LONG MEMORY AND TIME VARYING HEDGING OPPORTUNITIES BETWEEN CLEAN ENERGY, CRUDE OIL AND TECHNOLOGY SECTOR

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Abstract

In this paper, long memory and time varying hedging opportunities between clean energy, West Texas Intermediate (WTI) crude oil and technology share prices were analized between 3 May 2005-16 October 2019. The relationships were investigated by DECO-FIGARCH model with daily frequencies. According to findings, it is understood that volatility clusters were determined in crude oil, alternate source energy and technology returns. Due to this useful information shocks reach to all three investment tools and being eliminated at hyperbolic speed, also the volatility spillover lasted for a long time. The most important finding of the research is that long position risks arising in both clean energy and technology sectors can be effectively and efficiently hedged with WTI futures contracts. On the other hand, it was determined that WTI can be added to the portfolio in order to reduce the risks of portfolio to be established with clean energy and technology sector.

Keywords: Long Memory, Time Varying Hedging Opportinties, Clean Energy, WTI, Technology Sector.

Jel Codes: G11, Q42

1. Introduction

Supply of energy plays an important role in today's society, ranging from assuring basic human needs to independence of countries. There are three basic sources where can be provided. Traditional fossile sources like crude oil which has been in use for nearly more than a century, from renewable energy sources and from nuclear raw materials in the form of nuclear energy. However crude oil prices are determined according to demand and supply principle, local and international problems of the crude oil exporting countries which are called "OPEC", sudden shocks in the market, like contraction of demand or political and social restrictions taken for oil and its derivatives due to global climate change will cuase high volatility in the price changes. On the other hand, boost of oil price will trigger the demand on alternative sources, of course this will make a positive impact on the revenue stream of such companies. Although renewable energy capacity has doubled globally from 2007 to 2016, crude oil and other liquids share on global energy consumption is still around 32% (IRENA, 2017: 14; IEO 2019: 2) Although crude oil prices had gone down to 32 $/ barrel in 2008 crisis, than increased to 114 $/ barrel in 2011 and then went down to 26 $/barrel in 2016, which is a loss of 77 % compared to 2011 prices.

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Later on prices differed between 51 / 77 $ a barrel. During Covid19 pandemic due to decline of demand prices went down to 20 $/barrel but recovered to 30 $. Rise in the profits of Tech companies related with clean energy companies are highly expected due to this unstability of oil prices and markets. (Nasreen etc. 2020) Volatility models and estimations are mostly studied topics, because derivative pricing, portfolio optimization are the most efficient methods for risk management. You need the best volatility estimations and correlation for best protection from risks (Sadorsky, 2012).

ARCH and its derivative traditional short memory models are used in most studies investigating the determination of hedging effectiveness and portfolio diversification opportunities. However, in many empirical studies with financial statistics, it has been determined that the autocorrelations of the return and volatility series remain non-zero for a fairly wide delay (using remain non-zero expression of Ding et al. (1993), Baillie et. Al. (1996), Ding and Granger (1996), Andersen et. Al. (2001)). In all of these studies, it has been proven that autocovariance functions disappear at a slow rate. The most important originality of this study is that the volatility structures of the series, in which portfolio optimization and hedging opportunities are investigated, used the FIGARCH model, which takes into account the long memory (GARCH, EGARCH, APARCH, etc.) instead of short memory models in multivariate form.

The rapid progress in the renewable energy and technology sectors in recent years has reached remarkable levels. According to the "Global Trends in Renewable Energy Investment 2020" report of the UN Environment Program (2020), the investment made in renewable energy in the 2010-2019 period reached 2.7 Trillion dollars. Although the Covid-19 process is delayed, it is planned to make an additional $ 1 trillion additional non-hydro renewable energy investment until 2030 (UNEP, 2020). Recently, modeling and forecast of the volatility of financial assets with resistant methods attracts the attention of investors, especially in portfolio diversification. For this reason, the main motivation of this study is to demonstrate the conditional correlations between clean energy, technology and wti futures, as well as to measure the hedging opportunities of long position risks arising from investments made in both clean energy and technology sectors and fossil fuels.

In the following sections of the paper, firstly, a summary of the studies in the literature is presented, and then the econometric method used are introduced. In the fourth part, data and the obtained empirical findings are given and the last part includes results and discussions.

2. Previous Literature Review

There are not much study analyzing relation amidst share values of crude oil companies and alternate energy source & technology companies. The very first one was performed in 2008 by Henriques and Sadorsky. The empirical relation amidst share values of alternate energy source & technology companies and crude oil manufacturing companies were found to have “granger” effect.

