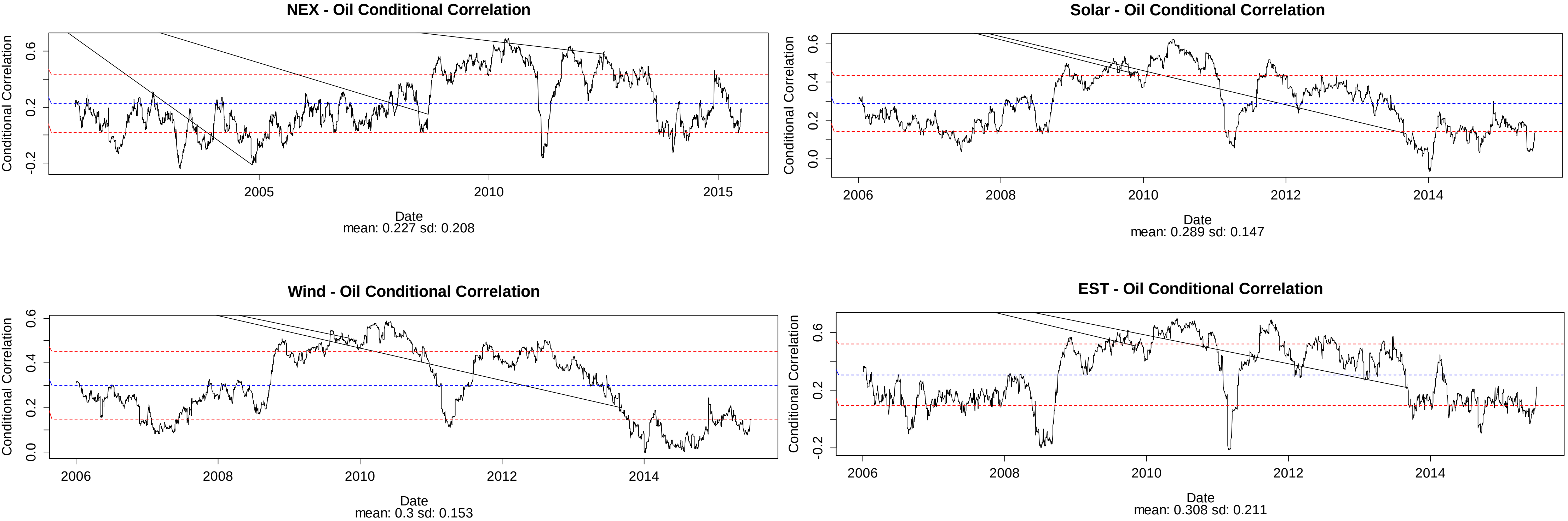
Table 8 – Summary Conditional Covariance
This table shows the summary statistics of the conditional covariance for all indexes.

	Average	Minimum	Maximum	Standard deviation
NEX	0.853	-0.860	14.983	1.670
Solar	1.463	-0.117	19.870	2.227
Wind	1.099	-0.03	15.901	1.705
EST	0.949	-0.5572	10.207	1.406
AMG	1.238	-0.548	14.878	1.867
EMG	1.488	-0.027	19.535	2.262
APG	0.667	0.021	7.795	0.938
SPG	1.344	-0.201	23.189	2.549
CEXX	1.694	-0.658	18.226	2.341
WAEX	1.180	-0.143	14.217	1.793
CSA	1.086	-0.570	17.255	1.890
DAX	0.726	-2.200	14.251	1.508
ET50	0.819	-2.396	15.567	1.644
MXWO	0.587	-1.614	11.056	1.252
SP	0.486	-1.696	10.234	1.154

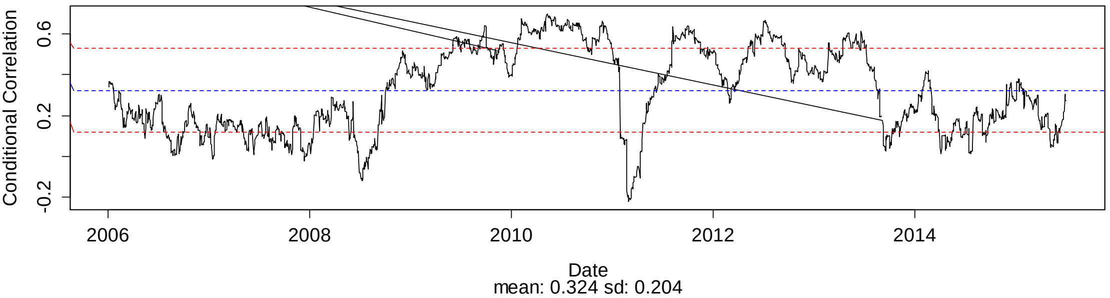
Appendix D – Dynamic Conditional Correlation plots

Figure 3 – Dynamic Conditional Correlation plots

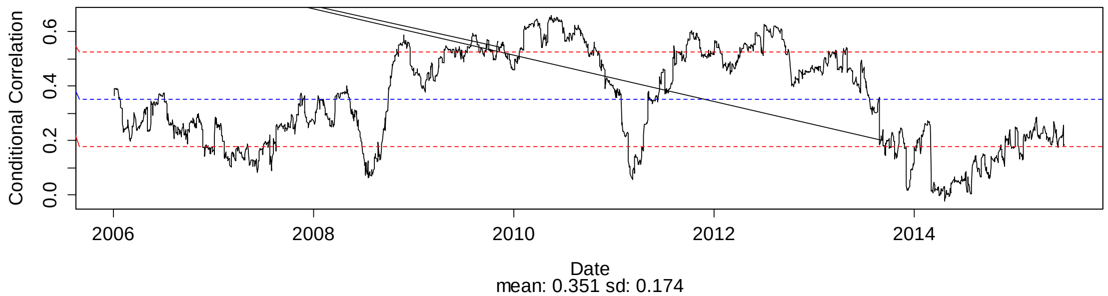
Figure 3 shows the dynamic conditional correlation for all indexes. The blue dotted line represents the mean, the red dotted lines the mean plus and minus the standard deviation.



