The Impact of Fossil Fuel Prices on Alternative Energy Stocks

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Abstract

The purpose of this paper is to determine if fossil fuel price fluctuations can influence the price alternative energy stock valuations. Employing a Lag Augmented VAR analysis, the research analyzes how natural gas and WTI oil prices impact the price of an alternative energy index. The analysis reveals that neither the price of natural gas nor the price of WTI have a statistically significant positive impact of the price of the alternative energy index. The results are attributed to natural gas and alternative energy acting as both substitutes and compliments given renewable energy intermittency.

JEL codes: G12, Q42

Keywords: alternative energy, fossil fuels, alternative energy intermittency, stock valuation

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I) Background

A) Introduction

Historically, since the early twentieth century, some industries across the economy have contributed to GDP by producing products and services requiring fossil fuels as a factor of production. Although fossil fuels are pivotal to our current energy needs, they have negative environmental externalities. As climate change and other environmental concerns come to the forefront of public policy and economic debate, transitioning to an economy that minimizes environmental degradation has become increasingly important. Facilitating this transition requires replacing fossil fuel energy sources, such as oil with alternative energy sources, such as solar, which do not result in high negative environmental externalities. However, the transition to renewable energy may be affected by the recent reduction in fossil fuel prices. The large price fluctuations that fossil fuels have exhibited motivated the following research to explore how fossil fuel markets may affect alternative energy market performance.

Specifically, I will evaluate how changes in fossil fuel prices drive the value of alternative energy companies. Transitioning to alternative energy from fossil fuels assumes the energy sources are substitutes, which implies a positive relationship. Although public policy has supported alternative energy, the substitutability of fossil fuels and alternative energy remains uncertain. For example, a recent article in the *Economist*, "Clean Energy's Dirty Secret" argues that alternative energy and fossil fuels are not actually substitutes(2017). The article highlighted that when alternative energy sources are deployed, all energy prices, including fossil fuel prices, decline. If the price incentive will always favor fossil fuels, public policy supporting renewable energy development may fail. Therefore, it is worthwhile to examine the connection between alternative energy stock prices and fossil fuel prices.

B) Energy Market Overview

The primary sources of energy production in the United States are petroleum, natural gas, coal, renewable energy, and nuclear power (Fig.1).

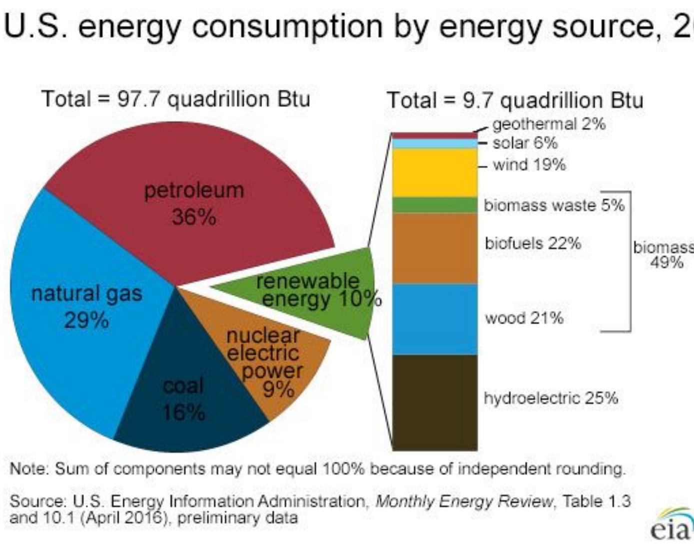

Fig. 1. EIA Energy Source Consumption

These primary sources can be used to generate secondary energy sources such as electricity. In 2015 the sectors of energy consumption were electric power(39%), transportation(28%), industrial(22%), residential(7%), and commercial(4%) (EIA, 2015). Within the energy consuming sectors the chosen fuel to generate energy differs. For example, in transportation 92% of power is generated from petroleum, but only 1% is used to generate electricity. Given the research is aimed at explaining the substitutability of renewable energy for other forms of energy consumption, ultimately differing economic industries will have unique substitutability dependent on the choice of fuel. In determining energy substitutability it is helpful to to understand petroleum, natural gas, and coal within the context of the fossil fuel markets.

C) Fossil Fuels

Along with coal and natural gas, oil energy is characterized within the fossil fuels market. Energy derived from fossil fuels emits high amounts of CO_2, which threatens the environment and questions the long term sustainability of fossil fuel usage. Specifically, CO_2 gases have amplified Climate Change, and numerous economic and environmental policies have been initiated to reduce CO_2 emissions. In addition, fossil fuels have a finite supply as a naturally occurring non-renewable resource. Consequently, renewable energy sources, such as solar, wind, and hydro, have become avenues to transition energy sources away from fossil fuels.

While supply and demand are the primary drivers of price for the oil commodity market, the oil markets geopolitical complexities influence short term changes in equilibrium prices. Recently, technological advancements in oil production such as fracking and the inability of organizations such as The Organization of the Petroleum Exporting Countries (OPEC) to control oil supply has the caused oil prices to crash from $119.13 to $53.60 in real terms in a six month period of 2014 (Fig. 2). OPEC accounts for 75% of global oil reserves and supply oil to the market via nationalized oil companies.

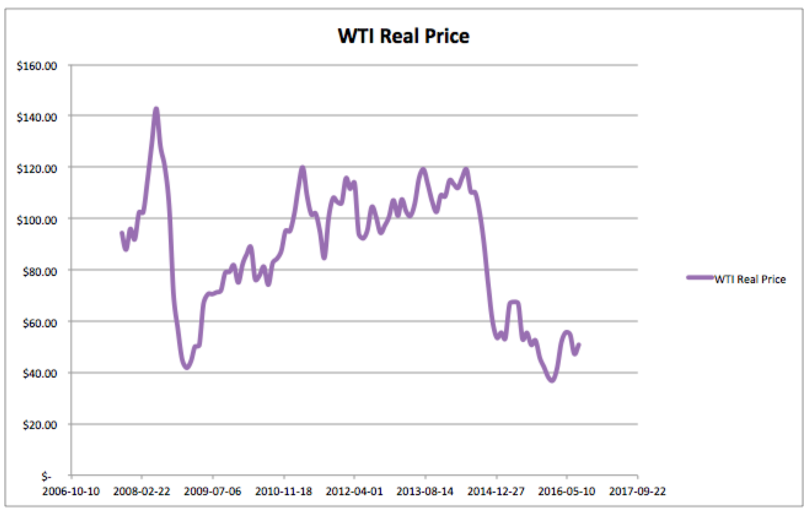

Fig. 2. FRED Economic Data

Crude oil is the most commonly traded oil product in the energy markets. As an unrefined energy source, crude oil can be further processed into gasoline or other inputs of production. There are numerous types of crude oil that are uniquely characterized depending on the sulfuric and viscosity levels. The benchmarks for the crude oil market are West Texas Intermediate(WTI) from Cushing Oklahoma and Brent Blend from the North Sea. WTI and Brent contracts trade on the New York Mercantile Exchange (NYSE). Although Brent Oil is currently priced at $59.52 in real terms above the WTI contract at $50.82 in real terms, historically the prices are highly correlated.

