The economic impact of crude oil price shocks on alternative energy stock prices

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Abstract

Over the past couple of decades, rising oil prices have had a positive impact on the alternative energy industry because of the substitution effect. In a society that is growingly concerned about environmental sustainability, would this substitution effect suggest that the reciprocal could also be true; that low oil prices could be destructive to the alternative energy industry? Previous work by Henrique and Sadorsky examined the impact of oil price shocks on U.S. alternative energy stock prices through 2001 to 2007. This paper uses a similar approach to follow up their findings, in light of the 2015 oil price collapse. A vector autoregressive (VAR) model is used to investigate the relationship between multivariate time-series, including the following variables: alternative energy stock prices, crude oil prices, general stock prices, and interest rates. Granger causality tests and impulse reaction functions are examined to determine whether oil price shocks have a significant effect on alternative energy stock prices.

Date:

I. Introduction

In recent years, "renewable" and "alternative" have become buzzwords in the energy industry. This is partially due to a growing concern for the environment, but it is also an issue of energy security, resulting from the notoriously volatile oil market. Although often incorrectly used interchangeably, the terms renewable energy and alternative energy have different meanings. Renewable energy is an energy source that is capable of being replenished naturally within a human lifetime (Natural Resource Canada, 2016); while alternative energy encompasses energy sources other than fossil fuels, and is *usually* environmentally sound (National Resources Defense Council, 2016). For the purpose of this research, the focus will be on the broader category of alternative energy, as the data used in this study incorporates a wide variety of companies in the Clean Energy sector (to be discussed further in Section III).

Alternative energy is not a new phenomenon; water energy technology, initially the waterwheel, was used throughout Europe in 200BC at industrial mills to crush grains, tan leather, shape iron and complete other industrial processes (Williams, 2006, p. 2). Since then, humans have learned how to harness a variety of alternative energies, including wind, hydro, solar thermal, and solar photovoltaic energy, as well as biofuel, and ethanol (Natural Resource, 2014). The development of these alternative technologies has progressed in leaps and bounds throughout the last century due to a variety of factors, including: the volatile crude oil market, general developments in technology, and the overall "well-being" of the world economy.

The market for crude oil has a reputation for being extremely sensitive to various economic, political, and sociological shocks, which has resulted in radical price changes from the beginning of the 1900s up until today (Huber, 2011, p. 818). Events such as the West Coast Gasoline Famine, the Great Depression, the OPEC Oil Embargo, various civil wars in the Middle East, and the Global Financial Crisis have contributed to the hills and valleys of oil price trends over the last one hundred years (Ro, 2014). Most recently, the United States had almost doubled their production of crude oil from 2010 to 2015 (Kristopher, 2015; Krauss, 2016), and, coupled with other growing non-OPEC oil sources, has increased overall supply significantly. This has resulted in a severe reduction in the price of crude oil from a high range of $90-$120 per barrel from 2011- 2014 to a low of $27 per barrel in 2016 (Nasdaq, 2016).

It is generally accepted that when one good (in this case, energy) becomes expensive, consumers will tend to substitute to other goods wherever possible (Mathis and Koscianski, 2002, p. 179). Naturally, one would expect the reverse to be true; the drastically reduced oil prices should encourage the consumption of oil, and reduce the consumption of other sources of energy, such as alternative energy. However, as a society that is becoming increasingly aware of negative externalities resulting from crude oil extraction, production, and consumption (through various forms of pollution), as well as the risks associated with depending on outside sources for fundamental energy supply, more and more countries are funneling money into alternative energy investment projects. The United Nations Environment Programme's 9th *Global Trends in Renewable Energy Investment 2015* indicates that in 2014, there was a worldwide 17 percent increase in alternative energy investment, totaling approximately 270 billion U.S. dollars (FS-UNEP, 2015).

The overall effect resulting from the opposing factors of the extremely low oil prices, together with the energy security and environmental concerns, poses an interesting and important question as to what will happen to alternative energy in both the short and long-term future. This empirical analysis aims to explore the impact of oil price shocks on alternative energy technology, focusing on the last ten years using data from the United States.

This paper is organized as follows. Section II explores previous research on the subject and outlines pertaining theoretical matters. Sections III and IV detail the data sources used in this study and the empirical methodology used, respectively. Section V discusses implications of the findings.