Kumar et. al. (2012) has claimed that alterations in the alternative energy source index is related with crude oil cost and share value of alternative energy source & technology companies, as well with previous alterations in rate of interests. Any rise in crude oil prices affects alternate energy source indices positively. In 2012 Sadorsky had performed one of the basic studies about this subject and analyzed the spread of unpredictability amidst crude oil prices and share value of alternate energy source & technology corporations. The results were showing a strong link in high technology share values with alternate energy source company shares values compared with crude oil company shares. If you buy a 20 cent oil share for short term, you can secure this investment with a 1 $ high techology company share for long term.

In 2013 Managi and Okimoto analyized structural breaks in the long run relation of alternate energy source shares and found a positive relation in crude oil and alternate energy source prices after the structural break in 2007. Bondia et al. (2016) has found long term relation in one or two endogenous breaking points between oil prices, alternative energy and high tech company stocks. In addition to this, while alternate energy source & high technology company share values were affected by crude oil prices and interest rates in the short terms but not in long terms

Zhang and Du’s study in 2017 showed that alternate energy source company share values have more correlation with high technology company share values rather than crude oil and coal prices. In 2017 Ahmed Ghorbel’s study has examined directional breakdown amidst crude oil prices and alternate energy source & high technology corporate share values and found that, alternate energy source & high technology corporate shares are playing a majör role in spread of unpredictability and profit in crude oil prices and they are dominant emitters in crude oil price earnings and spread of unpredictability.

In 2018 Reboredoa and Ugolini study evaluated the effect of cardinality of clean energy share profits in price alterations of fossile fuels (oil, natural gas, coal) and power generating costs. They have found that, whenever there is an up/down fluctuation in power generating costs, it has a major affect on renewable energy price dynamics. Moreover, electric prices in Europe and crude oil prices in United States are major determinants in renewable energy share fluctuations.

Ferrer et al.’s study in 2018 shows that correlation among these occure in short term, such as up to 5 days, but long term effects were small in United States. Also another important result of this study was, neither in long term nor short term crude oil price has major effect in the performance of alternate source energy corporate shares in the stock exchange market. In 2018 Lee and Baek have used ARDL model which considers asymmetrical effects and nonlinear. It was found that, alterations in crude oil prices have asymmetrical and positive effect on alternate energy source company shares in short term. In 2019 study of Song et al. shows that fossil fuel energy market, investors sentiment, alternate source energy and dynamic data in return between renewable energy market and spread of unpredictability. The results can be summarized as; spread of unpredictability is stronger than spread of returns, so the risk transfer amongst markets is apparent. The fossile fuel energy markets (especially crude oil) effect on alternate source energy shares in stock exchange markets are greater than investors sentiments. Finally investors sentiment in alternate source energy markets can be explained up to a certain degree with profits of these shares and their fluctuations. In 2019 Magyereh et al. study with a different approach from their previous study, examined correlations between crude oil shares and alternate energy source & technology shares. When resolving statistics, it was found that, short term profits from crude oil market shares does not effect and get effected from the profits of alternate source energy & technology shares, but in the long term, there is remarkable transfer of profit as an investment from crude oil shares to alternate source energy & technology corporate shares. Over all scales a strong return link was observed amongst alternate source energy shares and such high technology providing corporate shares. The spread of unpredictability was significant in all statistics and alterations.

In 2020 Nasreen et al. study dynamics of relevance among crude oil profits and alternate source energy & technology corporate share indexes were examined. Obtained findings showed that alternate source energy & technology corporate share indexes are perfect hedging tools for the risks in crude oil market. Portfolio of crude oil and alternate source energy & technology corporate shares are showing that optimum portfolio is the crude oil weighted. Finally they have stated that there are statistical significant relation amongst crude oil prices and alternate source energy & technology indexes between 2006 and 2009.

When we sum up all these with everthing that exists in the literature, the highlights are: positive relation amongst crude oil price and alternate source energy price, whenever crude oil price goes up there is a significant rise in the alternate source energy indexes. Also there is a causal connection between technology shares, crude oil prices and alternate source energy corporate shares, on the otherside the relation amongst alternate source energy corporate shares and high technology corporate shares are more intense than alternate source energy corporate shares and fossil fuel prices.

3. Econometric Model

MGARCH models are used frequently by researchers to determine portfolio selections, volatility spreads and hedge opportunities between financial markets. Financial series behavior of sharp and skewed distributed character, disapperance of information in hyperbolic speed after reaching financial assets, reluctancy of financial series to return to average are causing financial assets to be interpreted as showing long memory behavior. In this respect Fractional GARCH models are preferred instead of GARCH models to examine the volatility structures of financial assets.

In this study, we will examine dynamic volatilite interactions among crude oil prices, alternate source energy and high technology shares. In 1996 Baillie et. al. study, DECO model developed by Engle and Kelly (2012) which was a modified version of DCC (Dynamic Conditional Correlation) model called MGARCH model. The FIGARCH (Fractional Integrated GARCH) model will be annexed to the literature and we will explore the diffusion relationship between long memory dynamics and financial asset returns.