Similar to crude, the supply and demand fundamentals of the market determine natural gas market prices. Given the technological advancements in natural gas discovery, the supply of natural gas has increased 29% from 2008 to 2016(EIA, 2016). In addition, real demand has drastically increased for natural gas. Specifically, natural gas produces 40% to 60% less CO2 relative to coal for equivalent electricity generation. As carbon limits are set by policy such as the Carbon Pollution Standard for New Power Plants established by the EPA in 2015, which created a guideline for carbon pollution produced from power plants, the natural gas demand curve has shifted up given it's the "clean" fossil fuel choice.

Natural gas is traded on the NYSE under the ticker NG. Natural gas too, is refined from its natural sourcing state to isolate the energy driving compound, methane. The current price of an NG contract in real terms is $2.83 per mmBtu. After technological advancements increased the market supply of natural gas it fell all the way from $6.00 per mmBtu in 2014. Consequently, supply has outgrown demand in the a policy environment that favors natural gas. Furthermore, the US EIA projects that natural gas energy generation share will fall through 2020 with rising prices and competition of alternative energy resources.

D) Alternative Energy

An alternative to fossil fuel energy sources are renewable energy sources. Recent technological advancements have made renewable energy a feasible option. The US Department of Energy defines renewable energy as "as energy generated from solar, wind, biomass, landfill gas, ocean, geothermal, municipal solid waste, or new hydroelectric generation." Although there are numerous types of renewable energy technologies, all the processes emit minimal CO2 and are sourced from non-finite resources contrasting from oil derived energy.

Investments in renewable energy sources have been growing larger relative to investments in fossil fuels. Specifically, in 2015 renewable energy investment reached over $250 billion globally, but fossil fuel investment remained below $150 billion (Bloomberg, 2015). Various subsidies have influenced renewable energy investment and account for approximately 3% of total investment. Encouraging the transition to renewable energy sources, subsides have taken the form tax credits and portfolio obligations, while carbon taxing has discouraged fossil fuel production.

Although renewables only account for a small fraction of energy production in the United States, Bloomberg New Energy Finance forecasts that zero-emission energy will compose 60% of installed energy generating capacity by 2040. A rapid decline in the technology cost for renewable energy production is a fundamental assumption of Bloomberg's projection. The nascent nature of renewable energy currently requires high cost technologies, which favors lower cost fossil fuel technologies. Thus, policy support ensuring that renewable energy sources are financially incentivized is crucial to the development of the market. Global economic policy, such as the Paris Climate Accord ratified in 2015 illustrates support to reduce carbon emissions across the European Union, China, and the United States.

Despite being associated with the energy industry, renewable energy companies are considered by investors more similar to the technology industry. Investors can participate in the market by directly investing in corporate stocks, or benchmark indexes exposed to the renewable energy sector. For example one of the major benchmarks, the United States is the Wilderhill Clean Energy Index (ECO), provides exposure to companies that stand to gain from renewable energy usage. The following five sectors comprise the ECO index: renewable energy supplies, energy storage, cleaner fuels, energy conversion, power delivery, greener utilities. The renewable energy markets reliance on high cost technologies influences investors to allocate it as a higher risk investment similar to technology.

E) Fossil Fuels and Alternative Energy Interaction

Fossil fuels and renewable energy sources are substitutes for inputs in energy consumption. Economic theory predicts that an increase in the price of a good will lead to an increase in demand and an increase in both price and quantity of a substitute goods. Thus, an increase in fossil fuel prices increases the demand for alternative energy fuels and increases their prices. An increase of alternative energy prices will increase the profitability of alternative energy firms and raise their stock market value as measured by ECO.

However, alternative energy intermittency creates a complexity in the relationship between fossil fuels and alternative energy sources. Specifically, alternative energies are dependent on cyclical patterns such as the sun and wind, which cannot continuously generate power. Therefore, alternative energy cannot serve energy production needs alone, and must be supported by another source when the sun is not up or the wind is not blowing. If alternative energy infrastructure is supported by the deployment of fossil fuels, a clear subsite relationship may not be accurate.

Currently, fossil fuels are relatively cheaper compared to renewable energy sources, however, the growing forecast of renewable energy sources in the market illustrates the another complexity of substitution. Policy has been implemented to align the economic incentives to favor renewable energy production. There are two sides to the the policy. First, making fossil derived production more expensive through carbon taxing, a policy attempting to value the environmental degradation of fossil fuel production. Secondly, reducing the cost of alternative energy production to value its relatively positive impact on the environment. Measuring how responsive renewable energy index valuation is may illustrate the nature of the substitution effect.

In addition to considering the costs of underlying fuel when evaluating substitutability, analyzing which industries the fossil fuels and alternative energy companies operate in is important. In regards to fossil fuels, WTI is primarily used for the transportation industry, and NG is primarily used for electricity generation. In regards to renewable energy, alternative energy companies of the ECO index are primarily competing in the electricity generation industry. Given alternative energy companies in the ECO index and NG are both primarily competing for electricity generation there subsitute relationship is more clear, despite alternative energy intermittency issues when compared to WTI. However, WTI's scope in the energy markets has been found to impact both general stock valuations and alternative energy company valuations. Thus, it will be valuable to consider WTI's impact on the valuation of alternative energy companies in addition to the impact of NG.

Ultimately, the following research is aimed to analyze the relationship between the price of fossil fuels and the value of alternative energy stocks. The structure of the paper is as follows: I) Background, II) Literature Review, III) Data, IV) Empirical Specification V)Statistical Analysis, and VI) Conclusion. The background provided a summary of the current state of the fossil fuel and alternative energy markets and how they interact. Currently, I hypothesize fossil fuels prices and alternative energy stock valuation are positively associated because fossil fuels and alternative energy sources are substitutes. In the second section, I will highlight the conclusion of prior research that fossil fuels have a significant positive relationship and evaluate the respective Vector Autoregression(VAR) methodologies. Thirdly, I specify the chosen data sets for fossil fuels, alternative energy, and control variables. Following the precedent of prior research I will employ a Vector Autoregression in the fourth empirical specification section. In the fifth section, statistical analysis reveals a significant positive relationship between some fossil fuels and alternative energy assets. Finally, in the conclusion I provide an economic interpretation of the results and recommend potential opportunities for continued research.

II) Literature Review

Oil prices have been linked to overall economic activity in numerous studies. Perez and Cunado (2005)found that oil prices are a good predictor for economic growth. In addition, other studies determined oil is a valuable macroeconomic variable because it can measure inflation (Darby, 1982; Fama, 1981). However, I am interested in analyzing the impact of oil price fluctuations on only the alternative energy market. Therefore, I will focus the literature review in two areas. First, I will highlight how oil prices influence the overall stock market. Second, I will focus on how oil prices relate to alternative energy market performance.