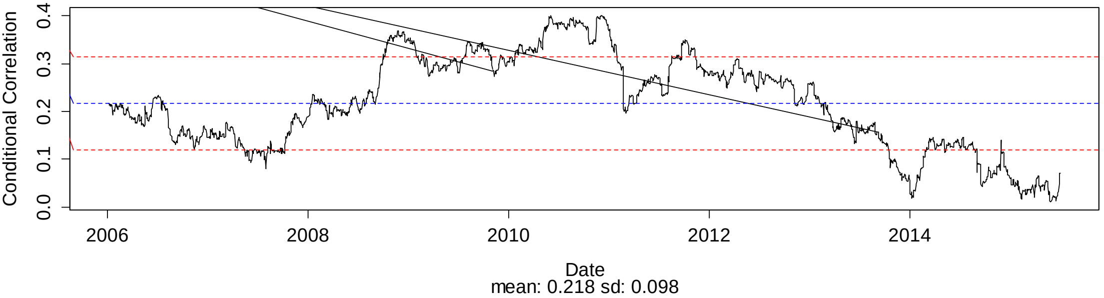
AMG - oil Conditional Correlation



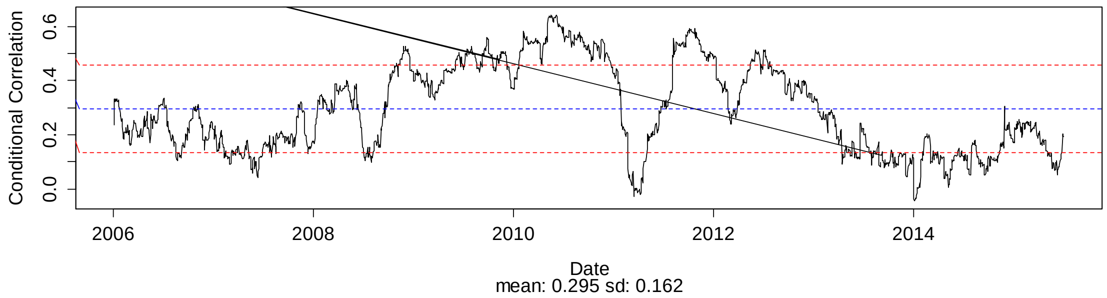
EMG - Oil Conditional Correlation



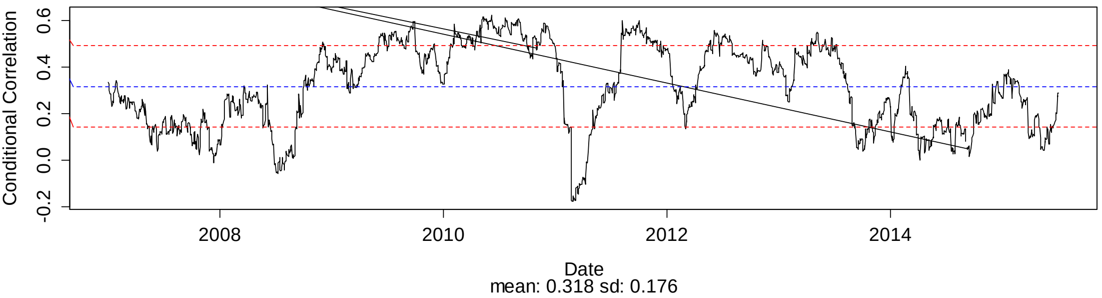
APG - Oil Conditional Correlation



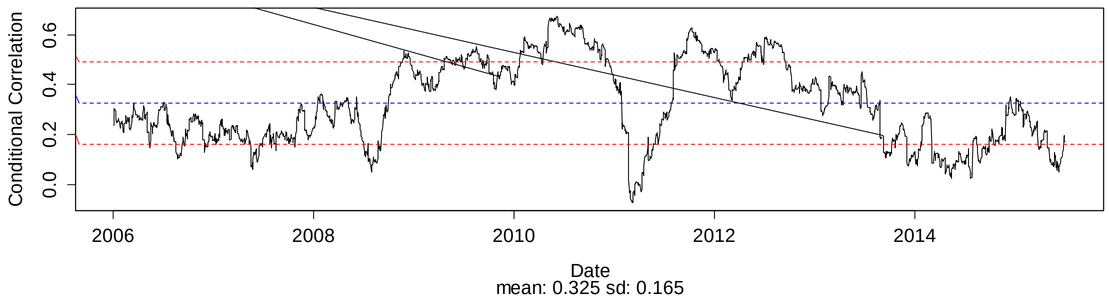
SPG - Oil Conditional Correlation

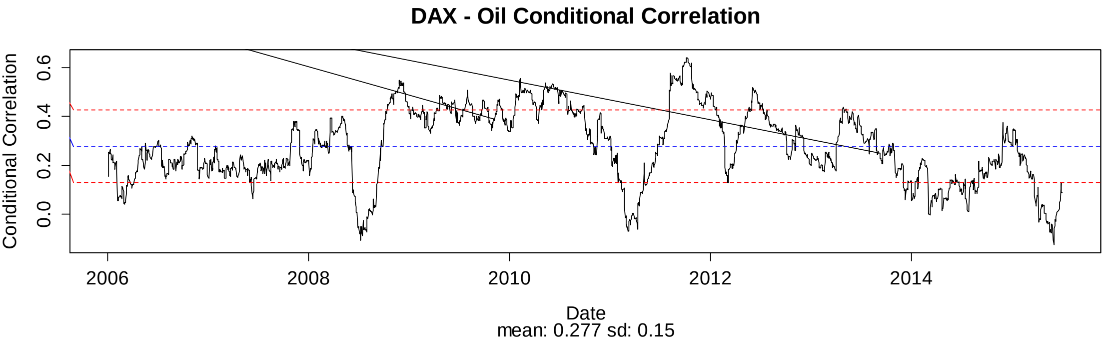


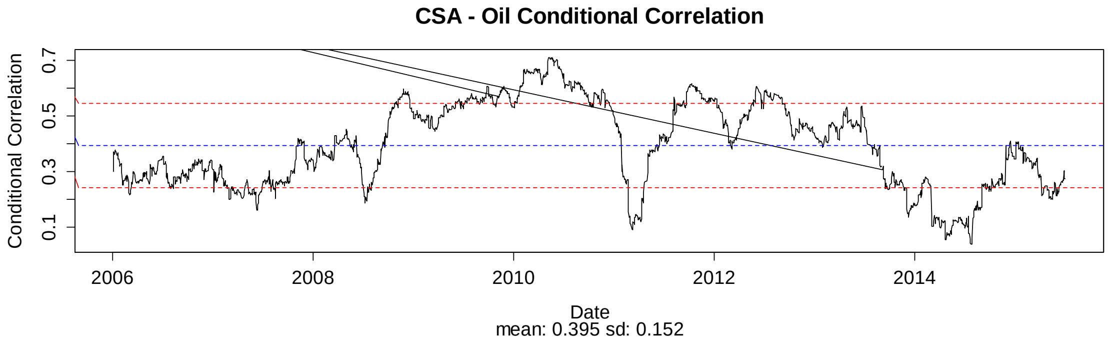
CEXX - Oil Conditional Correlation

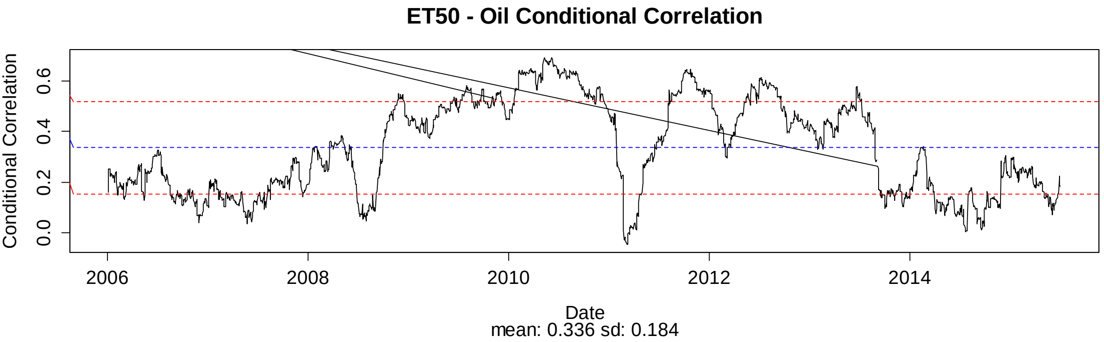


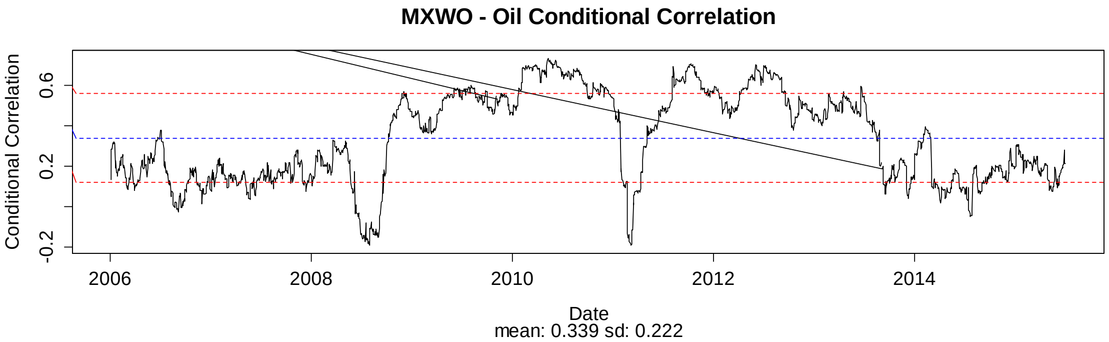
WAEX - Oil Conditional Correlation

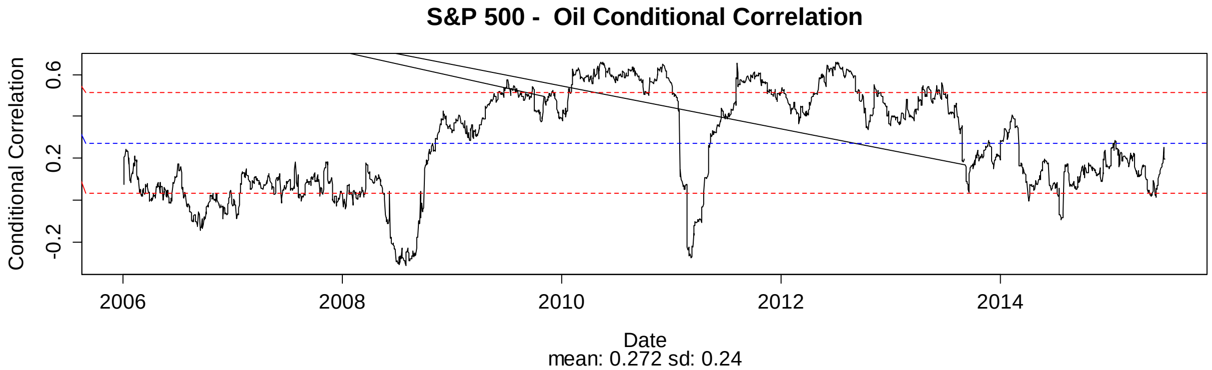



DAX - Oil Conditional Correlation
Conditional Correlation
0.0
0.2
0.4
0.6
2006
2008
2010
2012
2014
Date
mean: 0.277 sd: 0.15


CSA - Oil Conditional Correlation
Conditional Correlation
0.1
0.3
0.5
0.7
2006
2008
2010
2012
2014
Date
mean: 0.395 sd: 0.152


ET50 - Oil Conditional Correlation
Conditional Correlation
0.0
0.2
0.4
0.6
2006
2008
2010
2012
2014
Date
mean: 0.336 sd: 0.184

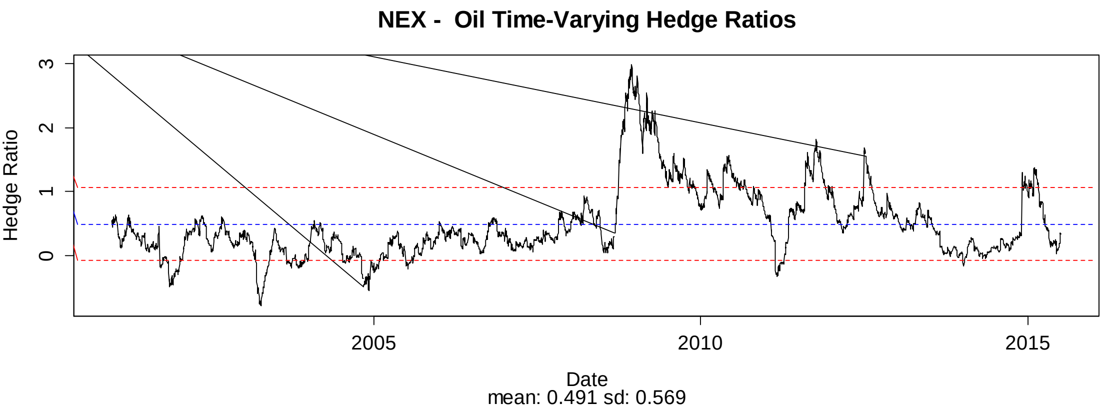

MXWO - Oil Conditional Correlation
Conditional Correlation
-0.2
0.2
0.6
2006
2008
2010
2012
2014
Date
mean: 0.339 sd: 0.222

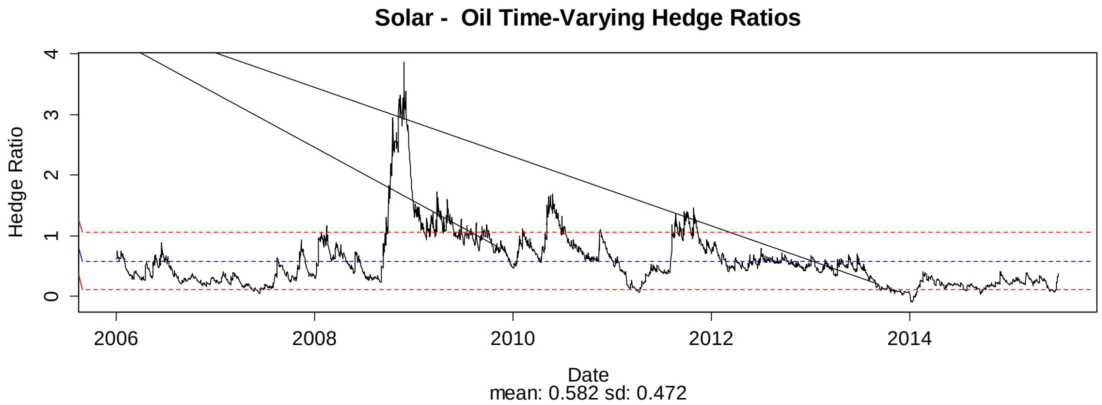

S&P 500 - Oil Conditional Correlation
Conditional Correlation
-0.2
0.2
0.6
2006
2008
2010
2012
2014
Date
mean: 0.272 sd: 0.24

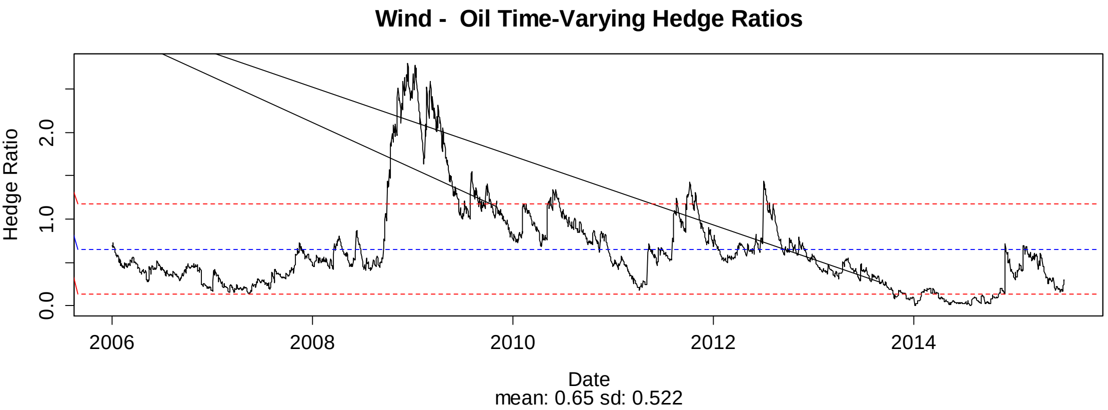
Appendix E – Time-Varying Hedge Ratio plots

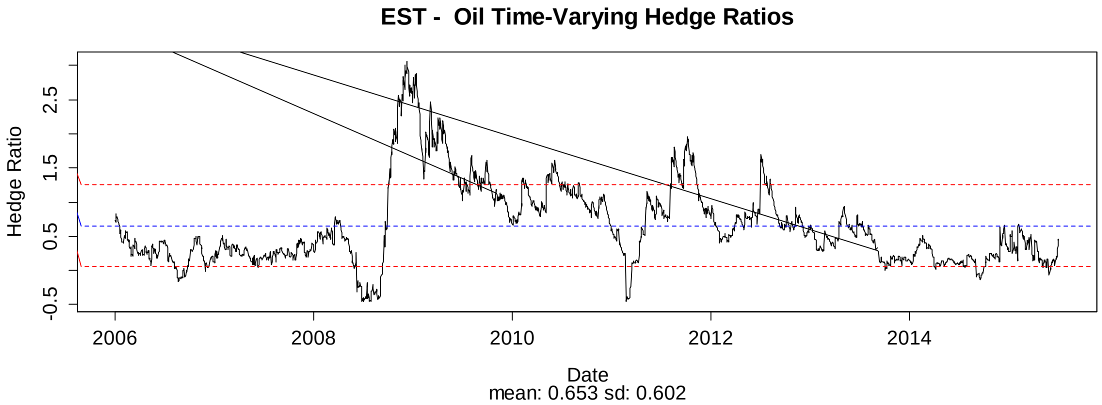
Figure 4 – Time-Varying Hedge Ratio plots

Figure 4 shows the time-varying hedge ratios for all indexes. The blue dotted line represents the mean, the red dotted lines the mean plus and minus the standard deviation.