II. Literature & Theory Review

The fundamental theory behind the question of this study relates to the Theory of Demand. One of the essential concepts of the Theory of Demand is price elasticity, which is used to measure responsiveness in quantity demanded to changes in price. More specifically, the cross-price elasticity of demand measures the change in quantity demanded of one good (X) as the price of a second good (Y) changes, *ceteris paribus*. The theory says that a substitute good is one that reflects a negative cross-price elasticity of another good, meaning that if price of Y goes up, quantity demanded of X will increase, as consumers substitute away from good Y. It is unlikely that oil specifically, and alternative energy technology more broadly, are perfect substitutes; there are certain uses for energy that lend better to certain types of energy forms, such as wind turbines for electricity generation, or solar thermal energy for home heating (Natural Resources

Canada, 2015). Regardless, previous research does indicate that there is imperfect substitution between oil and alternative energy as a whole (Terrado, Mendes, and Fitzgerald, 1989; Sadorsky, 2009; Haug, 2011).

During 1985 and 1986, crude oil prices fell approximately fifty percent in the world market for petroleum (Terrado, Mendis, and Fitzgerald, 1989, p. 2). The World Bank published a working paper in 1989 that discussed the impact of the low oil prices on alternative energy technologies, specifically technologies utilizing solar, wind, and biomass resources. The World Bank distinguished between alternative energy technology that competed as large-scale petroleum substitutes and alternative energy technology that was used to meet smaller (and typically rural) needs. The alternative energy technologies that the World Bank highlighted as being a substitute for petroleum included: dendrothermal power plants, bagasse, fuel alcohol, wind electricity, biomass gasifiers, heat gasifiers, power gasifiers, solar water heating, biogas, and photovoltaic and wind powered pumping (Terrado, Mendis, and Fitzgerald, 1989, p. 1-34).

The findings in the World Bank study suggest that there are a variety of factors that make the previously listed technologies vulnerable to influence from low crude oil prices. The first is scale of operation. For large-scale industrial operations, fuel costs generally comprise a large portion of overall costs, and if oil prices were to decrease, then a large portion of the operation costs could be reduced if oil was used as the primary fuel source. Large-scale operations are vulnerable to energy price shocks, and have an incentive to use less expensive energy sources, such as cheap oil. Not mentioned in the World Bank study is the idea in the longer term, firms might explore more efficient energy solutions, such as renewable energy. The second factor said to influence the sensitivity to oil price shocks is the location of the operation. The costs of petroleum increases the further an operation is from a city, because of transportation costs (Terrado, Mendis, and Fitzgerald, 1989, p. 22). As a result of increased transportation costs, rural areas have an incentive to use alternative energy sources such as wind or hydropower. The World Bank study results illustrate the price sensitivity of alternative energy technology to oil price shocks is a function of both the scale of operation as well as geographic location: although lower oil prices provide incentive to substitute away from alternative energy, certain operations may find that it is more viable to use alternative energy because of their size and/or location.

While the World Bank study from 1989 does provide insight on the qualitative factors influencing the sensitivity of alternative energy technology to oil price shocks, it is important to note that alternative energy technology is constantly developing, alongside information and computing technology. Prices of technology change greatly over time; as it becomes more accessible and more common, technology generally falls in price. An example of this is the standard laptop: a Toshiba laptop purchased in 1985 cost $4,000; today, a much better laptop could cost as little as $600 (Cheng, 2010). For this reason, it is more efficient to focus on the profitability of alternative energy technology companies. One way to do this is by studying the current stock prices.

Irene Henriques and Perry Sadorsky completed a study in 2008 examining the sensitivity of a composite alternative energy technology stock price in relation to the price of crude oil, in addition to technology stock prices and interest rates. The argument for examining technology stock prices rests within the notion that investors view alternative energy technology companies similarly to other high technology companies, in their goal to maximize their return on investment. For example, in the late 1990s, several fuel cell companies watched their stock prices skyrocket as the NASDAQ stock rose significantly, and when the technology bubble burst in 2000, the fuel cell companies' stock prices fell drastically with the other technology stock prices (Henrique and Sadorsky, 2008). Interest rates are examined because business cycles typically influence the overall stock market, and consequentially would have an impact on alternative energy stock prices.