In 2012 Engle and Kelly modeling ρ_t with the help of DCC model (Engle 2002) and its modified version cDDC by Aielli in 2011 has made conditional correlation matrix Q_t and after, taking the content off-diagonal elements in order to lessen the estimation time by simplifying the procedure. This method is named, dynamic equicorrelation (DECO) model, and written as:

$$\rho_t^{DECO} = \frac{1}{n(n-1)}(\acute{J}_n R_t^{cDCC} J_n - n) = \frac{2}{n(n-1)} \sum_{i=1}^{n-1} \sum_{j=i+t}^{n} \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \quad (1)$$

where $q_{ij,t}$ is (i,j)th component of matrix Q_t of cDCC model. This scalar equicorrelation is to estimate conditional correlation matrix:

$$R_t = (1 - \rho_t) I_n + \rho_t J_n \quad (2)$$

If J_n is nxn matrix of 1 and I_n is n-dimensional identity matrix. This presupposition of equicorrelation results as more simple equation when ρ_t is given by Eq. (3):

$$L = -\frac{1}{T} \sum_{t=1}^{T} (\ln(1-\rho_t)^{n-1} (1 + (n-1)\rho_t)) \frac{1}{1-\rho_t} \left(\sum_{i=1}^{n} \varepsilon_{i,t}^2 - \frac{\rho_t}{1+(n-1)\rho_t} (\sum_{i=1}^{n} \varepsilon_{i,t}^2) \right) \quad (3)$$

Baillie et al. study in 1996 introduced a fractional integrated GARCH model (FIGARCH) to specify long memory of volatility return. GARCH model is expressed as an ARMA (*mp*) for squared error form,

$$[1 - \alpha(L) - \beta(L) \varepsilon_t^2 = \omega + [1 - \beta(L) v_t \quad (4)$$

where $v_t = \varepsilon_t^2 - \sigma_t^2$. FIGARCH model roots from standard GARCH model with fractional difference implementer, $(1-L)^d$. FIGARCH is displayed as:

$$\emptyset(L)(1-L)^{\bar{d}} \varepsilon_t^2 = \omega + [1 - \beta(L)] v_t \quad (5)$$

When d is long memory parameter, $\emptyset(L)$ and $\beta(L)$ are delimited order lag polynomials with roots assumed to be outside of unit circle and $(1-L)^{\bar{d}}$ is fractional differencing operator. FIGARCH $(p, \bar{d}, q)$ model is turned to standard GARCH when $\bar{d}$ = 0 and IGARCH model when $\bar{d}$ = 1.

4. Data and Empirical Findings

In this study we have used data from The WilderHill Clean Energy Index (ECO), NYSE Arca Tech 100 Index (PSE) and daily closing prices of crude oil at West Texas Intermediate (WTI). They are obtained from www.finance.yahoo. The WilderHill Clean Energy is the oldest index, who covers 54 alternate source energy companies. The abbreviation for "Clean Energy Index" in the stock market is "ECO". NYSE Arca Tech 100 Index was founded in 1986 and shows share prices of computer hardware & software companies, health equipment manufacturers, telecommunications and other technology companies. Its abbrevation in the stock market is "PSE".

Table 1. Information on the Data Set of the Study

Abbreviation of Variables	Variables Used in the Study	Researches Using the Variables
ECO	The WilderHill Clean Energy Index	Henriques and Sadorsky (2008), Kumar et al. (2012), Managi and Okimoto (2013), Ahmad (2017), Reboredoa and Ugolini (2018), Ferrer et al. (2018), Song et al. (2019), Magyereh et al. (2019), Nasreen et al. (2020)
PSE	NYSE Arca Tech. 100 Index	Henriques and Sadorsky (2008), Kumar et al. (2012), Managi and Okimoto (2013), Bondia et al. (2016), Ahmad (2017), Ferrer et al. (2018), Lee and Baek (2018), Nasreen et al. (2020)
OIL	West Texas Intermediate Crude Oil	Henriques and Sadorsky (2008), Kumar et al. (2012) Managi and Okimoto (2013), Bondia et al. (2016), Ahmad (2017), Reboredoa and Ugolini (2018), Ferrer et.

		al. (2018), Lee and Baek (2018), Song et al. (2019), Magyereh et al. (2019), Nasreen et al. (2020)