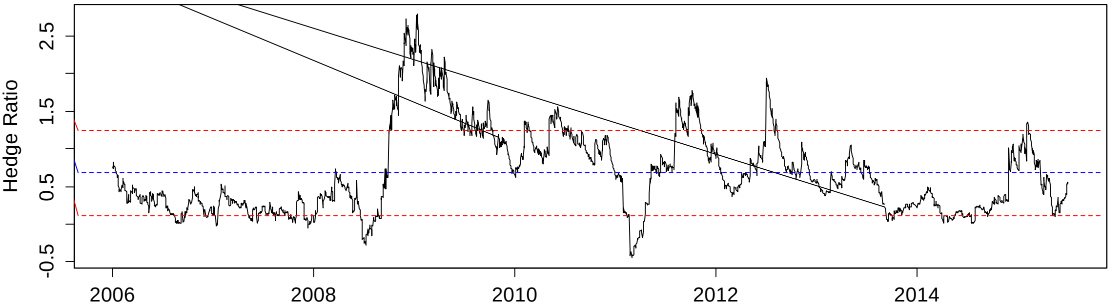






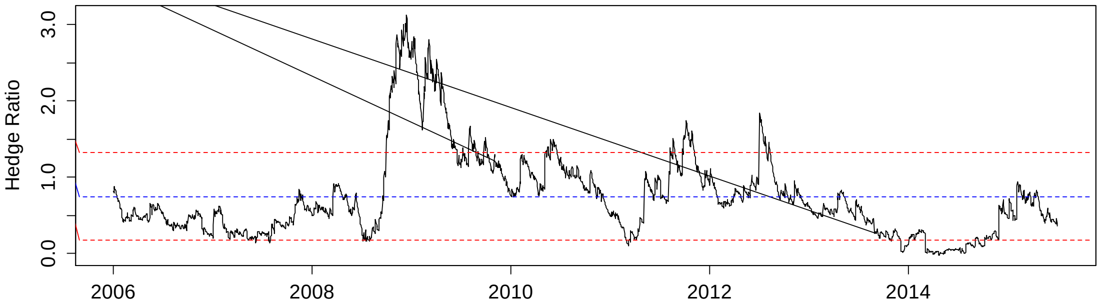


AMG - Oil Time-Varying Hedge Ratios



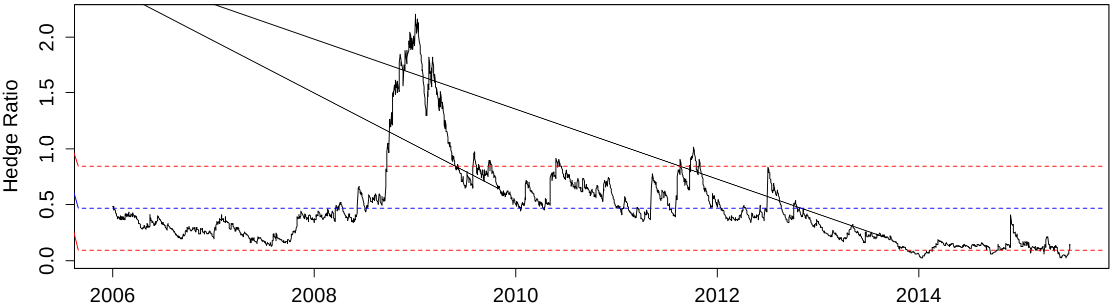
Date
mean: 0.681 sd: 0.561

EMG - Oil Time-Varying Hedge Ratios



Date
mean: 0.75 sd: 0.568

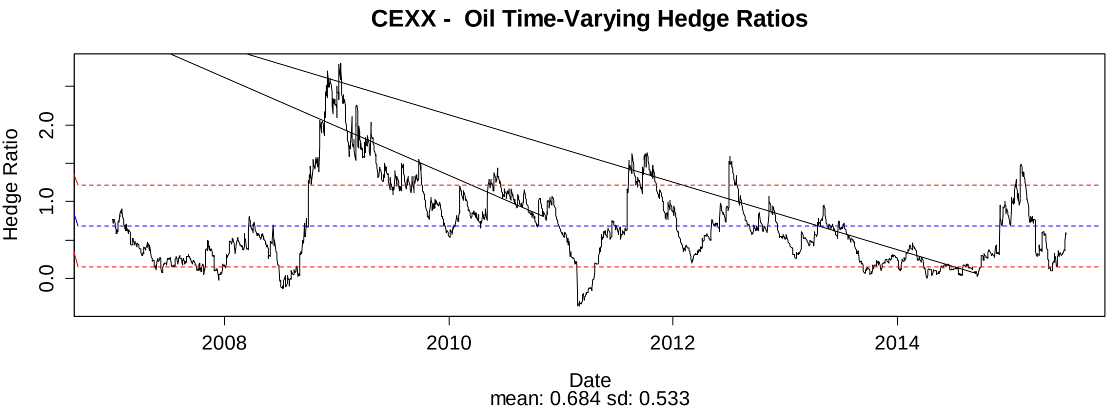
APG - Oil Time-Varying Hedge Ratios

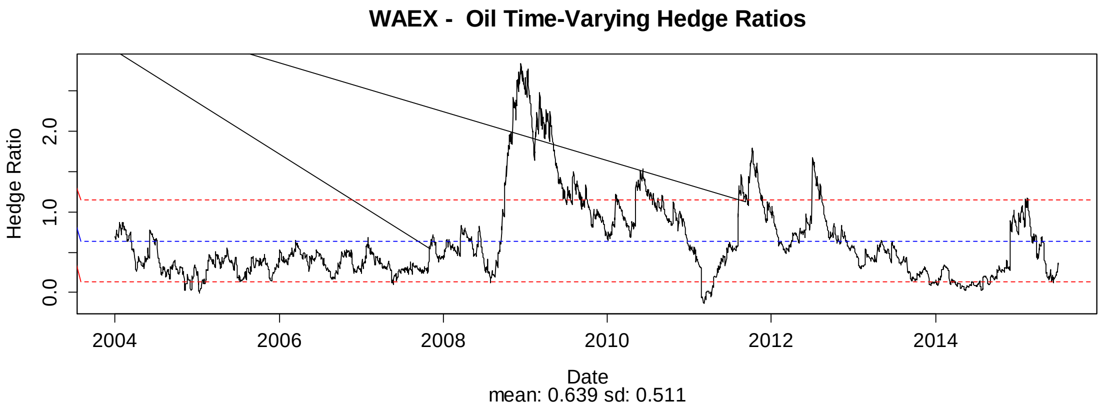


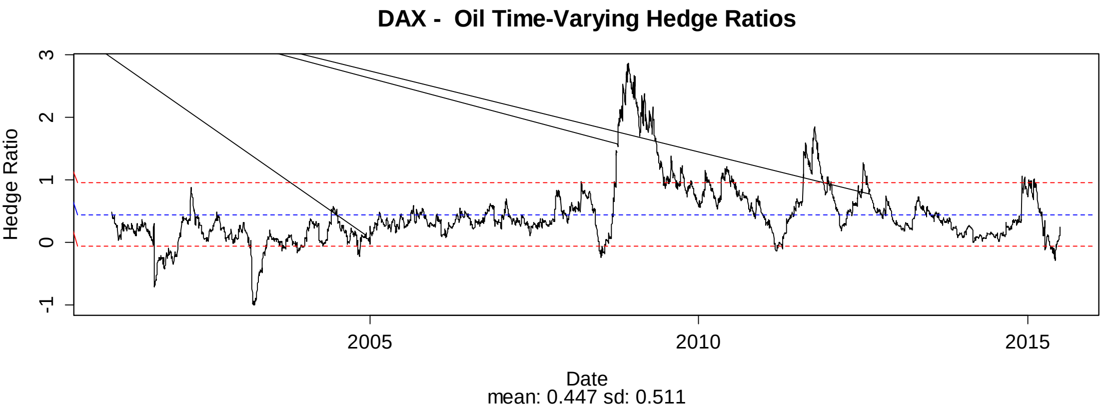
Date
mean: 0.467 sd: 0.374

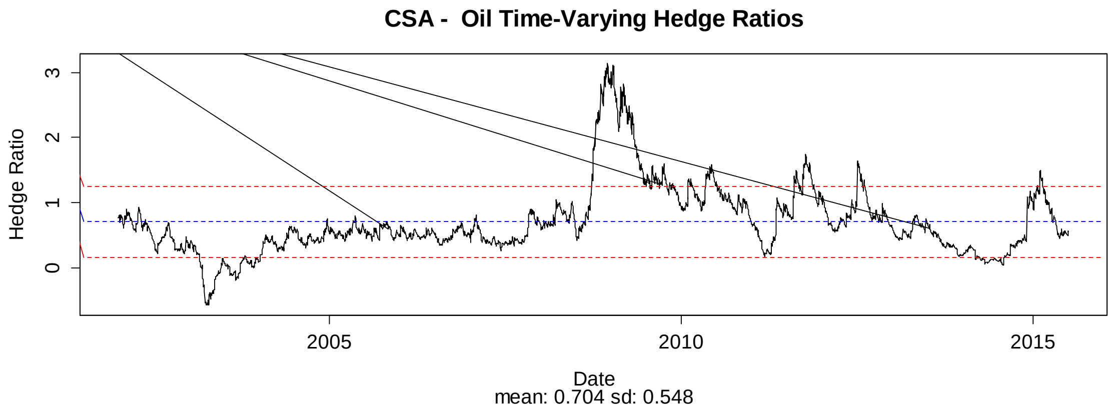
SPG - Oil Time-Varying Hedge Ratios

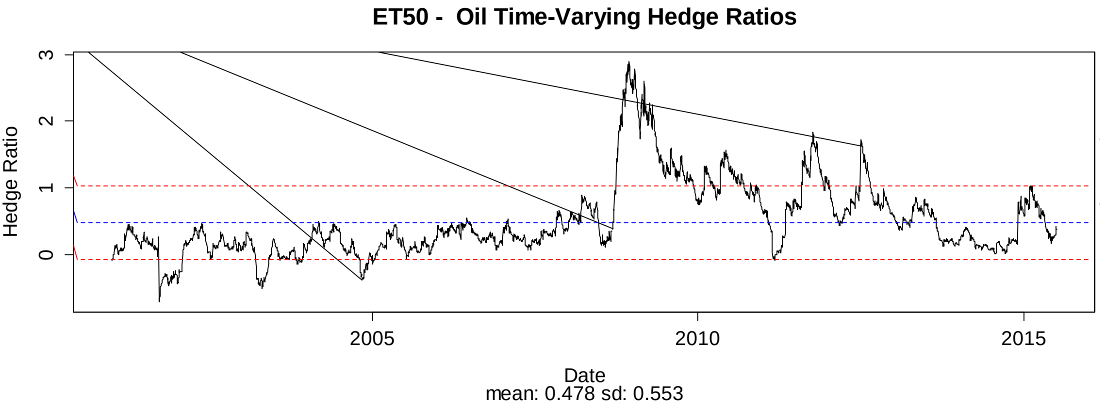
Date
mean: 0.58 sd: 0.505

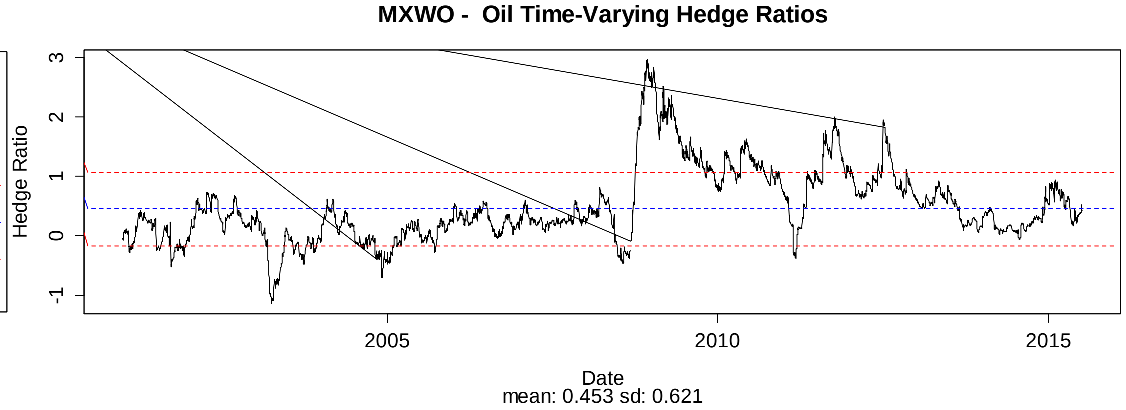

CEXX - Oil Time-Varying Hedge Ratios
Hedge Ratio
0.0
1.0
2.0
2008
2010
2012
2014
Date
mean: 0.684 sd: 0.533

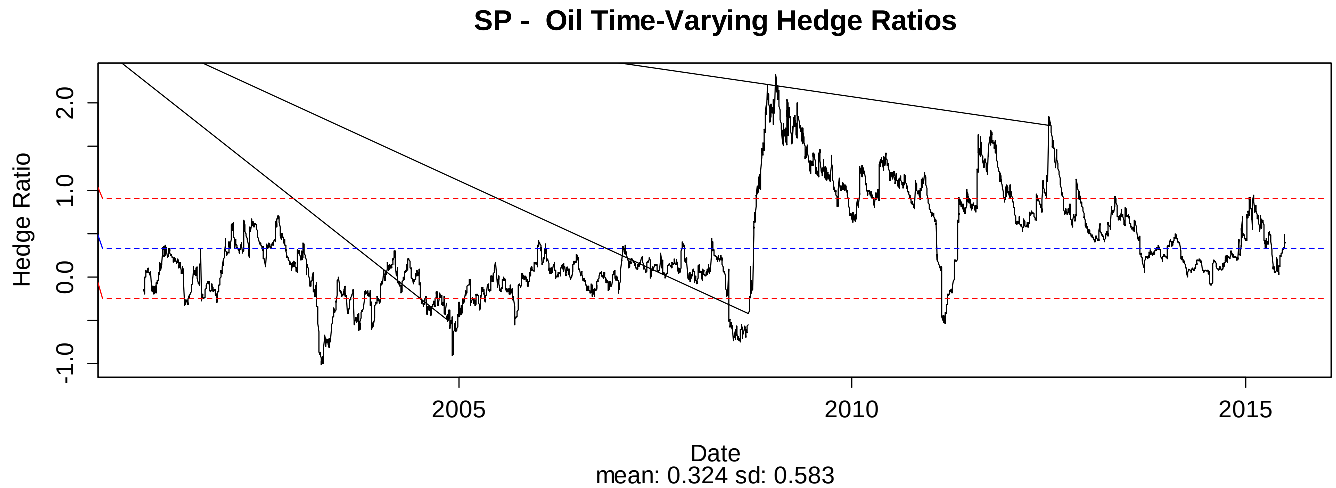