Henrique and Sadorsky found that in a time of relatively consistent increases in oil prices, alternative energy stock prices were significantly impacted by changes in oil prices, but not as strongly as they were affected by changes in technology stock prices. These results were found using a vector autoregression (VAR); an econometric model that treats each time-series variable as dependent, regressing each variable against lags of the other variables, as well as against lags of itself. The advantage to using VAR is that it can capture "rich dynamics" in multiple time series data (Stock & Watson, 2001, p. 3), as it treats each variable as an endogenous part of the whole picture. Henrique and Sadorsky found that, as oil prices climbed slowly from 2001-2007, there was a significant negative effect on the stock prices of alternative energy companies. If the trend were to change suddenly as it did with oil prices in 2009 and in 2015 (see Figure 1), would their findings still hold true, or would a more immediate drastic price shock produce different effects than consistent price changes over a longer period? The analysis outlined in the following sections aims to provide an answer to the former question by examining data from 2006-2016 utilizing the same variables and econometric model specified by Henrique and Sadorsky in 2008.

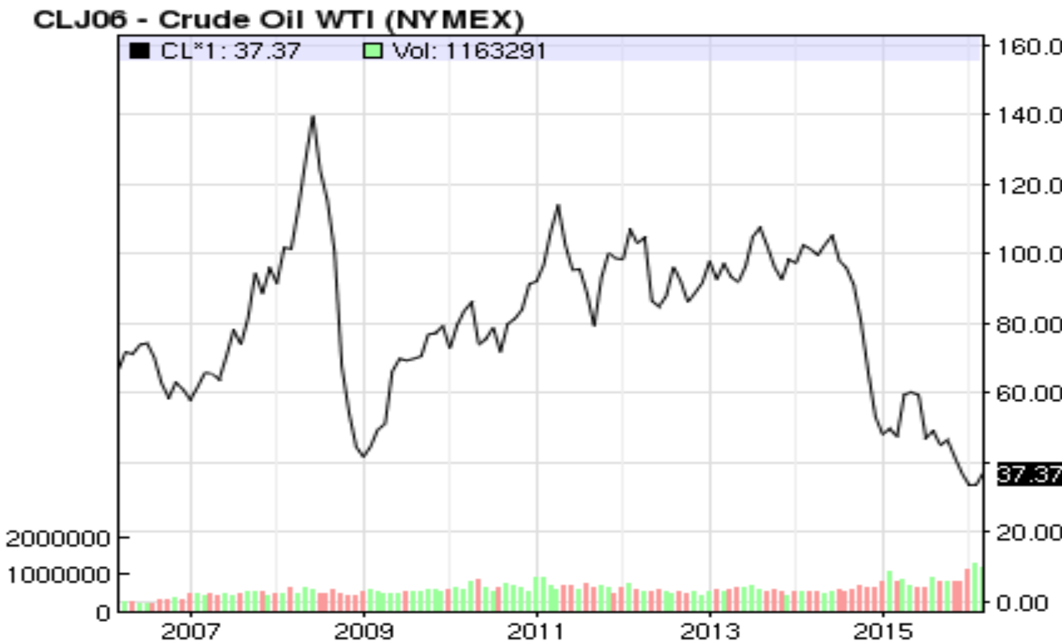

Figure 1: End of day commodity futures price quotes for crude oil
Source: NASDAQ. (2016). Retrieved from http://www.nasdaq.com/markets/crude-oil.aspx?timeframe=10y

III. Data

The time-series data used in this study includes 522 weekly observations spanning February 2006 to February 2016. Four variables are used: alternative energy stock prices, oil prices, technology stock prices, and interest rates. Data for alternative energy, oil, and technology in the United States was obtained using Datastream and the interest rates were taken from the St. Louis Federal Reserve website.

i. Alternative Energy

The alternative energy stock price used in this study is the Wilder Hill Clean Energy Price Index (ticker symbol ECO), a composite stock price index comprised of 42 companies in the Clean Energy sector (as of Q1, 2016). The Wilder Hill Clean Energy