A) Oil Prices and the Stock Market

Kilian and Park (2009) concluded that stock valuations are affected by a change in the price of oil; however, the impact is dependent on whether the oil prices are supply or demand driven. The conclusion reconciled prior research in the field that identified differing relationships between the price of oil and stock market values. Chen et. al (1986), for example, concluded that oil price changes have no statistical impact on asset values. Wei (2003) supported this view by concluding that the oil price increase of 1973-1974 could not explain the US stock market decline. Conversely, Kling (1985) concluded that oil price increases drive stock market declines. Kilian and Park questioned the implied limitations of the prior research in their conclusion that oil shocks account for 22% of the long run variation in U.S. real stock returns. First, Kilian and Park noted that oil prices were treated as an exogenous variable with respect to the U.S. economy, however, Hamilton (2003) highlighted that oil prices and stock markets respond to similar economic environments resulting in some reverse causality. Second, Kilian and Park noted that prior research considered the price of oil as given without regard to what was driving the change in price.

To account for the interdependency of stock market performance and oil prices to similar economic conditions, Kilian and Park construction a Structural Vector Autoregression Model (VAR). The monthly vector time series contained the following variables: percent change in oil crude production, real price of crude oil imported by the US, and real stock returns in the US. The "structure" of the VAR model imposed restrictions on the interdependency of the time series to three factors: oil supply shock, aggregate demand shock, oil-specific demand shock, such as precautionary demand from geopolitical concerns. The results verified that the price of oil responds differently to these effects.

Developing a new methodology Kilian and Park were able to account for discrepancies in prior research by concluding that the impact on asset values is dependent economic drivers for the change in the price of oil. Specifically, large increases in the price of oil driven by precautionary demand results in reduced stock values. However, if the price of oil is driven by an increase in general demand of commodities stock market values, supporting anecdotal evidence that global growth supports equity markets. In contrast, supply shocks driving the price of oil do not have a long term impact.

Consequently, Kilian and Park identified essential factors of the oil market dynamics and created a VAR methodological framework upon which I will build my own research.

B) Oil Prices and Alternative Energy Companies

Sadorsky and Henriques (2008) were the first researchers to explicitly look at the statistical relationship between oil prices and alternative energy companies. Interested in learning how the alternative energy financial market behaves, Sadorsky and Henriques highlight the need to transition to alternative energy sources. Concluding that oil prices do impact stock market values, Sadorsky and Henriques claim fundamentally understanding the characteristics of the renewable energy market is necessary to implementing appropriate policy.

Similar to Kilian and Park, Sadorsky and Henriques identified the price of oil is driven by and drives other macroeconomic variables. Thus, in the Vector Autoregression Model attempting to identify the impact of oil prices on alternative energy stocks they also considered interest rates and the price of technology stocks.

The advantage of using the four variable vector autoregression model is each variable is considered endogenous and dependent on the the time series of lagged variables. Consequently, the choice of the amount of time lagged(p) is important in determining the quality of the statistical data of n observations. In the model the endogenous variables analyzed were alternative energy stock prices, technology stock prices, oil prices, and interest rates. The Arca Tech 100 Index for technology stocks was used as an endogenous input in the VAR model since it is a pure play technology ETF. For the value of alternative energy stocks the benchmark Wilderhill Clean Energy Index (ECO) was used. The yield on the three month treasury bill was considered the interest rate value. For the price of oil the daily closing price of West Texas Intermediate was used.

Sadorsky and Henriques concluded that oil prices have positive impact on the stocks of renewable energy stocks and technology stocks. This may reflect investor view that alternative energy companies are more similar to technology companies. In addition, technological stock are very sensitive to business cycles, and oil prices are a metric for business cycles. Therefore, the prices of technology stocks and alternative energy stocks should be positively associated when oil prices are increasing. This hypothesis assumes increasing oil prices increase the prices of technology stocks because the business cycle effects of oil prices.

More recently Nazlioglu et. al (2015) analyzed the performance of alternative energy stocks in response to oil price shocks in the context of other energy indexes. By comparing the performance of fossil fuel energy companies to alternative energy companies the research highlights the significance of relative performance in an economic energy transition.

Due to Vector Autoregressions limitation in finding time series with the same stochastic trend, Nazlioglu et al. utilized Toda and Yamamoto's(1995) procedure to determine the long-run relationship between oil prices and alternative energy stocks, which optimizes the choice of lag times.

Determining the short term impacts required required similar Vector Autoregressions used in the prior research highlighted above. In addition, to determine how shocks in one variable flow through the vector autoregression model, Nazlioglu et. al utilized generalized impulse responses developed by Koop et. al (1996). Specifically, the impulse response function measure the time profile of the effect of shocks at a given point in time on the future variables within the Vector Autoregression system.

The data required for the vector autoregression encompassed the stock value of specific energy subsectors, the daily oil price returns, daily USD/EUR exchange rate returns, and S&P 500 index returns. The asset values of energy sub sectors petroleum, coal, natural gas, solar, nuclear, wind, and biofuel were calculated by creating an index for each subsector. The data was gathered from CRISP data bases and each index value was rebalanced from 0 to 100 daily based on the closing price of the companies.

Although constructing their own indexes and weighting systems provided greater control over industry analysis, the complexity of creation and opportunity for personal error influences me to use an established index. If my research was focused on a particular area of renewable energy, such as electric vehicles, creating my own index may be necessary. However, in this research I am concerned with general performance of an overall market, thus an industry benchmark should be sufficient.

Nazlioglu et. al results highlighted that the strongest responses to oil prices shocks were other related fossil fuel companies, such as coal which had a 1.5% response. For non-fossil fuel companies the strongest response to oil prices was witnessed in solar with a 1.1% response. All of the impulse responses were in the short term and had no impact after two days. While the research is aimed at understanding the inner dynamics of the energy subsectors for portfolio allocation purposes, it is important to consider contextualizing renewable energy research in the context of the alternative, fossil fuel energy.

III) Data

Prior research demonstrates the statistical relationship between the price of oil and alternative energy stock market valuations differs depending on the macro context and the time frame of consideration−short term vs. long term. The VAR methodologies, which incorporate more than the price of oil and renewable stock market values, demonstrate the importance of incorporating macroeconomic variables such as interest rates. While considering the VAR inputs endogenously helps account for macroeconomic context, comparing the performance of alternative energy stocks to other sectors such as technology markets helps build an understanding of the new renewable energy market and how the investing agent operates within it.