WAEX - Oil Time-Varying Hedge Ratios
Hedge Ratio
0.0
1.0
2.0
2004
2006
2008
2010
2012
2014
Date
mean: 0.639 sd: 0.511


DAX - Oil Time-Varying Hedge Ratios
Hedge Ratio
-1
0
1
2
3
2005
2010
2015
Date
mean: 0.447 sd: 0.511


CSA - Oil Time-Varying Hedge Ratios
Hedge Ratio
0
1
2
3
2005
2010
2015
Date
mean: 0.704 sd: 0.548


ET50 - Oil Time-Varying Hedge Ratios
Hedge Ratio
0
1
2
3
2005
2010
2015
Date
mean: 0.478 sd: 0.553

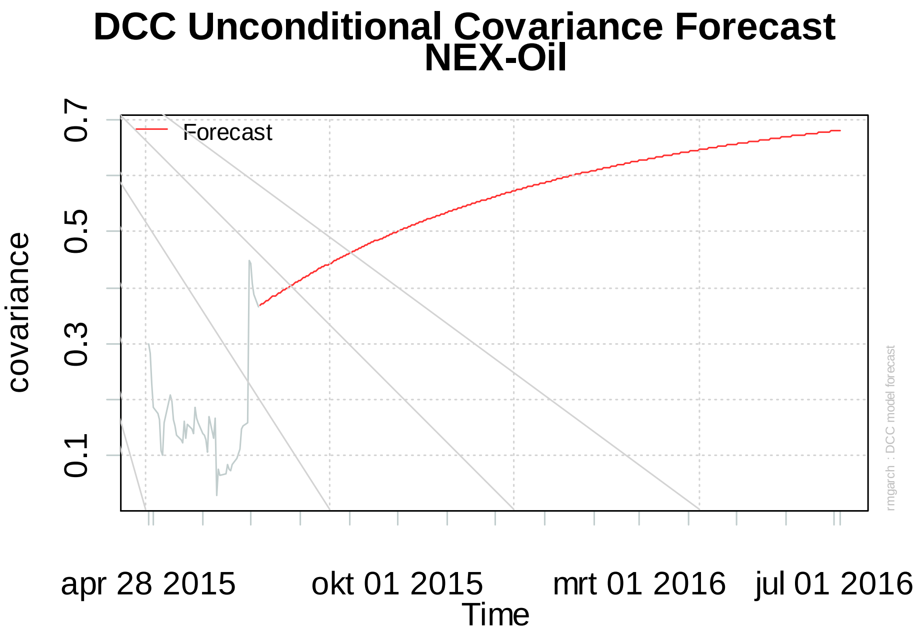

MXWO - Oil Time-Varying Hedge Ratios
Hedge Ratio
-1
0
1
2
3
2005
2010
2015
Date
mean: 0.453 sd: 0.621

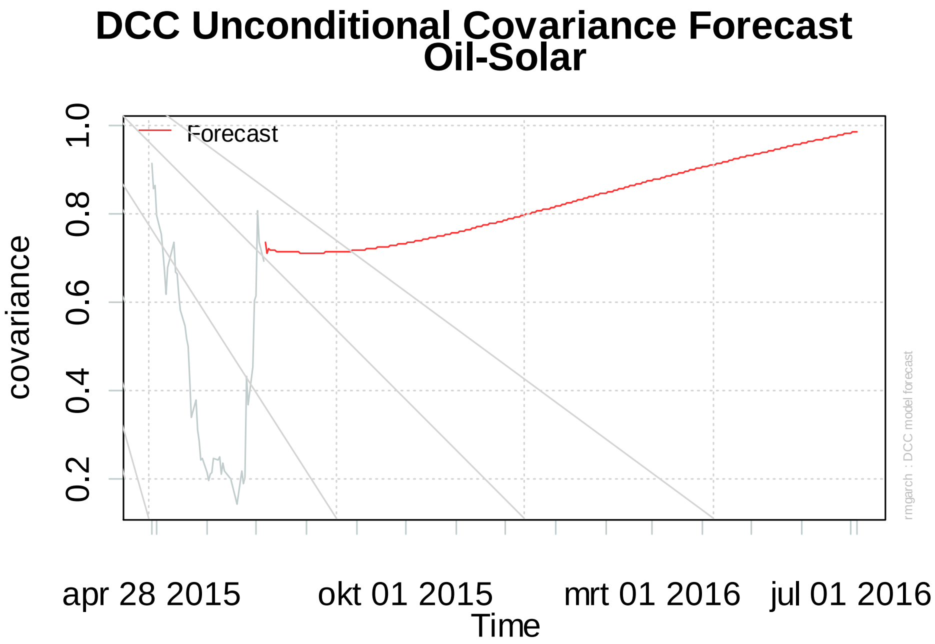

SP - Oil Time-Varying Hedge Ratios
Hedge Ratio
-1.0
0.0
1.0
2.0
2005
2010
2015
Date
mean: 0.324 sd: 0.583

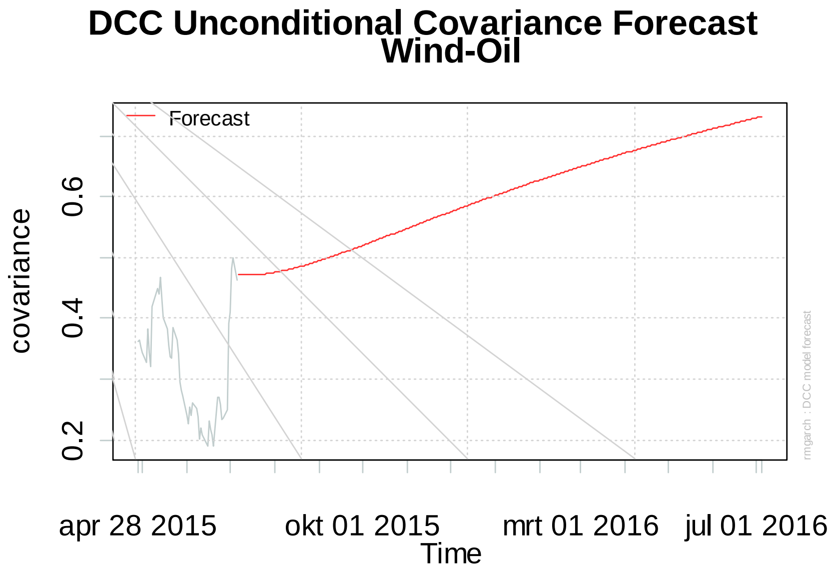
Appendix F – Forecasted Covariance plots