Price Index was the first index of its kind and has since become a benchmark index (Henrique and Sadorsky, 2008). The companies selected for the index are chosen based on technological and ecological criteria, including: "importance of the stock and sector to clean energy, relevance to climate change, pollution prevention, technological significance, intellectual property rights, salience to preserving biodiversity or ecological integrity and other non-financial criteria" (WilderShares, 2014). The businesses included in the ECO Index fall into the following categories: renewable energy supplies harvesting; energy storage; cleaner fuels; power delivery and conservation; and greener utilities. The weighting of the ECO Index stocks and sectors are based on their "significance for clean energy, technological influence and relevance to preventing pollution in the first place" (WilderShares, 2014). The ECO Index uses modified equal dollar weighting, and requires that no single stock exceed 4 percent of the weight of the index weight. Stocks in the index must be listed on a major U.S. exchange (NASDAQ, NYSE, or AMEX). Data is listed in U.S. dollars.

ii. Oil

Oil prices are measured using the West Texas Intermediate (WTI) Crude Oil Price; one of three primary oil price benchmarks (the other two being Brent Blend and Dubai Crude). WTI Crude Oil is used as the primary benchmark for the US, and is the underlying commodity of the NYMEX oil futures contract (NASDAQ, 2016). Data is listed in U.S. dollars.

iii. Technology

Technology stock prices are measured using Arca Technology 100 Index (ticker symbol PSE); a composite technology stock price comprised of securities from 100 businesses across a variety of technology sectors (Nationwide Financial, 2016). These sectors include: information technology (65.9 percent), healthcare (22.8 percent), industrials (5.9 percent), energy (3.2 percent), consumer discretionary (1.1 percent), telecom services (1.0 percent), and consumer staples (0.1 percent) (Nationwide Financial, 2016). The weighting of stocks in the index is determined by stock prices. Data is listed in U.S. dollars.

One disadvantage of this technology stock price index is that 3.2 percent of the index is comprised of energy technology. A portion of the 3.2 percent is alternative energy technology, and since this technology index is being compared to an alternative energy stock price, a very small portion of alternative energy technology companies may be double-counted.

iv. Interest Rate

The interest rate of an American three-month treasury bill is used to capture business cycle fluctuations for this study. Data is weekly, not seasonally adjusted, and is listed in percentages.

IV. Empirical Methodology

Table 1 provides descriptive statistics on the variables used in this model. The mean for the alternative energy stock price was \$108.71, although it ranged from as low as \$37.37 up to \$288.36. Crude oil prices rose as high as \$145.18 per barrel and sunk as low as \$28.47 per barrel. The technology stock price experienced a similar range to alternative energy; with a high of \$242.31 and a low of \$44.54.

Table 1: Descriptive statistics

	Observations	Std. dev.	Mean	Max	Min
Alternative energy stock price (US$)	522	65.65	108.71	288.36	37.37
Crude oil price (US$/barrel)	522	21.70	80.47	145.18	28.47
Technology stock price (US$)	522	42.42	119.09	242.31	44.54
Interest rate (%)	522	1.77	1.06	5.05	0.00

As illustrated in Figure 2, stock prices for alternative energy technology and general technology fell drastically during the 2008 global financial crisis, and have still not risen to pre-recession prices. Oil prices also fell considerably in 2008, but eventually rose up through 2011-2014. Interest rates decreased through the recession and have remained low since then (Figure 3).