Given the prior researches' emphasis on contextualizing the performance of alternative energy assets, I will be using the yield on the three month treasury bill as measure for short term interest rates, and the ARCA Tech 100 Index, listed under "PSE" as a measure of the market performance of technologically driven companies. Given my interest in the relationship between fossil fuels and alternative energy assets, I will also be analyzing the spot price of West Texas Intermediate Oil(WTI), the spot price of Henry Hub Natural Gas(NG), and the price of the ECO index, listed as "PBW."

Due to the transparency in secondary market trading all the variables of interest have accessible data sources online. Specifically, the price of PBW, PSE, WTI, NG, and the yield on the three month treasury bill were collected from Datastream.

The timeframe chosen for the data is from 1/3/2001 to 1/4/2017. A longer time frame of analysis would be valuable, however, the alternative energy index is the limiting data set only dating back to the chosen timeframe.

Table 2: Correlation Table

	ECO	**WTI**	**NG**	**TECH**	**INT**
ECO	1				
WTI	-0.19	1			
NG	0.6913	0.2098	1		
TECH	-0.654	0.4554	-0.4147	1	
INT	0.7863	-0.4399	0.5249	-0.6192	1

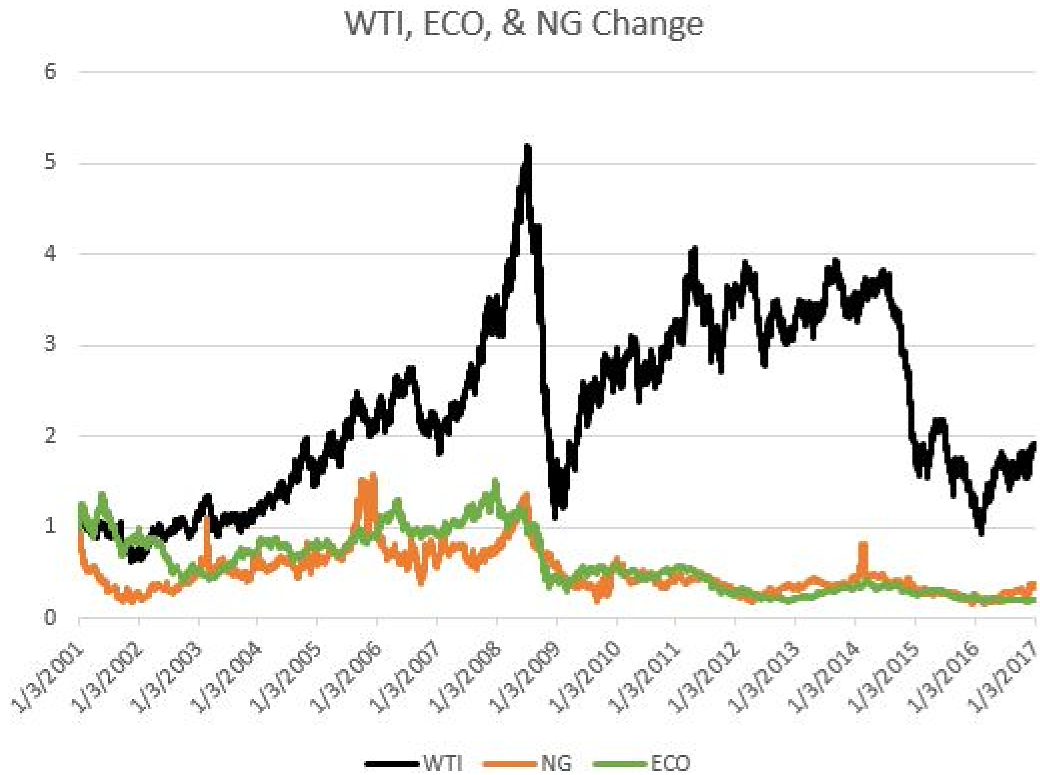

Fig. 4. Indexed WTI vs. ECO performance

Table 2 provides a correlation matrix of the respective data. Note PBW and PSE are coded as ECO and TECH respectively In addition, each variable has been logarithmically transformed to reduce heteroskedasticity of the data. While the correlation table highlights all variable inputs, Fig. 4 focuses on the relationship between fossil fuels and the alternative energy index.

ECO and WTI are negatively correlated with a value of -0.19, which is not consistent with the hypothesis of substitution. Although the ECO and WTI are negatively correlated, the relationship is not clear in Fig. 4 above. Graphically, the relationship between WTI and ECO appears positive from 2001 to 2008 but negative from 2008 to 2017. During the 2008 to 2017 period, large changes in the value of WTI do not appear to drive large changes to ECO. Generally, from 2008 to 2017 ECO trends downward, which may be driving the negative correlation. In developing an economic interpretation of the results, it will be important to determine whether this relationship is a result of macroeconomic factors or industry factors.

Conversely, NG is positively correlated to ECO with a value of 0.6913, and the relationship is clearly illustrated in Fig. 4.

There are two important parts of these fossil fuel alternative energy correlations. First, that natural gas would be positively correlated with the performance of the alternative energy index supports the proposed hypothesis of substitution. Specifically, if the price of natural gas rises the relative value of alternative energy companies would increase. Secondly, it is unintuitive that WTI is negatively correlated to ECO given it is a fossil fuel like natural gas. The latter may result from the notion discussed above that natural gas is viewed as a "clean" energy source due to policy. Although the positive correlations support the hypothesis that NG and the ECO index are substitutes, I will be conducting VAR analysis which is concerned with correlation of lagged variables rather than simultaneous variables.

IV) Empirical Specification

In conducting my own research I will be employing a VAR analysis. Similar to the method of Sadorsky and Henriques I will be utilizing Toda and Yamamoto's(1995) lag augmented VAR(LA-VAR) model to avoid pre-test bias. I am driven to the LA-VAR because of the relative simplicity of testing non-stationary series. Specifically, Sims, Stock, and Watson(1990) demonstrated that in a traditional VAR model, non-stationary data does not follow asymptotic theory and requires complex restrictions on the parameters when evaluating Granger causality.

Toda and Yamamoto's(1995) lag augmented VAR process is robust to the integration and cointegration properties of data. The first step of the process requires determining the maximum order of integration of data, d_{max}. Second, the appropriate maximum lag length, p for the VAR model is determined. Then a VAR model is constructed with $p + d_{max}$ lags, but Granger Causality tests only evaluate the first p lags.

While the results of the LA-VAR model will provide numerous coefficients, the coefficient estimates are not valuable in evaluating the relationship between fossil fuels and alternative energy stocks. The LA-VAR model will be utilized as a means to evaluate both the Granger relationship of data and generate impulse response functions. Granger causality tests evaluate whether a lagged variable helps predict another variable in the VAR model. The research is particularly interested in which lagged variables influence the performance of alternative energy stocks. In addition, the impulse response functions illustrate how a variable in the VAR model responds to a one standard deviation shock from another variable in the model. Consequently, the results should highlight what is Granger related to alternative energy stock performance and what is the degree and magnitude of their dynamic relationship.