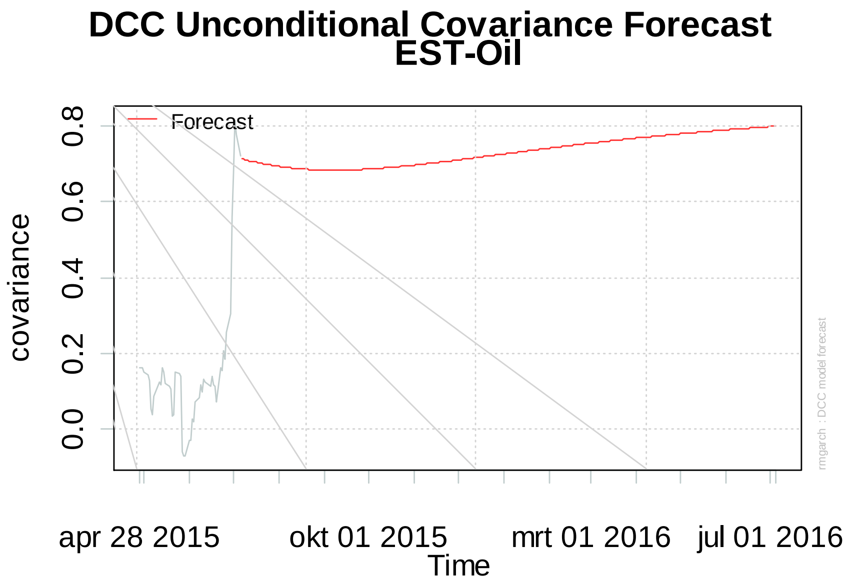
Figure 5 – Forecasted Covariance plots

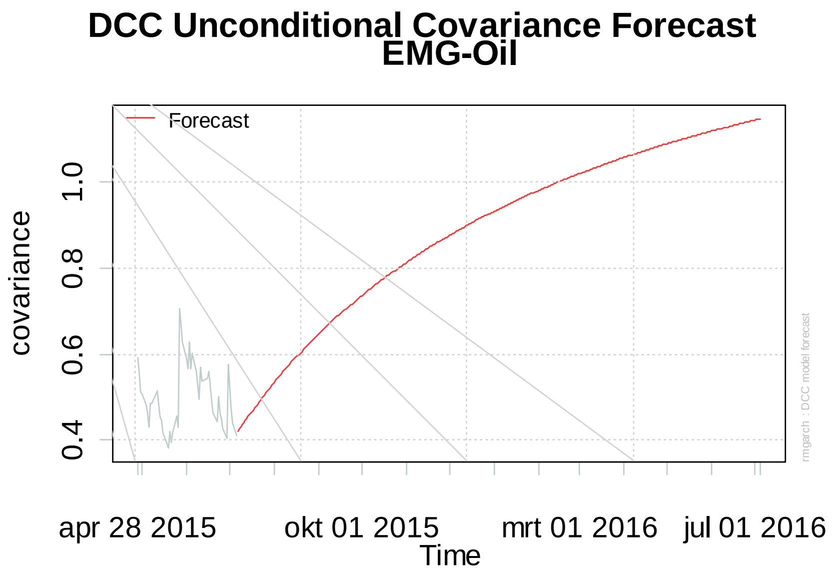
Figure 5 shows the plotted one-year ahead forecasts of the covariance matrices for all indexes.

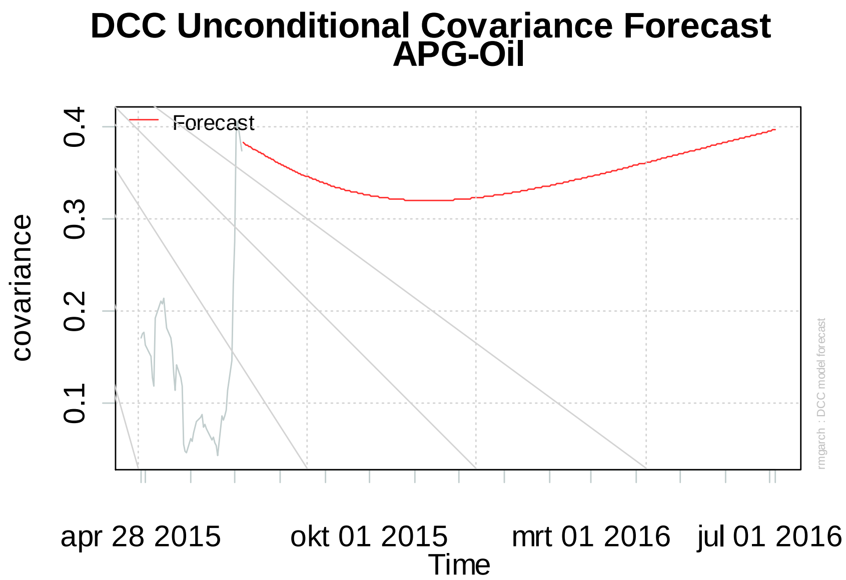


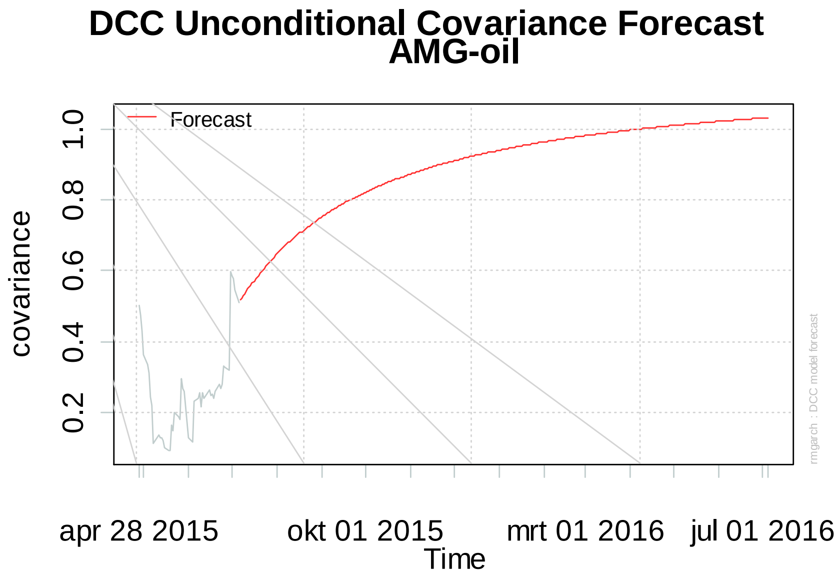


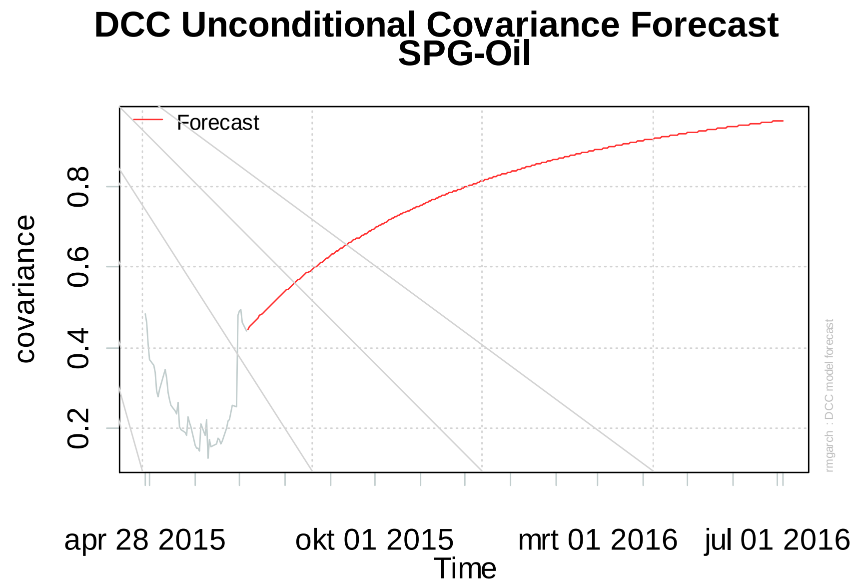

DCC Unconditional Covariance Forecast
Wind-Oil
Forecast
covariance
0.2
0.4
0.6
apr 28 2015
okt 01 2015
mrt 01 2016
jul 01 2016
Time

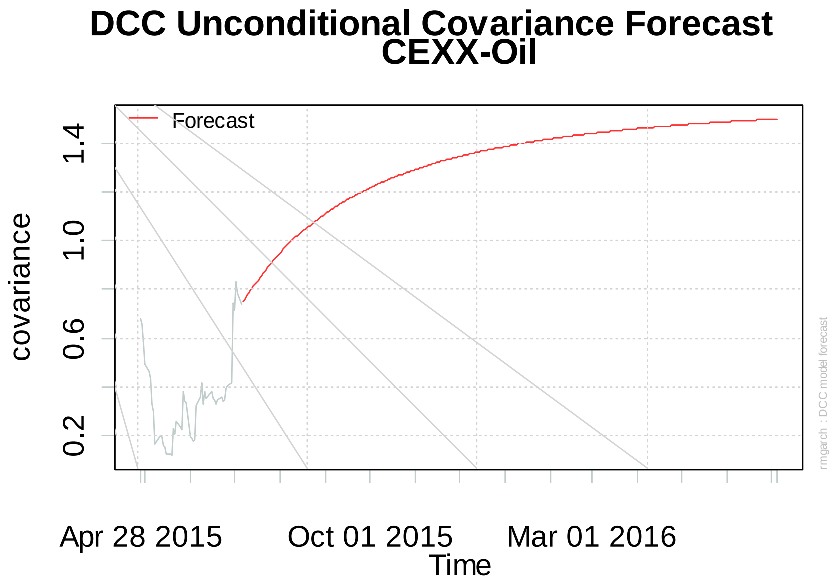

DCC Unconditional Covariance Forecast
EST-Oil
Forecast
covariance
0.0
0.2
0.4
0.6
0.8
apr 28 2015
okt 01 2015
mrt 01 2016
jul 01 2016
Time

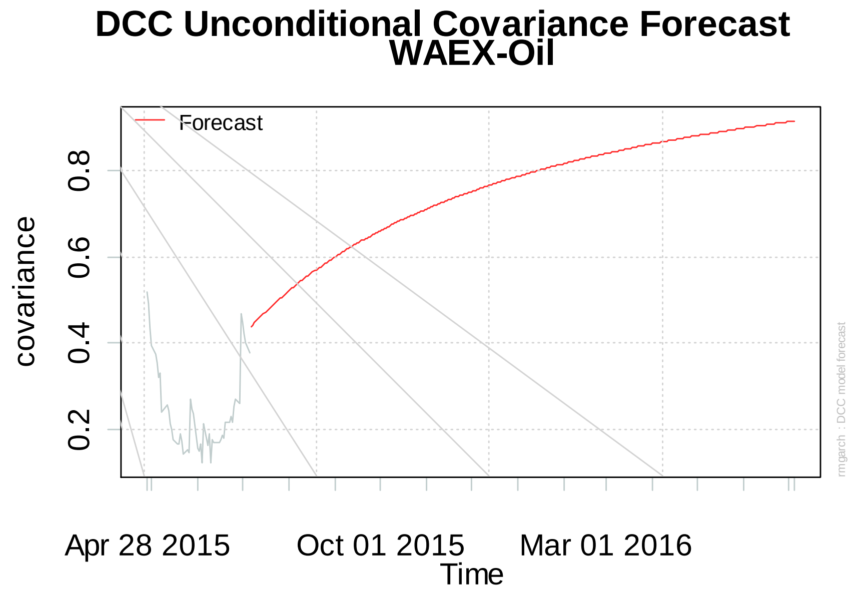

DCC Unconditional Covariance Forecast
EMG-Oil
Forecast
covariance
0.4
0.6
0.8
1.0
apr 28 2015
okt 01 2015
mrt 01 2016
jul 01 2016
Time