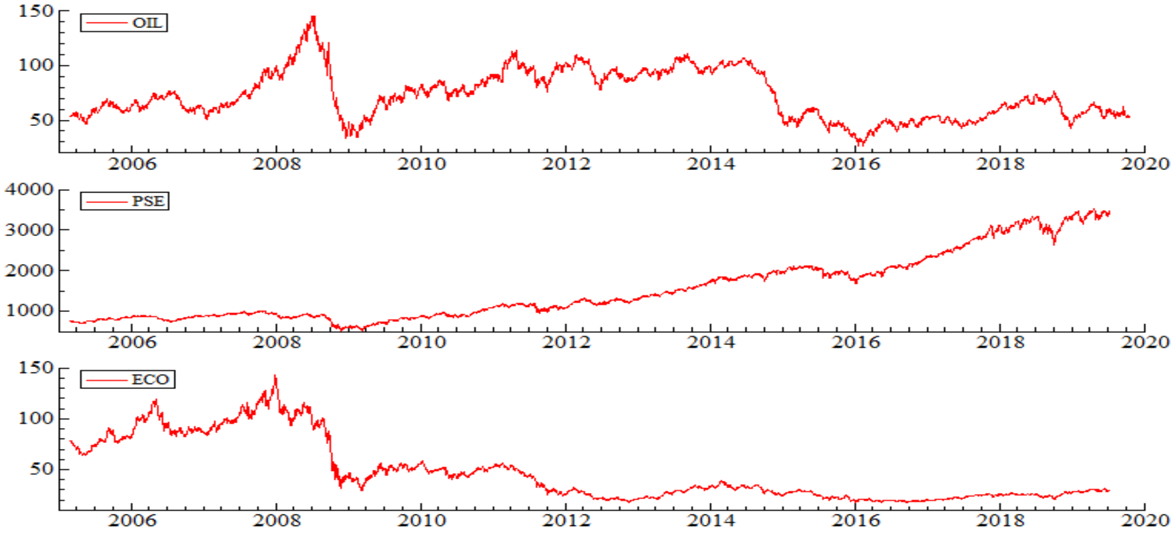

Figure 1: Time Series of Plots in The WilderHill Clean Energy Index (ECO), West Texas Intermediate (WTI) crude oil index and NYSE Arca Tech 100 Index (PSE)

In this study examplication period is between 3 May 2005-16 October 2019, estimations were calculated by relentless unordered daily returns in (Pt/Pt-1) formula for each data set. In Figure 1 from charts for each price set, you can see the great collapse and recession in 2008. From Table 2 you can see the explicated statistics of return data series. In Skewness, Kurtosis and JB statistics, you can see irregular and keen distribution of all return series issued around 0 with comparison of normal distributions. ARCH effect and autocorrelations were identified in 20 retardation value of returns and double returns. The results show earning series have queueing theory characteristrics and volatility aggerations.

Table 2: Detailed Statistics of Everyday Recompensations.

	OIL	**PSE**	**ECO**
Mean	-.0000030	.0004113	-.0002638
Maximum	.1641	.10099	.1582
Mininum	-.13065	-.081202	-.14555
Std. Dev.	.023078	.012059	.020077
Skewness	.15596	-.24132	-.39842
Excess Kurtosis	4.6058	6.0990	5.9514
Jarque-Bera	3332.5***	5853.5***	5638.0***
ADF	-35.7537***	-36.4234***	-35.3616***
Q (20)	47.7502***	69.1620***	67.5182***
Qs (20)	3500.38***	4183.07***	6387.26***

ARCH (10)	77.902***	104.54***	153.99***

Note: Q (20) and Qs (20) are factual statistics from Ljung-Box test for autocorrelation of recompensings and squared recompensing series commonly. ADF is referring to factual statistics of the Augmented Dickey-Fuller (1979) unit root test respectively. The ARCH (10) test was proposed by Engle in 1982 and used to control the validity of ARCH effects. *** implies the exclusion of 0 hypotheses of normality, unit root, no autocorrelation and conditional homoscedasticity at 1 % significance level.

Table 3: Genuine Interactions between Everyday Recompensations.

	OIL	**PSE**	**ECO**
OIL	1.000	0.263	0.329
PSE	0.263	1.000	0.777
ECO	0.329	0.777	1.000

In table 3 when unconditional correlation parameters analyzed, positive relationship between PSE and ECO is observed. Although the correlation between both OIL & PSE and OIL & ECO is weak, positive relationship was observed. In Chart 3, correlation parameters between double returns show similarity with the results in tablo 1. When Figure 2 is analyzed clusters are clearly seen in the volatility series of all three entities where volatility increases / decreases follow volatility increases / decreases. This result causes suspicisions about presence in long recalls of asset series. From the graphic it can be clearly seen that the 2008 global financial crisis caused a serious increase in the volatility of all 3 series.