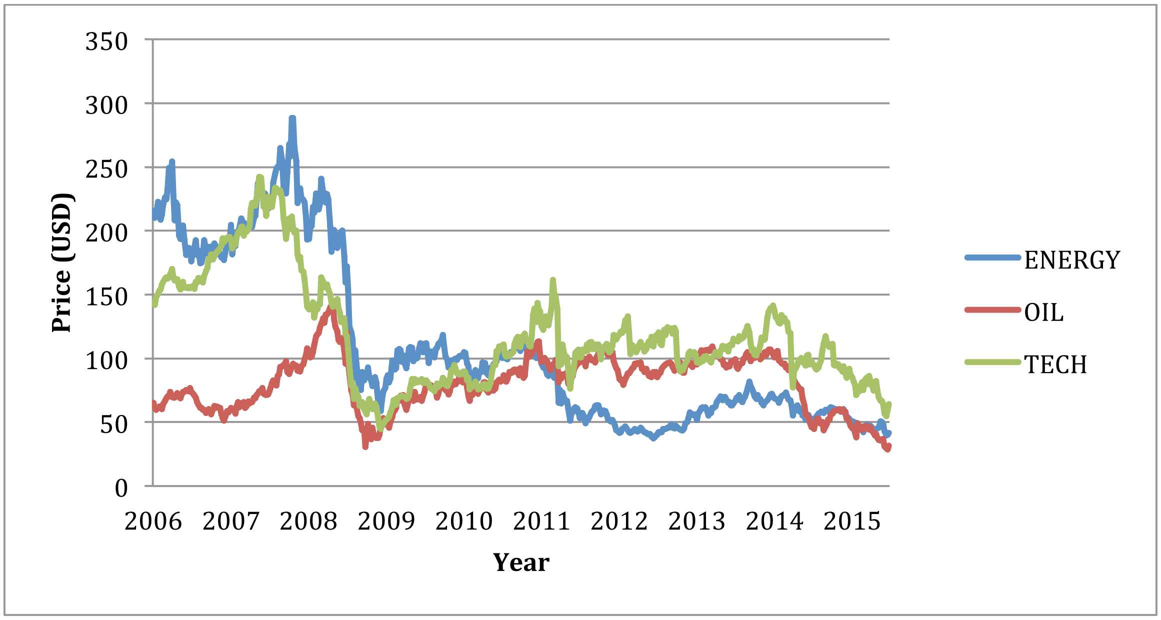

Figure 2: Alternative energy stock price, oil price and technology stock price, 2006-2015

Figure 3: Three-month U.S. treasury bill interest rate, 2006-2015

i. Stationarity

Augmented Dickey-Fuller (ADF) tests are used to test for stationarity in each variable. Tests are conducted in three ways: using no constant and no trend, constant with no trend, and constant with trend. The results of the initial tests indicate that each of the four variables contains a unit root, and display a stochastic trend. First-differencing the data results in first-difference stationary variables at the 1 percent level of significance by the same ADF tests, as shown in Table 2, meaning that each series is integrated of order one, I(1).

Table 2: ADF test for unit roots, lags(0)

	Levels	**First differences**
ENERGY		
no cons, no trend	-1.73	-23.469*
cons, no trend	-1.507	-23.505*
cons, trend	-2.089	-23.489*
OIL		
no cons, no trend	-0.748	-23.234*
cons, no trend	-1.467	-23.216*
cons, trend	-1.43	-23.277*
TECH		
no cons, no trend	-1.02	-22.563*
cons, no trend	-1.356	-22.556*
cons, trend	-1.859	-22.542*
RATE		
no cons, no trend	-2.646	-21.120*
cons, no trend	-1.979	-21.230*
cons, trend	-0.672	-21.375*

* Significant at the 1% level of significance

ii. Co-integration

Before proceeding with a regression for the first-difference stationary variables, it is necessary to ensure that the variables are not co-integrated, so as to avoid using an incorrect model. To test for co-integration, Engle and Granger suggest a two-step approach: predict the residuals using a simple ordinary least squares (OLS) regression, and then complete an ADF test (Engle & Granger, 1987, p.269). The ADF test statistic suggests no co-integration at the 95 percent level of confidence. Since there is no co-integration, a vector autoregression (VAR) model can be used for hypothesis testing. If there had been evidence of co-integreation, it would be more appropriate to use a vector error correction (VEC) model.

iii. VAR

The vector autoregression (VAR) model is a multivariate time-series model in which each variable is explained by its own lagged values, together with the current and lagged values of the other variables (Stock & Watson, 2001, p. 3). The advantage to using a VAR model is that it treats all variables as endogenous, allowing the model to capture certain co-movements that might not be detected in other models. Using lags makes sense for weekly financial data, as each observation is effected by previous observations.

The coefficients fabricated by the VAR model are not especially informative to look at because there are so many[1]; instead, Granger causality tests and impulse response functions (IRFs) are analyzed to determine causal relationships between variables.

[1] See Appendix for the full list of VAR coefficients.

iv. Lags

Since the goal of using the VAR model is to explain each variable by lags of itself and lags of the other variables, it is very important to choose an appropriate lag length for the model. Estimated lag lengths that are different from the true length can either overfit the lags (specify too many), resulting in an increased mean-square forecast error, or underfit the lags (specify too few), resulting in autocorrelated errors (Ozcicek & McMillin, n.d., p. 2). STATA (the software program used in this study) has a command, "varsoc," that creates a table of optimal lag estimates based on various criteria, including: LL, LR, FPE, AIC, HQIC, and SBIC. In 2005, Studies in Nonlinear Dynamics & Econometrics published a study that explored the various VAR lag choice criteria in order to determine the most reliable one. Their findings suggest that AIC-based estimates were "always at least as accurate as those based on other criteria," and for larger sample sizes, AIC "dominates across the board" (Ivanov & Kilian, 2005, p. 11). Considering the sample size in this paper is 522, the AIC-based estimates seem to be the best fit. The various criteria lag suggestions for this model are outlined in Table 3. AIC indicates that a lag length of seven is optimal.