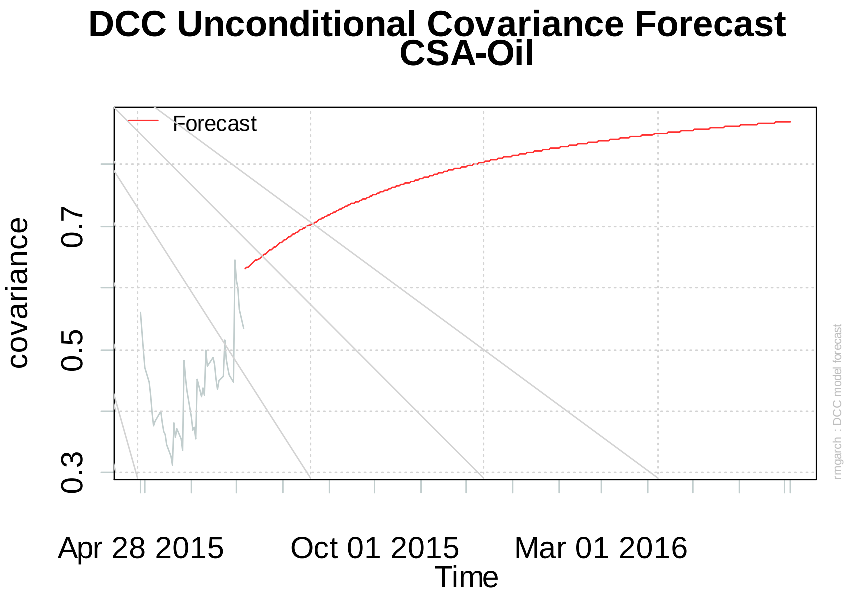

DCC Unconditional Covariance Forecast
APG-Oil
Forecast
covariance
0.1
0.2
0.3
0.4
apr 28 2015
okt 01 2015
mrt 01 2016
jul 01 2016
Time

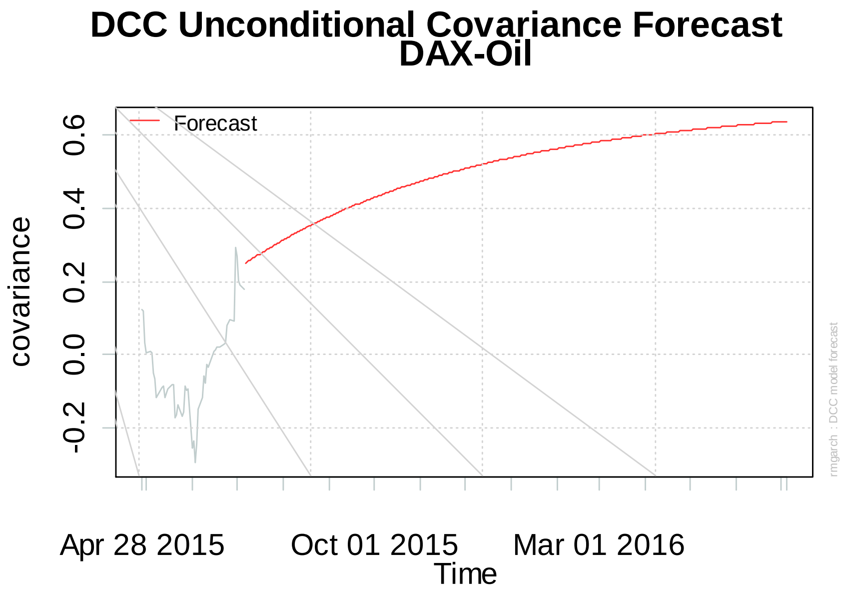

DCC Unconditional Covariance Forecast
AMG-oil
Forecast
covariance
0.2
0.4
0.6
0.8
1.0
apr 28 2015
okt 01 2015
mrt 01 2016
jul 01 2016
Time

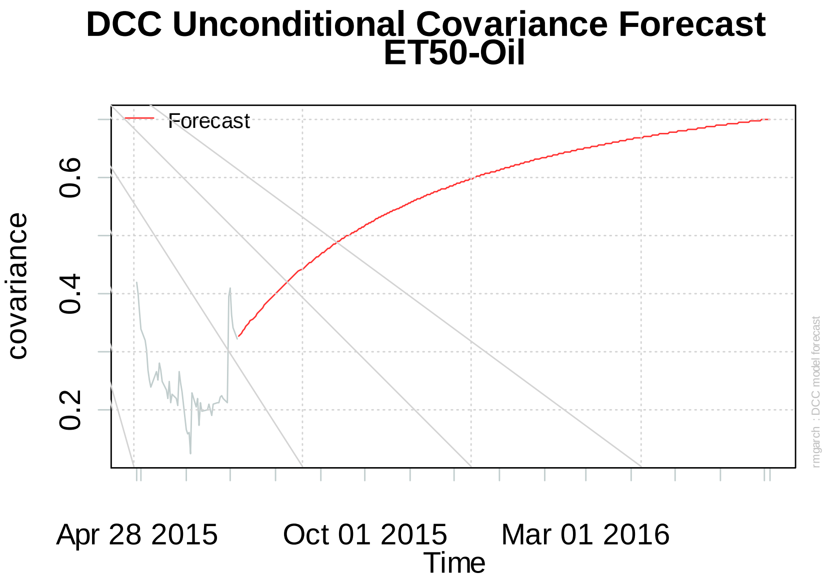

DCC Unconditional Covariance Forecast
SPG-Oil
Forecast
covariance
0.2
0.4
0.6
0.8
apr 28 2015
okt 01 2015
mrt 01 2016
jul 01 2016
Time

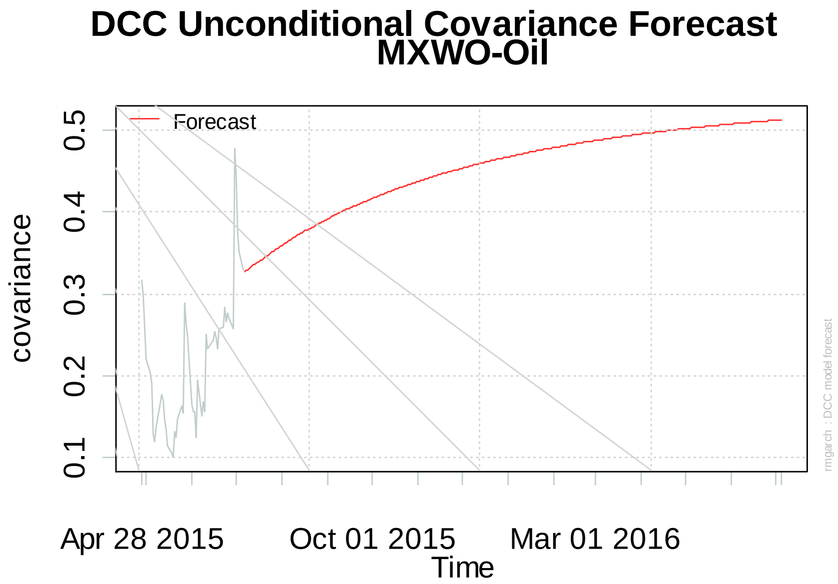

DCC Unconditional Covariance Forecast
CEXX-Oil
Forecast
covariance
0.2
0.6
1.0
1.4
Apr 28 2015
Oct 01 2015
Mar 01 2016
Time

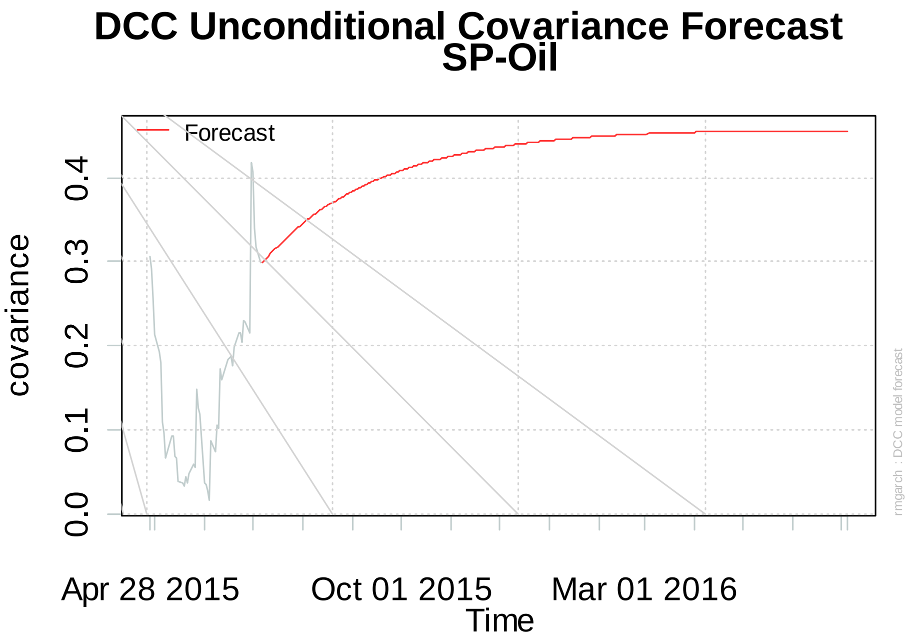

DCC Unconditional Covariance Forecast
WAEX-Oil
Forecast
covariance
0.2
0.4
0.6
0.8
Apr 28 2015
Oct 01 2015
Mar 01 2016
Time


DCC Unconditional Covariance Forecast
CSA-Oil
Forecast
covariance
0.3
0.5
0.7
Apr 28 2015
Oct 01 2015
Mar 01 2016
Time


DCC Unconditional Covariance Forecast
DAX-Oil
Forecast
covariance
-0.2
0.0
0.2
0.4
0.6
Apr 28 2015
Oct 01 2015
Mar 01 2016
Time


DCC Unconditional Covariance Forecast
ET50-Oil
Forecast
covariance
0.2
0.4
0.6
Apr 28 2015
Oct 01 2015
Mar 01 2016
Time