The data inputs for LA-VAR model will include the price of the ECO index, the price of the natural gas(NG), the price of the WTI(WTI), the price of the Arca Tech 100 index(TECH), and the yield on the three month treasury bill(INT):

$$A_0 z_t = \alpha + \sum_{i=1}^{t} A_i z_{t-i} + \varepsilon_t$$

The benchmark for alternative energy performance in prior research, the Wilderhill Clean Energy Index broadly defines the indexes function to track "businesses that stand to benefit substantially from a societal transition toward cleaner energy and conservation." The ECO index is calculated using a modified equal weighting methodology, whereby stocks are assigned to an industry with a given weighting. The individual stocks within the industry are given an equal weighting. The industries are defined by Renewable Energy Harvesting, Power Deliver & Conservation, Energy Conversion, Greener Utilities, Energy Storage, and Cleaner Fuels. The index is recalculated quarterly, and no company may exceed a 4% weight in the index. It is important to note investors cannot directly purchase shares, but can invest in an ETF directly mirroring the ECO's performance. Given the scope of the ECO index across the sectors within alternative energy it is a reasonable proxy for the general performance of the renewable energy industry.

The motivation to identify a potential predictive relationship between the market performance of renewable energy assets and fossil fuels necessitates the use of WTI and natural gas in the VAR analysis. While WTI prices have been identified as an important macroeconomic variable, the complexity of the energy production and consumption market requires supplementing it with a natural gas measurement. Specifically, WTI is primarily used for transportation energy, but natural gas is increasingly important for electricity generation. Analyzing both WTI and natural gas will provide a good metric for fossil fuel energy performance overall.

To account for inflation in the VAR model, I will use the yield on the three month treasury bill. In addition to being an inflationary benchmark, the ETF is positively related to short term yields which according to Chen(1986) has impact on general stock performance. Based on the results of Nazlioglu et. al(2015) the energy market only responded in the short term to impulse functions. Thus, using 3 month treasury bill will control for short term market sentiment.

Prior research highlighted the high correlation between the variance in renewable energy indexes and technology indexes. Investors view them with similar portfolio considerations given both of their dependence on high cost technologies. However, the current research is being conducted with decreasing costs to renewable energy production. To determine whether technology is a predictor of renewable energy performance I will be using the Arca Tech 100 index. While this is index is similarly applied in Sadorsky and Henriques research, I am driven to it because accessibility of data. Specifically, it is the oldest pure play technology index with daily data dating to 1982. Furthermore, many technology indexes currently focus on internet and computer technology. However, the Arca Tech 100 index selects companies leveraging innovative technologies including including computer hardware, software, semiconductors, telecommunications, aerospace and defense, and biotechnology. Given the constructed innovative nature of the Arca Tech 100 index, it will be interesting to note whether the lower-cost of technology has changed the correlated variability.

V) Results and Discussion

In the following statistical analysis employing the LA-VAR model proposed above, I will first determine the order of integration of each data series. Second, I will determine the optimal number of lags. Third I will apply the Toda and Yamamoto lag augmented VAR(LA-VAR) and evaluate the of fit of the model. Fourth I will conduct Lagrange multiplier (LM) tests to determine if there is serial correlation, before fifthly determining which endogenous variables have Granger Causality Relationship. Finally, I will utilize the LA-VAR to generate impulse response function graphs of granger related variables and provide intuitive framework interpreting the relationships illustrated.

It is important to note that the following statistical analysis was applied to a daily, weekly, and monthly frequency. Prior studies have traditionally chosen a weekly frequency because despite a daily frequency increasing the available data points the inter-week variability creates noise in the analysis. In addition, some argue the monthly frequency is too long to intuitively consider causality. Granger Causality tests demonstrated no significant relationship between the alternative energy index and fossil fuels for the weekly and monthly frequency. Thus, the results highlight each statistical step only for a daily frequency.

Integration properties(unit root) of the data series are evaluated using Augmented Dickey-Fuller (ADF) tests, Phillips and Perron (PP) tests, and Kwiatkowski-Phillips-Schmidt -Shin(KPSS) unit root tests. Both ADF and PP's null hypothesis states that the series does has as unit root. Conversely, the null hypothesis for the KPSS test states that series does not have a unit root or is stationary. The results of the unit roots tests are highlighted in table 3. Note the highest order of integration for ECO, WTI, NG, TECH, and INT is one(I(1)). After first differencing the ADF and PP null is rejected across all variables, while the KPSS null that the data is stationary is accepted across all data. Applying the Toda and Yamamoto Lag Augmented VAR analysis requires adding an extra lag to the optimal number lags for each order of integration . Given the results, a single lag will be added.

Table 3: Test for Cointegration

	Levels				
	ECO	WTI	NG	TECH	INT
ADF(lags)	-0.845(0)	-1.979(0)	-3.311(0)**	-0.284(0)	-7.132(0)***
PP(lags)	-0.934(9)	-1.901(9)	-3.067(9)***	-0.147(9)	-3.804(9)***
KPSS(lags)	2.79(15)***	4.21(15)***	2.89(15)***	2.48(15)***	2.04(15)***

Table 3: Test for Cointegration Cont.

	First Differences				
	ECO	WTI	NG	TECH	INT
ADF(lags)	-61.047(0)***	-68.096(0)***	-61.462(0)***	-65.770(0)***	-100.385(0)***
PP(lags)	-61.072(9)***	-68.180(9)***	-61.673(9)***	-65.948(9)***	-158.899(9)***
KPSS(lags)	0.0508(15)	0.0397(15)	0.0398(15)	0.0543(15)	0.0342(15)

Augmented Dickey-Fuller (ADF) tests, Phillips and Perron (PP) tests, and Kwiatkowski-Phillips-Schmidt -Shin(KPSS) unit root tests. All unit root test regressions include an intercept. The number in parentheses are the optimal number of lags. ***,**,* denote a test statistic that is statistically significant at the 1%,5%, and 10% level of significance.

In order to apply a VAR analysis it is necessary to determine the optimal number of lags. Too many lags increases the error in forecast, and too few lags may leave out relevant information. The number of lags will be determined by conducting Akaike Information Criterion(AIC), Hannan-Quinn Criterion (HQIC), and the Schwartz's Bayesian Information Criterion(SBIC). The AIC and SBIC are common lag determinants and both determine the optimal number of lags by minimizing the sum of squared residuals in a VAR model. AIC, SBIC and HQIC selected a lag length of 12, 5, and 4 respectively. Given the differences in lag selection evaluating which test may be more accurate in the given context is necessary. Ivanov and Kilian(2005) demonstrated that AIC tends to produce the most accurate in VAR models with weekly and monthly data, while HQIC appear most accurate for quarterly VAR models. In addition, Davidson and MacKinnon indicate that parsimonious models(model with fewest parameters) minimize error and AIC may fail to choose the most parsimonious model(2004, 676). However, Stock and Watson(2007) claim including more parameters is better than omitting significant parameters. Thus, there is support for the both parsimonious model and the AIC model which may contain significant parameters. Without a clear understanding of which number of lags is superior, I conducted Todo and Yamato's LA-VAR for two cases-12 and 4 lags and compared the the fit of the models.