Table 3: Criteria for choosing lag length

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-4144.72				132.441	16.2376	16.2506*	16.2708*
1	-4126.39	36.652	16	0.002	131.241	16.2285	16.2935	16.3943
2	-4103.41	45.967	16	0	127.704	16.2012	16.3182	16.4997
3	-4086.83	33.163	16	0.007	127.417	16.1989	16.3679	16.63
4	-4061.23	51.186	16	0	122.729	16.1614	16.3824	16.7251
5	-4049.6	23.26	16	0.107	124.857	16.1785	16.4515	16.8749
6	-4020.75	57.718	16	0	118.744	16.1282	16.4532	16.9572
7	-4003.3	34.901	16	0.004	118.092*	16.1225*	16.4995	17.0842
8	-3990.53	25.534	16	0.061	119.624	16.1351	16.5642	17.2295
9	-3984.13	12.793	16	0.688	124.242	16.1727	16.6537	17.3997
10	-3964.29	39.678*	16	0.001	122.435	16.1577	16.6907	17.5173

* indicates optimal lag length

v. Autocorrelation

Testing for autocorrelation is one way to determine whether the lag selection is appropriate. In this study, the Lagrange-multiplier (LM) test was calculated seven different times, using one, two, three, four, five, six, and seven lags. The LM test results support the AIC lag selection of seven, determining that autocorrelation is found at each level up until seven lags are specified. Table 4 illustrates the seventh LM test.

Table 4: Lagrange-multiplier test for autocorrelation

lag	chi2	df	Prob > chi2
1	19.2682	16	0.255
2	16.5634	16	0.41438
3	14.8193	16	0.53791
4	40.5251	16	0.00065
5	26.9612	16	0.04192
6	17.2724	16	0.36818
7	35.0003	16	0.00397

H0: no autocorrelation at lag order

vi. Granger Causality

Granger causality tests are conducted after VAR to determine whether or a variable can be predicted by lagged values of another variable. The findings of the Granger test, shown in Table 5, indicate that lagged values of both oil prices and interest rates help predict alternative energy stock prices, statistically significant at the 99 percent confidence level. Based on this analysis, technology stock prices are not found to help predict alternative energy prices.

Table 5: Granger causality Wald tests

Equation	**Excluded**	**chi2**	**df**	**Prob > chi2**
D_ENERGY	D.OIL	18.986	7	0.008
D_ENERGY	D.TECH	8.7859	7	0.268
D_ENERGY	D.RATE	22.132	7	0.002

vii. Impulse Reaction Functions

In addition to the Granger tests, impulse reaction functions are indicative of causal relationships in the VAR model. In the words of Stock and Watson (2001):

> Impulse responses trace out the response of current and future values of each of the variables to a one unit increase in the current value of one of the VAR errors, assuming that this error returns to zero in subsequent periods and that all other errors are equal to zero. (p. 6)

The first row of graphs in Figure 4, listed left to right, show: an alternative energy stock price shock to itself, as well as: an oil price shock, an interest rate shock, and a technology stock price shock, on the alternative energy stock price. The "shocks" are equal to an unexpected 1-percentage point increase in the variable in question. In the very short-run (about two weeks), oil prices and technology stock prices are found to have a statistically significant negative impact on alternative energy prices at the 95 percent level of confidence. Interest rates do not appear to have a statistically significant impact on alternative energy stock prices. Although oil prices and technology stock prices display a short-term impact on alternative energy, the graphs show a convergence back to zero by week eight, indicating that the change resulting from the shocks is not "persistent" (does not stick).