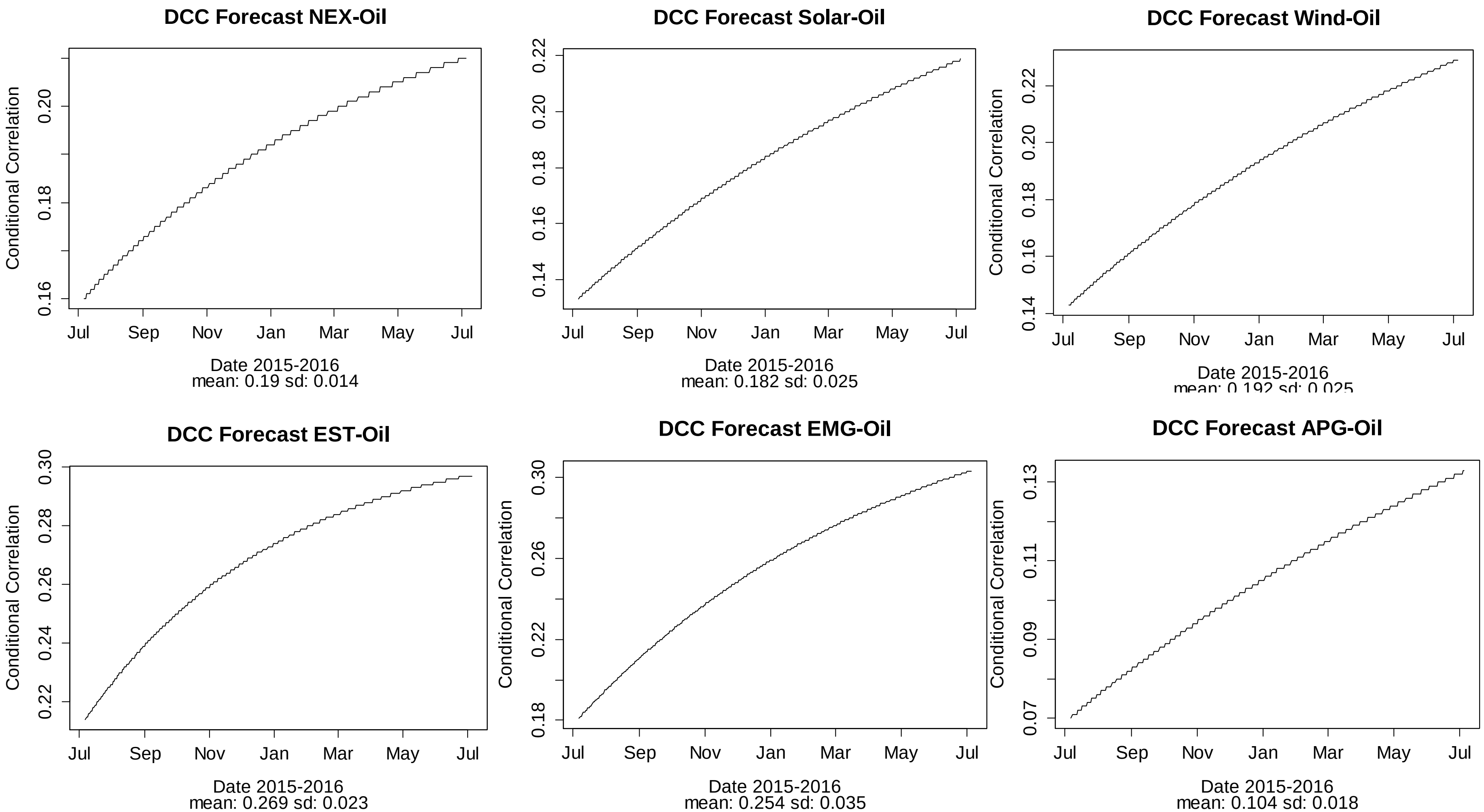

DCC Unconditional Covariance Forecast
MXWO-Oil
Forecast
covariance
0.1
0.2
0.3
0.4
0.5
Apr 28 2015
Oct 01 2015
Mar 01 2016
Time


DCC Unconditional Covariance Forecast
SP-Oil
Forecast
covariance
0.0
0.1
0.2
0.3
0.4
Apr 28 2015
Oct 01 2015
Mar 01 2016
Time
rmgarch : DCC model forecast

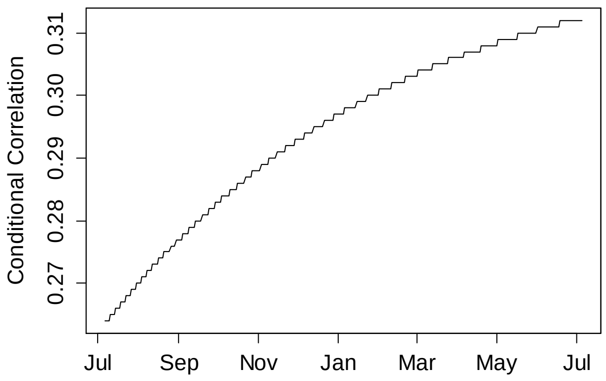
Appendix G – Forecasted DCC plots

Figure 6 – Forecasted DCC plots

Figure 6 shows the plotted one-year ahead forecasts for the dynamic conditional correlation for all indexes.

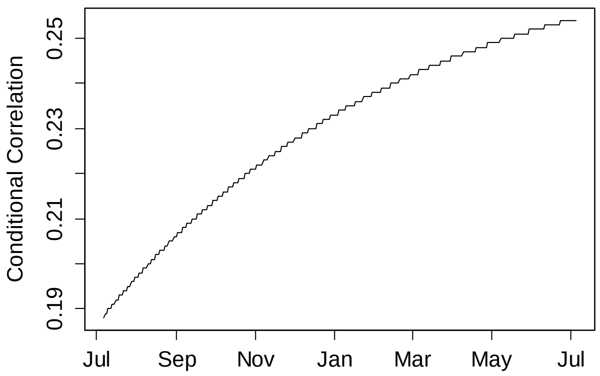


DCC Forecast AMG-Oil



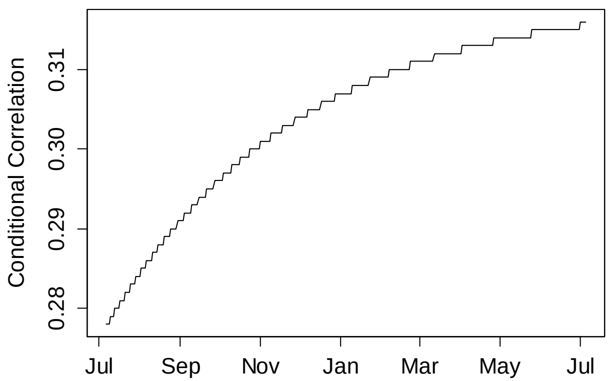
Date 2015-2016
mean: 0.294 sd: 0.014

DCC Forecast SPG-Oil



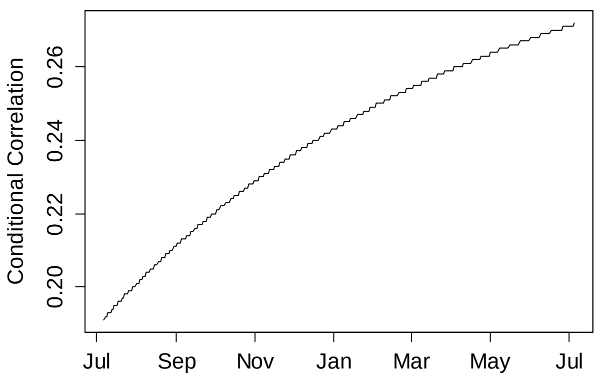
Date 2015-2016
mean: 0.23 sd: 0.019

DCC Forecast CEXX-Oil



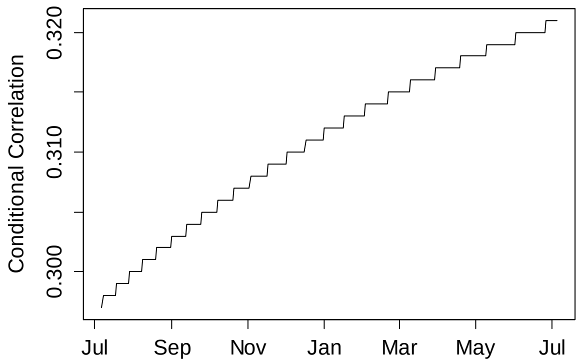
Date 2015-2016
mean: 0.304 sd: 0.01

DCC Forecast WAEX-Oil



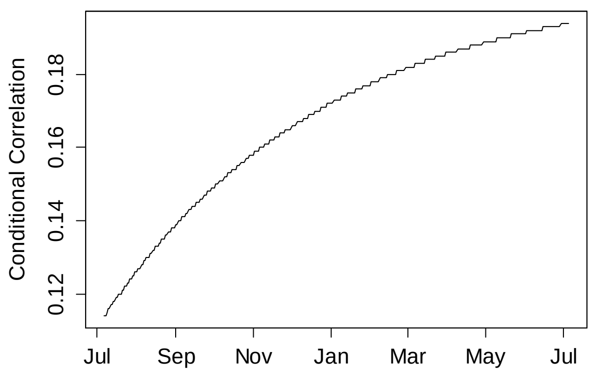
Date 2015-2016
mean: 0.24 sd: 0.023

DCC Forecast CSA-Oil

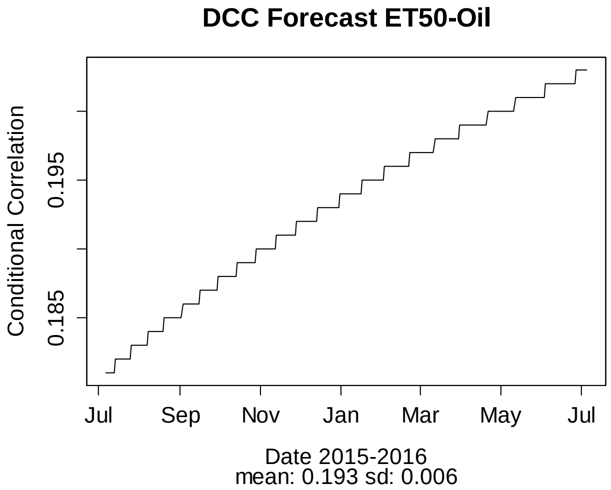


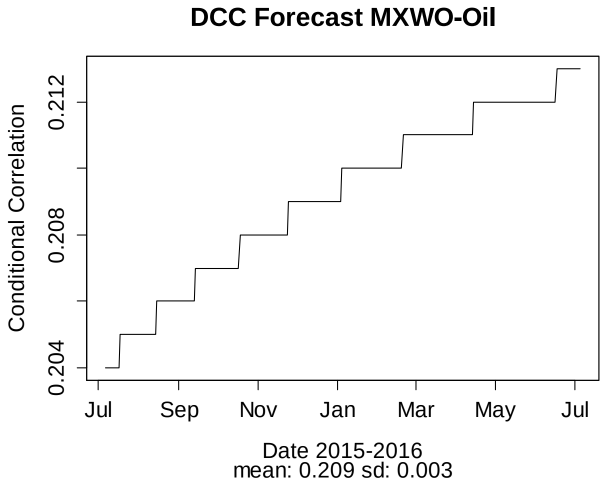
Date 2015-2016
mean: 0.311 sd: 0.007

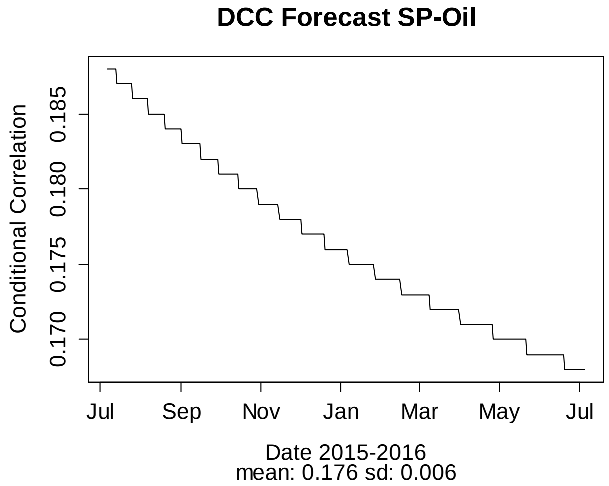
DCC Forecast DAX-Oil



Date 2015-2016
mean: 0.167 sd: 0.022


DCC Forecast ET50-Oil
Conditional Correlation
0.185
0.195
Jul
Sep
Nov
Jan
Mar
May
Jul
Date 2015-2016
mean: 0.193 sd: 0.006