The VAR's were estimated using 13 and 5 lags. Recall Todo and Yamamoto's LA-VAR adds a lag for the maximum order of integration to of the data series. Model fit tests illustrate that the model fits well for both 13 and 5 lags. Table 4 demonstrates that the R-squared values and RMSE values are approximately equal for differing lag selections. Overall, for 14 lags the R-squared(R-sq) value ranges from .9693 for interest rates (INT) to .9989 . For 5 lags the R-squared(R-sq) values vary from .9680 for interest rates (INT) to .9989 for the technology index(TECH). Thus, in both LA-VAR models the least accurate is interest rates and the most accurate is the performance of the technology index.

Table 4: VAR Fit Model for 13

AIC 13 lags (12+1)					
Equation	Parms	RMSE	R-sq	chi2	P>chi2
ECO	66	0.020237	0.9987	3296639	0
WTI	66	0.024183	0.9975	1662518	0
NG	66	0.040653	0.9915	487321.9	0
TECH	66	0.014235	0.9989	3841413	0
INT	66	0.335491	0.9693	131257.3	0

Table 5: VAR Fit Model for 5

SBIC 5 lags (4+1)					
Equation	Parms	RMSE	R-sq	chi2	P>chi2
ECO	26	0.020315	0.9987	3251924	0
WTI	26	0.024239	0.9975	1644534	0
NG	26	0.040932	0.9913	477922.9	0
TECH	26	0.014262	0.9989	3790664	0
INT	26	0.341095	0.968	126027.2	0

Lagrange multiplier (LM) tests for residual serial correlation demonstrates evidence of serial correlation for the LA-VAR with five lags at the 1% level. Given the serial correlation, the

LA-VAR with five lags will not be used to evaluate causality. However, LA-VAR with 13 lags demonstrate no evidence serial correlation at the 10% level(table 7). Consequently, the LA-VAR with 13 lag model fits well and can be used for analyzing the dynamic properties of the data and Granger hypothesis testing.

Table 6: Lagrange Multiplier Test AIC.

Lagrange Multiplier Test for AIC chosen model			
lag	chi2	df	Prob > chi2
1	25.5409	25	0.43241
6	25.7759	25	0.41963
12	47.1379	25	0.00472

Null hypothesis states there is no serial correlation. ***, denotes a test statistic that is significant at the 1% level of significance.

Table 7: Lagrange Multiplier Test SBIC.

Lagrange Multiplier Test for SBIC chosen model			
lag	chi2	df	Prob > chi2
1	56.7584	25	0.00029***
6	71.5137	25	0***
12	60.2741	25	0.0001***

Null hypothesis states there is no serial correlation. ***, denotes a test statistic that is significant at the 1% level of significance.

The results of the Granger Causality tests evaluating the relationship between fossil fuels and the alternative energy index are highlighted in table 8. For the complete results please refer to table 4 in the appendix. The results demonstrate that not all fossil fuels are predictive of alternative energy index performance. Alternative energy index performance is explained by past movements in WTI oil prices but not past movements in natural gas prices. In addition, WTI oil prices (WTI) Granger cause natural gas prices (NG) at a 1% significance level. Consequently, lagged WTI oil prices help explain the performance the alternative energy index and natural gas prices.

Another important conclusion of the Granger Causality tests is that interest rates are not predicted by any stock index or fossil fuel performance. This supports the Federal Reserve's policy of setting interest rates on future growth and inflation expectations as opposed to past performance.

Table 8: Granger Causality Tests

Equation	Excluded	chi2	df	Prob > chi2
Section I: ECO Driven by Variables				
ECO	WTI	31.894	13	0.002***
ECO	NG	8.4145	13	0.816
ECO	TECH	20.823	13	0.076*
ECO	INT	6.8501	13	0.91
Section II: Variables Driven by ECO				
WTI	ECO	15.535	13	0.275
TECH	ECO	26.318	13	0.015**
INT	ECO	14.396	13	0.347
NG	ECO	14.968	13	0.309
Section III: Fossil Fuel Relationships				
NG	WTI	90.242	13	0***
WTI	NG	9.3285	13	0.748

Section I highlights the the Granger tests for whether ECO is Granger caused by all the tested variables. Section II highlights the Granger tests for whether ECO Granger causes all the test variables. Section III highlights the granger test results for fossil fuels. The null hypothesis states that the excluded variable does not Granger cause the equation variable. ***,**,* denote a test statistic that is statistically significant at the 1%,5%, and 10% level of significance.

After establishing the significant Granger Causality it is helpful to view dynamic relationships via impulse response functions(Fig. 4-8). The graphs demonstrate how endogenous variables in the LA-VAR model respond to a one standard deviation from another variable. Consequently this process is more valuable than analyzing the LA-VAR coefficients directly because the impulse response function generates point estimates for periods into the future utilizing the LA-VAR coefficients. Confidence intervals are constructed to gauge the significance of the impulse response functions.

Analysis of the impulse response functions is broken into two sections. First, I highlight the relationship between fossil fuels and alternative energy stocks to evaluate whether a substitution relationship between fossil fuels and alternative energy explains the valuation of alternative energy companies. Second, I analyze other relationships within the VAR model to check the theoretical consistency of the model.