Table 4: Unconditional Correlation between Daily Squared Returns

	OIL_{sqr}	**PSE_{sqr}**	**ECO_{sqr}**
OIL_{sqr}	1.00		
PSE_{sqr}	0.251	1.000	
ECO_{sqr}	0.267	0.744	1.000

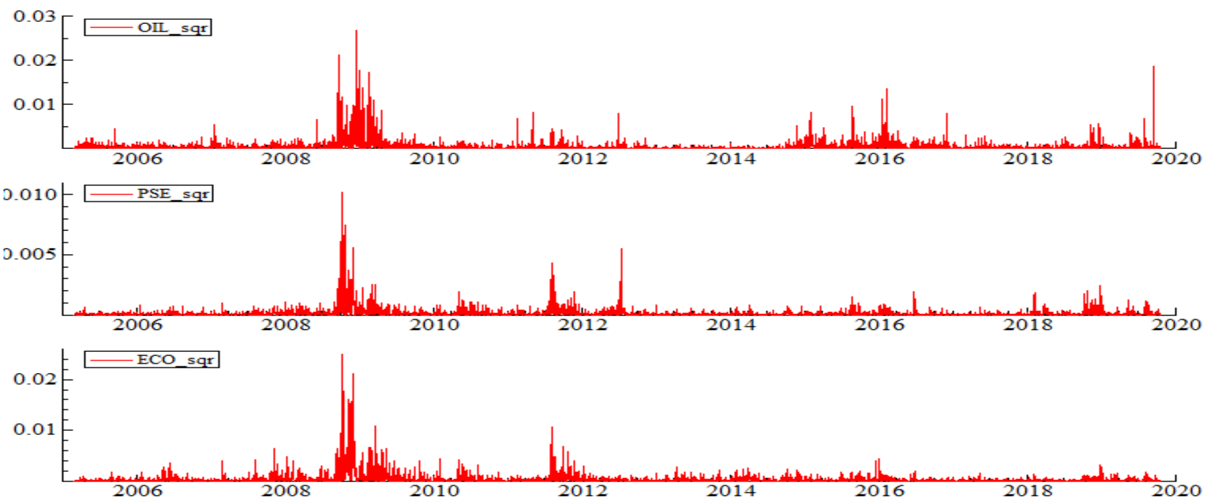

Figure. 2 Squred Returns (volatility) Plots in The WilderHill Clean Energy Index (ECO), West Texas Intermediate (WTI) crude oil index and NYSE Arca Tech 100 Index (PSE)

Table 5: Experimental Results of the DECO-FIGARCH (1, d, 1) Model.

Panel 1: Estimates of the univariate	FIGARCH Model		
	OIL	PSE	ECO
Const. (m)	0.000360	0.000762***	0.000274
	(0.00029303)	(0.00015304)	(0.00025046)
Const. (v)	0.061354	0.046648***	0.148661***
	(0.046204)	(0.016009)	(0.053903)
d-FIGARCH	0.563584**	0.492477***	0.367613***
	(0.27974)	(0.12459)	(0.053230)
$\emptyset_{Arch(1)}$	0.297525***	0.155611**	0.130540
	(0.096015)	(0.065081)	(0.092358)
$\beta_{Garch(1)}$	0.762875***	0.547758***	0.403404***
	(0.18667)	(0.13472)	(0.11442)
Panel 2: Estimates of the DECO	Model		
ρ_{DECO}	0.500312***		
	(0.043734)		
α_{DECO}	0.032182***		
	(0.0093985)		
β_{DECO}	0.959701***		
	(0.013876)		
Log L	32,534.834		
AIC	-17.3279		
SIC	-17.2964		
Panel 3: Diagnostic tests			
Qs (10)	7.55659	17.3197	5.02591
	[0.6720601]	[0.0675829]	[0.8894408]
Qs (20)	15.7504	25.0172	19.3946
	[0.7319821]	[0.2007752]	[0.4963235]

Notes: Qs (10) and Qs (20) refering to Ljung-Box test data performed to the squared standardized particles with 10 and 20 delays respectively. The asterisks *, ** and *** shows significance at 10 %, 5 % and 1 % levels, respectively. The p-values are shown in brackets and the standard errors are in parentheses.

In Table 5 estimated results of DECO-FIGARCH model were shown. The estimations of the invariable FIGARCH model in Panel 1 are showing consolidated portion of coactive "d" which is important for all sequences. So the outcome reveals a high level of shock persistance "d" parameters of West Texas Intermediate (WTI) crude oil index is higher than other indexes.

In Panel 2 of Table 5 displaying estimation results of DECO. α_{DECO} and β_{DECO} coefficients are positive and major. Furthermore β_{DECO} criterion is very close to 1. This reveals a higher persistance of volatility across indices. Also sums of α_{DECO} and β_{DECO} coefficients are <1, indicating estimated DECO criterion scatter in the range of typical GARCH model. ρ_{DECO} (dynamic equicorrelation criterion) is statistically significant at the 1% level. The results are showing investment instruments can be used to manage risks arising from another. The diagnostic test results were summarized in Panel 3, but it shows no inaccuracy in DECO-FIGARCH model. The Ljung-Box test for regulated and double regulated bits do not deny 0 hypothesis of "no serial interaction in most cases".