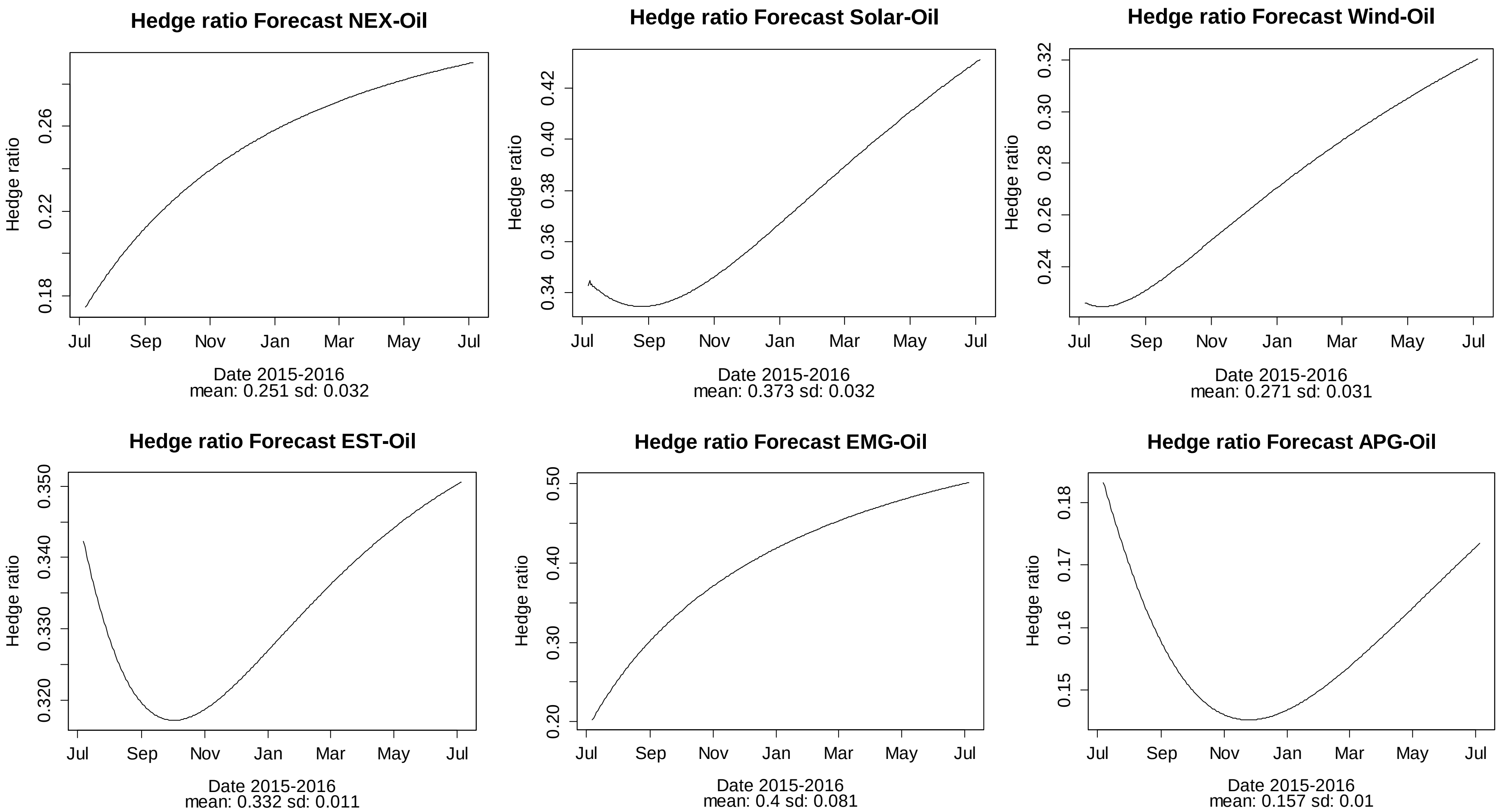

DCC Forecast MXWO-Oil
Conditional Correlation
0.204
0.208
0.212
Jul
Sep
Nov
Jan
Mar
May
Jul
Date 2015-2016
mean: 0.209 sd: 0.003

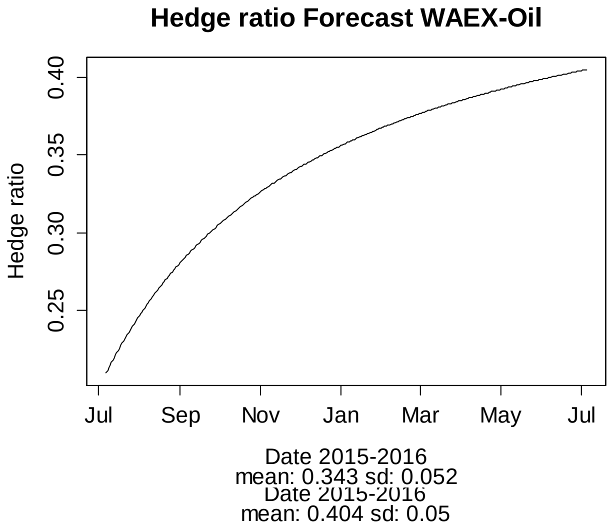

DCC Forecast SP-Oil
Conditional Correlation
0.170
0.175
0.180
0.185
Jul
Sep
Nov
Jan
Mar
May
Jul
Date 2015-2016
mean: 0.176 sd: 0.006

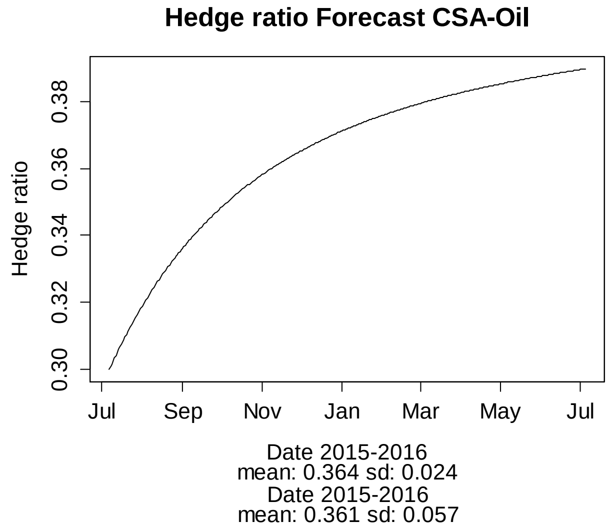
Appendix H – Forecasted Hedge Ratio plots

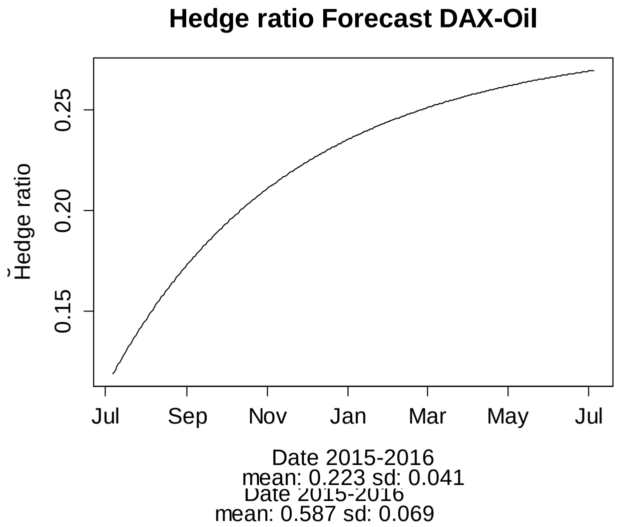
Figure 7 – Forecasted Hedge Ratio plots

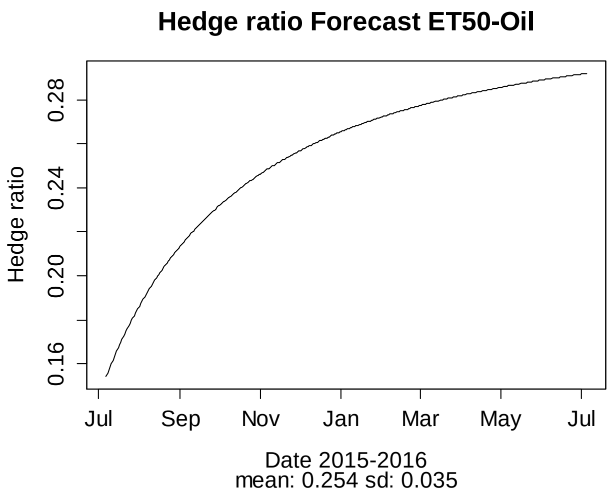
Figure 7 shows the plots of the one-year ahead forecasts of the time-varying hedge ratios for all indexes.

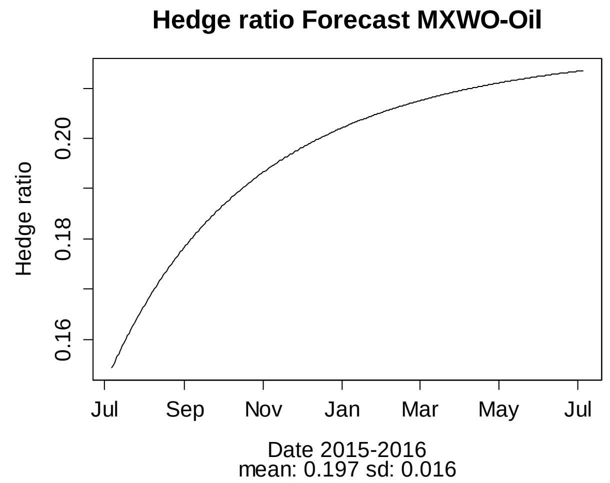


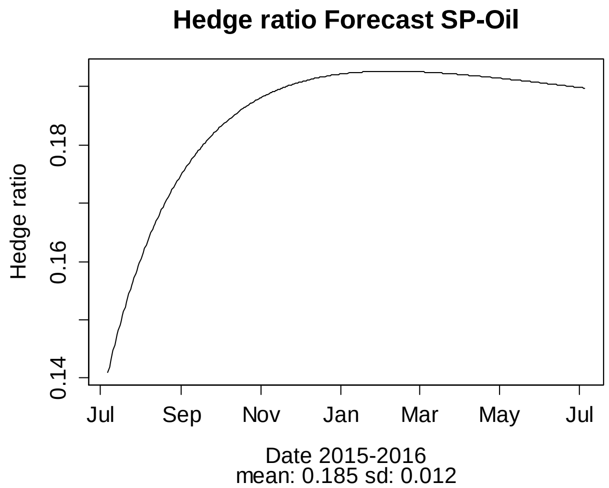

Hedge ratio Forecast WAEX-Oil
Hedge ratio
0.25 0.30 0.35 0.40
Jul Sep Nov Jan Mar May Jul
Date 2015-2016
mean: 0.343 sd: 0.052
Date 2015-2016
mean: 0.404 sd: 0.05


Hedge ratio Forecast CSA-Oil
Hedge ratio
0.30 0.32 0.34 0.36 0.38
Jul Sep Nov Jan Mar May Jul
Date 2015-2016
mean: 0.364 sd: 0.024
Date 2015-2016
mean: 0.361 sd: 0.057


Hedge ratio Forecast DAX-Oil
Hedge ratio
0.15 0.20 0.25
Jul Sep Nov Jan Mar May Jul
Date 2015-2016
mean: 0.223 sd: 0.041
Date 2015-2016
mean: 0.587 sd: 0.069


Hedge ratio Forecast ET50-Oil
Hedge ratio
0.16 0.20 0.24 0.28
Jul Sep Nov Jan Mar May Jul
Date 2015-2016
mean: 0.254 sd: 0.035


Hedge ratio Forecast MXWO-Oil
Hedge ratio
0.16 0.18 0.20
Jul Sep Nov Jan Mar May Jul
Date 2015-2016
mean: 0.197 sd: 0.016


Hedge ratio Forecast SP-Oil
Hedge ratio
0.14 0.16 0.18
Jul Sep Nov Jan Mar May Jul
Date 2015-2016
mean: 0.185 sd: 0.012