A) Impulse Response Functions: Alternative Energy Index Response to Fossil Fuels

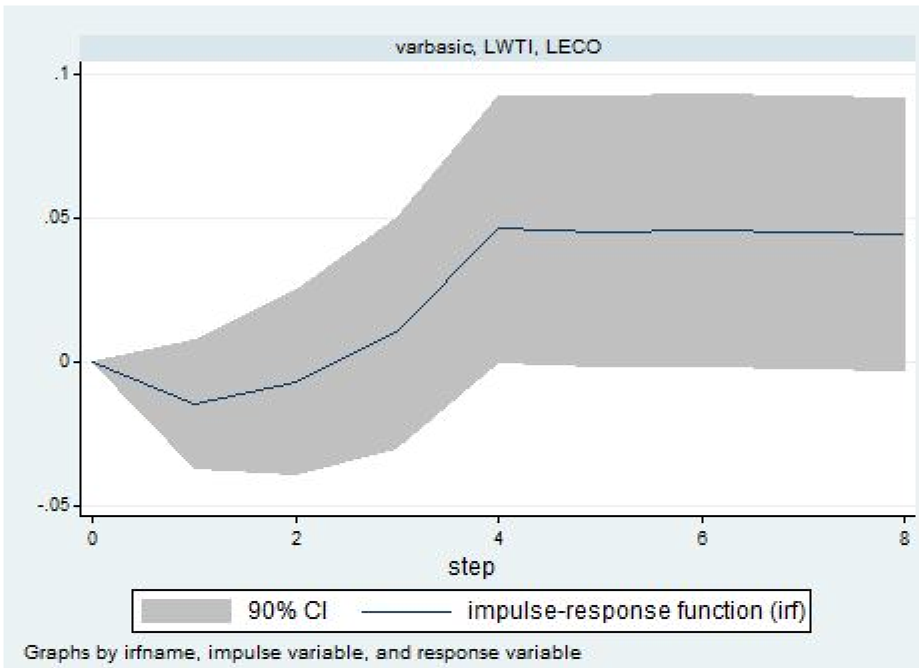

Fig. 4. ECO Response to 1 STD in WTI

WTI Oil prices do not have a statistically significant impact on alternative energy prices for 8 days(Fig. 4) because zero is always in the confidence interval. However, the effect may be significant in magnitude. Initially, for the first day there is a slight negative relationship that transitions to positive for periods 2 through 4 before plateauing. Thus, it takes 4 periods for oil prices fluctuations to fully permeate to the alternative energy markets, and the impact remains over the 8 day period.

Given there is no statistically significant relationship, the result negates the hypothesis that investors view alternative energy assets as more attractive when oil prices increase. Thus, investing agents do not perceive alternative energy sources as substitutes for WTI oil. However, the positive magnitude implies a substitute relationship.

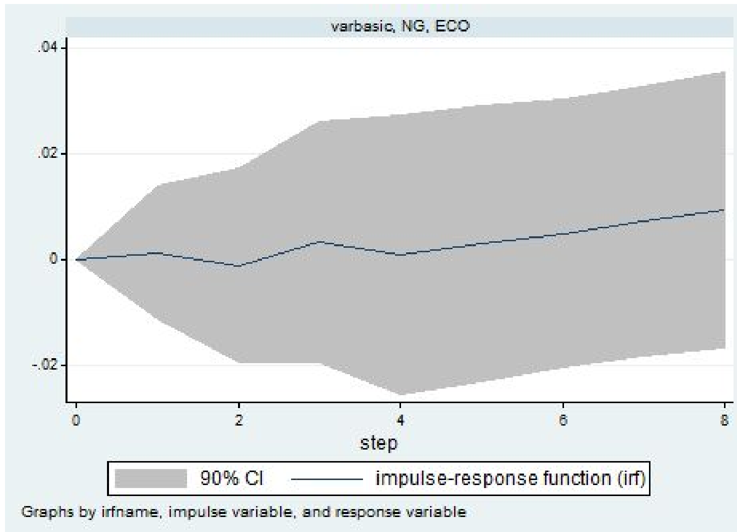

Fig. 5. NG ECO to 1 STD in NG

Again because zero is always included in the confidence interval, the relationship between ECO and NG is not significant. Consequently, investors do not allocate investments as if natural gas and alternative energy sources are substitutes. In addition, the the magnitude does not imply a clear positive or negative relationship.

This research has aimed to identify the relationship between fossil fuels and alternative energy assets. However, supplementary analysis is valuable. Below are the results of impulse response functions that help contextualize the fossil fuel and alternative energy results. Specifically, they provide an additional means to check the validity of the VAR model by determining if the results agree with theory and prior literature.

B) Other Relationships

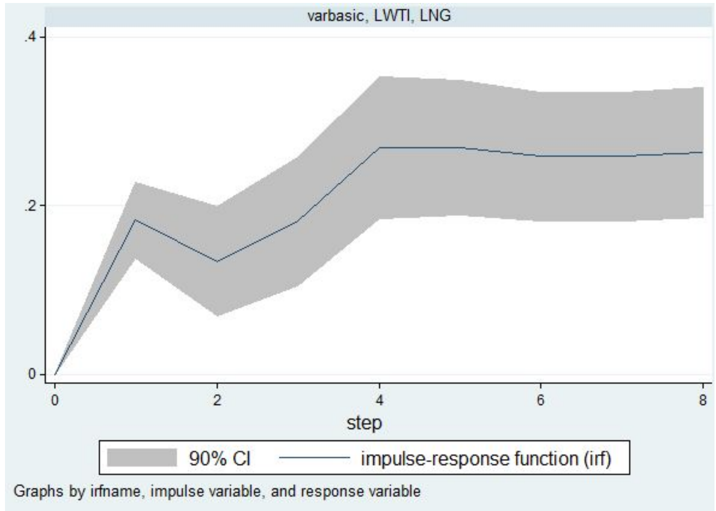

Fig. 6. NG response to 1 STD in WTI

Supporting the hypothesis of fuel source substitutability, oil prices have a significantly positive impact on natural gas prices(Fig. 6) because zero is not included in the confidence interval. Differing from the preceding dynamic relationships, oil price increases cause a 20% increase in natural gas prices in the first period and gradually increase for the duration of the 8 day period to 25%. The magnitude of increase is much greater than the increase in alternative energy stocks implying it is more substitutable. Given that natural gas and WTI are both fossil fuels the large positive relationship is reasonable and supports the validity of the VAR model.

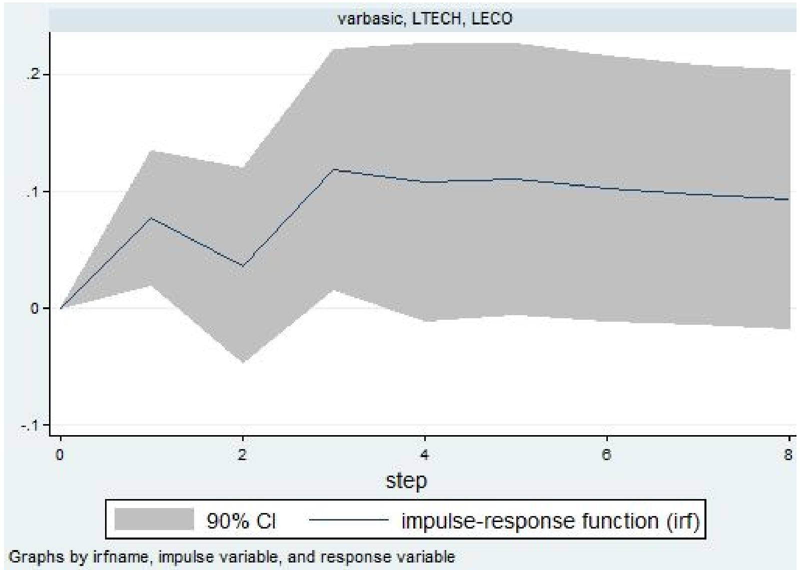

Fig. 5. ECO response to 1 STD in TECH

Technology stock performance has a significantly positive impact on alternative energy prices(Fig. 5) on days one and three. For the remaining days zero is included in the confidence interval, and thus, not significant. The dynamic relationship is similar to oil, as the initial positive increase occurs for three periods and plateaus for duration of the 8 day period. It is interesting to note the magnitude of alternative energy response to technology is 10% which is greater than the 5% increase generated from oil shocks. These results confirm the findings of previous literature mentioned in section II, that investors view alternative energy stocks as more related to the technology market as opposed to the energy market.