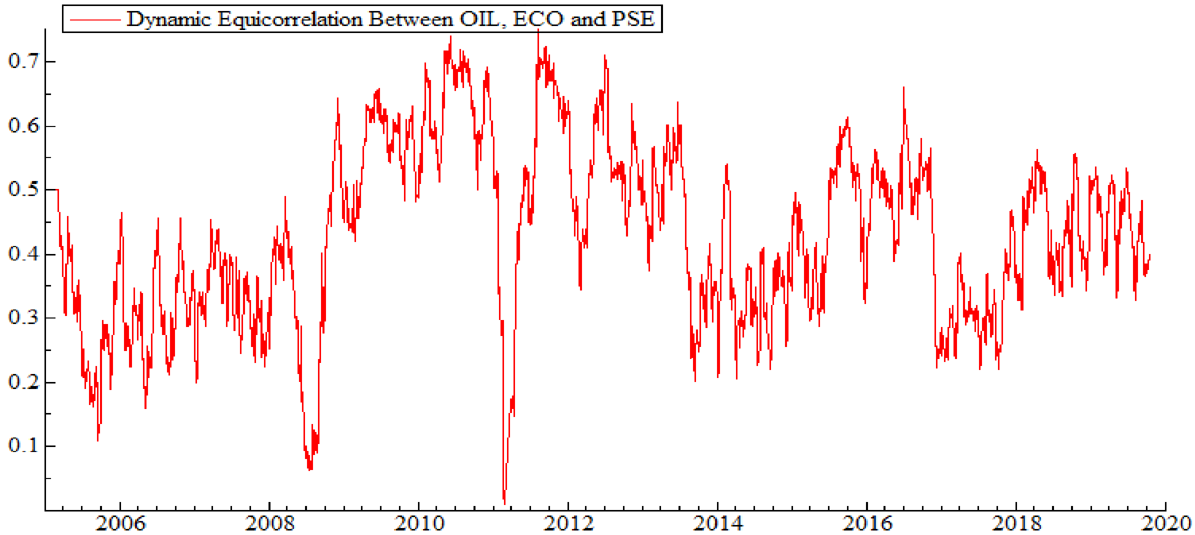

Figure 3: Time & Change flow of equivalence amongst The WilderHill Clean Energy Index (ECO), West Texas Intermediate (WTI) crude oil index and NYSE Arca Tech 100 Index (PSE)

Flow of equivalence amongst The WilderHill Clean Energy Index (ECO), West Texas Intermediate (WTI) crude oil index and NYSE Arca Tech 100 Index (PSE) reaches low values in 2008, exceeds 0.70 value first in 2008 and last time 2010. Yet Time-Change flow of equivalence dynamic equicorrelation spread around 0.5 value. Long term positions in ECO, WTI or PSE can hedged with short term positions with other shares. We calculate time varying hedge ratio with the help olf conditional volatility series and be used eq. 6