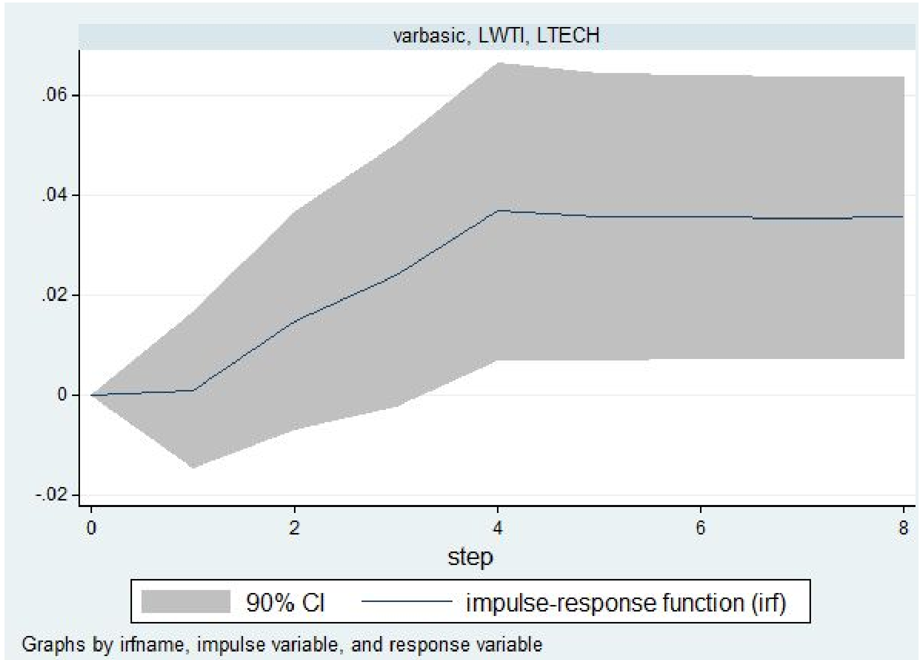

Fig. 8. TECH response to 1 STD in WTI

Technology stock performance demonstrated a significant positive response to a one standard deviation oil price shock for days four through eight. The positive relationship between WTI oil prices and technology prices is consistent with Sadorsky's (1999) findings referred to in the literature review. In addition, Kumar, Managi, and Matsuda (2012) support similar findings with the hypothesis that investors view the stocks of technology firms in the same way they view the stocks of alternative energy sources.

Therefore the response of NG to WTI, ECO to TECH, and TECH to WTI support the validity of the VAR model.

VI) Conclusion

The goal of this research was to evaluate whether markets view alternative energy sources as substitutes for fossil fuel energy. Specifically, I attempted to determine if the stocks of alternative energy companies respond positively to increases in the value of fossil fuels. The analysis fails to establishes a significant statistical relationship between WTI oil and renewable energy assets. However, the magnitude of impulse response functions illustrated that WTI is positively related to renewable energy stocks supporting the theory of substitution. However, natural gas highlighted no significant relationship with alternative energy stocks, and the magnitude did not indicate a positive or negative relationship.

The results indicate that markets may not perceive alternative energy sources as substitutes for fossil fuel energy. Although ECO responded positively to oil price shocks, it potentially is the result of indirect mechanisms rather than substitution. As mentioned in the literature review, WTI oil is considered a macroeconomic indicator variable for business cycles, but natural gas is not. Thus, the positive relationship between WTI oil and renewable energy stocks may be a result of business cycles rather than substitution effects.

Interpreting natural gas and alternative energy as both complements and substitutes, which have negative and positive relationships respectively, may explain the results of an unclear magnitude in the impulse response functions. The substitution relationship has been described in detail, but the complementary relationship is less intuitive and rests on the notion of renewable energy intermittency. Specifically, alternative energies cyclicality require the support of other energy sources, which in these results imply may be natural gas. Consequently, the unclear relationships between alternative energy stocks and natural gas may be be a net result of a substitute and complement relationship. Although the dual relationship is not certain, it provides logical support for the given results.

Nevertheless the results bring to question why renewable energy stocks do not perform as clear substitutes for fossil fuels in the market. Assuming rational agents, the economic incentives must not support alternative energy. In addition, markets could perceive alternative energy stocks as more similar to technology stocks. This hypothesis assumes renewable energy companies are similar to technology companies in both their risk profile and their potential to disrupt existing industries--the energy industry in the renewable case.

With unclear results regarding substitution, further research should aim to clarify the relationship between fossil fuels and alternative energy sources. There are two models that may provide an alternative method to evaluate substitutability. First, research with a similar methodology that expands the renewable energy performance measurement beyond an index.

Following prior literature, I utilized the ECO index, however, I believe increasing the specificity of renewable energy companies to specific industries such as electricity generation may be valuable. Second, consider using real renewable energy investment values as a measure of performance as opposed to stock values. Given renewable energy investment data sources are limited to a quarterly basis, a non-VAR methodology may be necessary.

Transitioning to alternative energy from fossil fuel sources has been a major public policy solution to address climate change. Such a transition assumes the substitutability of energy sources, however, with unclear results governments should create incentives that create substitution rather than assume substitution.

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Appendix

Table 1: Granger Causality Tests

Equation		Excluded	chi2	df	Prob > chi2
LECO		LWTI	31.894	13	0.002
LECO		LNG	8.4145	13	0.816
LECO		LTECH	20.823	13	0.076
LECO		LINT	6.8501	13	0.91
LECO		ALL	73.727	52	0.025
LWTI		LECO	15.535	13	0.275
LWTI		LNG	9.3285	13	0.748
LWTI		LTECH	13.444	13	0.414
LWTI		LINT	16.285	13	0.234
LWTI		ALL	62.682	52	0.147
LNG		LECO	14.968	13	0.309
LNG		LWTI	90.242	13	0
LNG		LTECH	15.406	13	0.283
LNG		LINT	9.8949	13	0.703
LNG		ALL	125.32	52	0
LTECH		LECO	26.318	13	0.015
LTECH		LWTI	29.46	13	0.006
LTECH		LNG	7.6013	13	0.869
LTECH		LINT	4.1762	13	0.989

LTECH		ALL	70.228	52	0.047
LINT		LECO	14.396	13	0.347
LINT		LWTI	18.754	13	0.131
LINT		LNG	10.53	13	0.65
LINT		LTECH	6.6651	13	0.919
LINT		ALL	55.541	52	0.343

Data Sources

Datastream International. (March 10, 2017). Available: Datastream International