$$\beta_{ij} = \frac{h_{ij}}{hjj} \tag{6}$$

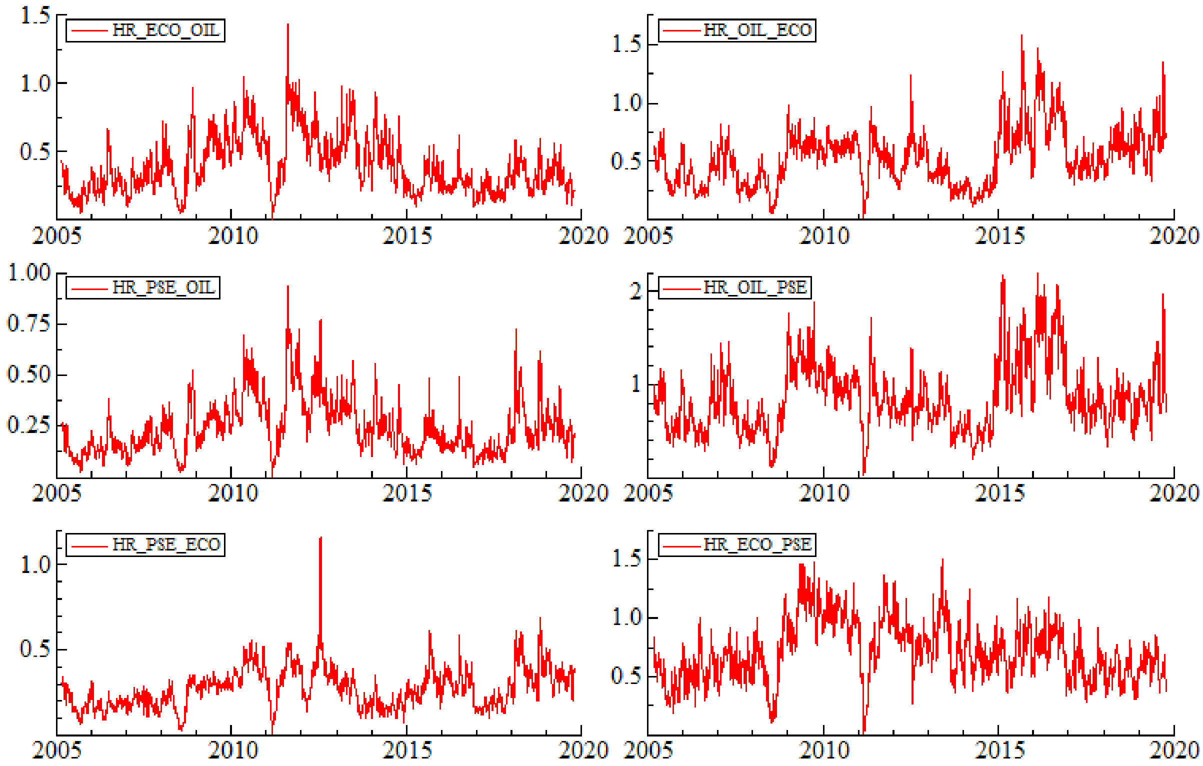

Figure 4: Time-Change Hedge Ratio Computed from DECO-FIGARCH.

Provisional volatilities in DECO-FIGARCH could be practiced for estimation of time-change hedge ratio. Figure 4 and Table 6 showing a 1 $ long term position in crude oil, which can be hedged with 53 cents in short term position at ECO. Average 1$ long term position in ECO, can be hedged with 39 cents with short term position in WTI. Also average 1$ long term position in WTI, can be hedged with 85 cents with short term position in PSE. On the other hand, 1$ long term position in PSE, can be hedged with 24 cents with short term position in WTI. Future oil contracts can be used to manage long term position risks arising from alternate source energy and technology shares.

Table 6: Time-Change Hedge Ratio Analysis Data

	Mean	Min	Max	Std Dev
ECO/OIL	0.39031	0.0076177	1.4306	0.20307
OIL/ECO	0.52948	0.013973	1.5821	0.23564
PSE/OIL	0.24169	0.0054803	0.93379	0.13227
OIL/PSE	0.85026	0.019422	2.1848	0.36133
PSE/ECO	0.27212	0.0074223	1.1637	0.11743
ECO/PSE	0.70383	0.014341	1.5099	0.25282

Note: First asset is long, second asset is short in the portfolio.

Calculating amount of these assets are important within the optimal portfolios, also calculating short term positions to avoid any long term position risks arising from financial assets. Conditional volatility obtained from DECO-FIGARCH can help to calculate amounts of portfolio by using equation 7 and 8.

$$w_{ij,t} = \frac{h_{jj,t} - h_{ij,t}}{h_{ii,t} - 2h_{ij,t} + h_{jj,t}} \quad (7)$$

$$w_{ij,t} = \begin{cases} 0, & if\ w_{ij,t} < 0 \\ w_{ij,t}, & if\ 0 \leq w_{ij,t} \leq 1 \\ 1, & if\ w_{ij,t} > 1 \end{cases} \quad (8)$$

$w_{ij,t}$, showing amount of 1st investment in 1$ investment portfolio, $h_{ij,t}$, showing covariance between these two investments. $h_{jj,t}$, representing variance in both investments. When 1 represents value of asset, the remaining part will show the second investment value in the portfolio. Figure 5 shows time rates of financial asset amounts amongst the prospective portfolios.

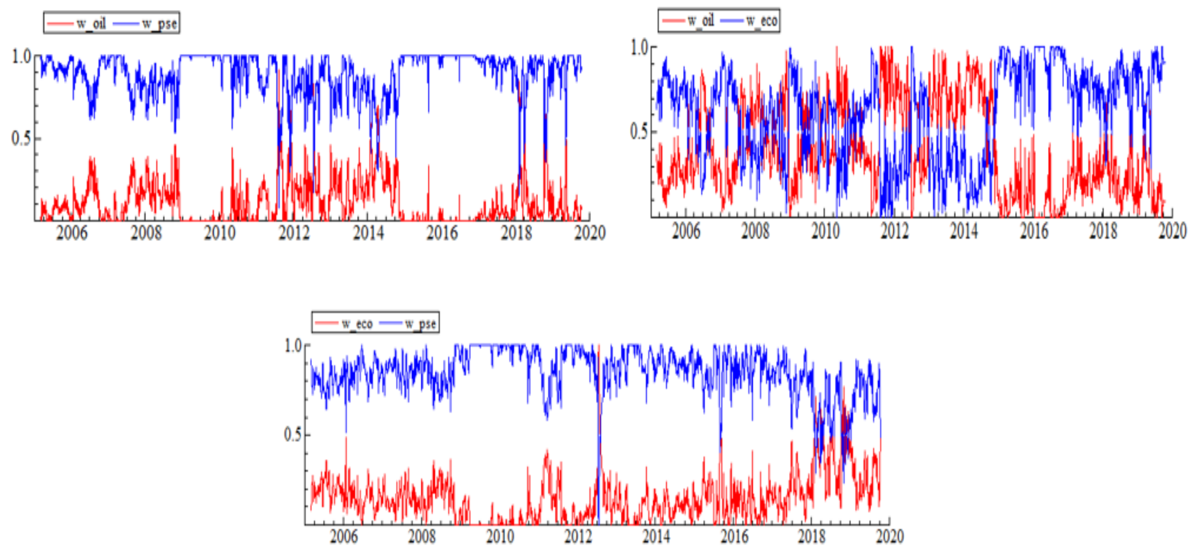

Figure 5: Time Varying Optimal Portfolio Weights.

Table 7: Rundown Figures of Portfolio Weights

	Min	Mean	Max	Std. dev.
ECO/PSE	0.000	0.150	1.00	0.132
PSE/ECO	0.000	0.849	1.00	0.132
OIL/ECO	0.000	0.390	1.00	0.257
ECO/OIL	0.000	0.609	1.00	0.257
OIL/PSE	0.000	0.110	0.920	0.134
PSE/OIL	0.079	0.889	1.00	0.134

When asset values analyzed similiar results like hedge ratio was found. When the invester wants to create a portfolio of 1$ from renewable energy and tech companies, Technology future shares must be 0,85 $. Similarly a portfolio of 1$ with technology and oil industry, technology shares must be 0,85 $.

5. Conclusion and Policy Recommendation

Increase in energy demand issue due to energy security, results of climate changes and economic growth efforts of countries, has recently started to take an important place in the political agendas of countries on a global scale. All these contributed to accelerated research development in alternate source energy category in the last 10 years. Especially the effects of price shocks caused by uncertainties in oil prices, like in many other industries, clean energy and technology sector has become a subject of interest in the finance literature recently. This study was made to expose time varying interaction amongst crude oil, alternate source energy & technology industries and helps to manage the risks of investment tools for long positioning and present hedging opportinity skills of investment tools in portfolio diversifications. With the help of DECO-FIGARCH model, both long memory properties in volatility, and time rates volatility spillover structure were explored.

Final outcome of study volatility clusters were found in crude oil, alternate source energy and technology returns. Due to this, useful information shocks reach to all 3 investment tools and being eliminated at hyperbolic speed, also the volatility spillover lasted for a long time. These were found in DECO-FIGARCH model results. Detailed results were shown in Fig.3, After the 2008 global financial crisis, increase of conditional correlation between investment tools were observed. The result of the research reveales that the technology sector could not contribute to hedging the risks caused by the long positioning in any of the selected investment tools. Time fluctuating hedge rates were considered to manage risk of 1$ alternate source energy long term position, wti shorting of 0,39 $ is needed, also to manage a risk of 1$ technology long term position, wti shorting of 0,24 $ is needed. Especially to manage a risks of 1$ investment in technology category, 0,27 $ investment should be made in alternate source energy cathegory. When hedging opportunities were considered, technology cathegory can not offer serious opportunities in comparison to other investment alternatives, main reason is high correlation in alternate source energy cathegory.

DECO-FIGARCH model used in the study creates binary portfolios amongst investment tools with help of conditional variance and covariance matrices. The avarage weight of ECO/OIL assets in the study is 0,61. This result can be interpreted as, a portfolio of 1$ should be consist of 0,61 $ clean energy and 0,39$ WTI futures. According to the results of study, correlation between clean energy (ECO) and technology (PSE) should be 70 % and should be noted that the technology sector cannot offer any hedging opportunities since it is relatively high. Hedge of long term positioning risks in alternate source energy and technology cathegory with short term positioning investments are to be made in wti future, on the other side long postioning risks of wti futures can be repaired by clean energy asymmetric positions, Also it is observed that similar hedging opportunities are provided by the technology industry. For the investors who do not make portfolio diversification between two highly correlated investment instruments such as alternate source energy and technology, Recommendation of placing WTI futures in the portfolio exists, which will provide serious opportunities for managing risks.

In this paper, modeling the volatility of financial assets with a more robust method with the DECO-FIGARCH model will fill an important gap in this area. Although Sadorsky (2012) previously listed among the short memory models Dynamic conditional correlation, Constant Conditional Correlation etc. Although the subject is examined with models, it is the first study to examine these relationships by using models that take into account that information shocks that affect financial assets disappear at hyperbolic speed, which differentiates the study from previous studies.

Whereas The S&P Global Clean Energy Index, The MSCI Global Alternative Energy Index, MSCI World Information Technology index and many other similar indices were used in such related studies, energy and technology cathegory indices were not included, this constitutes most important constraints. By including more energy and technology indices in future studies, it will also be possible to develop studies to select between multiple models in terms of predictive performance. Considering multivariate Fractional GARCH models, which take into account that time series are fractal (self similarity) instead of short memory (CCC, BEKK, DCC GARCH etc.) models, which have been used many times before, in modeling the return volatility of renewable energy and technology sectors, in terms of portfolio optimization and hedging opportunities. It will offer important advantages to investors.

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