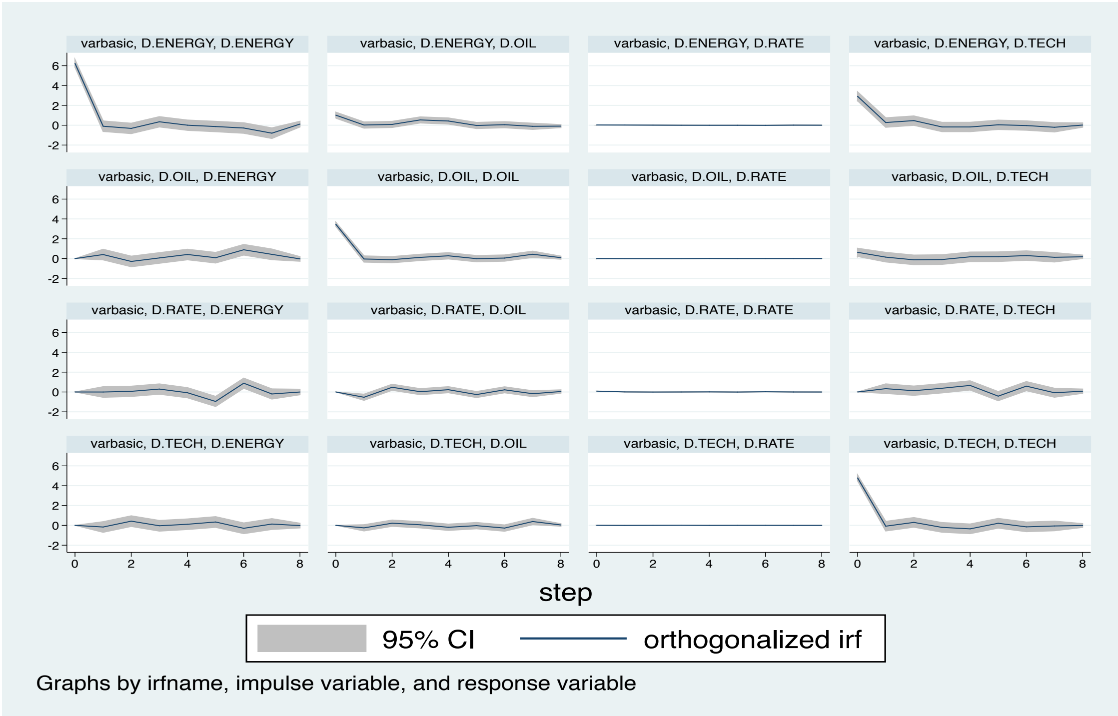

Figure 4: Impulse response graphs

V. Conclusion

Granger causality tests indicate that lagged values of both oil prices and interest rates help predict alternative energy stock prices, and impulse response functions (IRFs) suggest that shocks in oil prices and technology stock prices impact alternative energy stock prices in the short run, though the changes are not persistent over a longer period. Common to both the Granger and IRF tests is the result that oil price shocks have an impact on alternative energy. However, despite the extreme negative oil price shock observed in 2015, alternative energy stock prices appear to only suffer in the short-run. These findings differ from the findings of Henrique and Sadorsky, who observed that both technology stock prices and oil prices had statistically significant impact on alternative energy stock prices over the span of about ten weeks. These findings imply that sudden, extreme shocks might not be as prominent in the longer run as the gradual changes observed in Henrique and Sadorsky's financial data from 2001 to 2007.

Stock and Watson (2001, p.103) state that the number of variables used in a VAR model is limited only by the "inventiveness of the researcher." There are many factors contributing to the success of alternative energy companies, and further studies could improve the robustness of a study such as this one by using more variables to create a richer dataset. Nevertheless, this study has important implications for the alternative energy industry. Sudden and drastic oil price shocks appear to only have a negative persistent effect on alternative energy stock prices over the span of about two weeks. The extremely low oil prices seem to not be enough to dissuade investors from procuring alternative energy stocks. Perhaps society's environmental concerns and realization of energy security issues trump the enticement of cheap oil, over a longer term.

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VII. Appendix

VAR Coefficients

Alternative energy stock price (with first differencing)						
	Coef.	**Std. err.**	**z**	**P>|z|**	**[95% Conf. interval]**	
ENERGY						
LD.	-0.0198698	0.0525705	-0.38	0.705	-0.1229061	0.0831666
L2D.	-0.0843667	0.0536779	-1.57	0.116	-0.1895734	0.02084
L3D.	0.0423022	0.0533892	0.79	0.428	-0.0623388	0.1469431
L4D.	-0.0574922	0.0531198	-1.08	0.279	-0.1616052	0.0466208
L5D.	-0.021424	0.0533986	-0.4	0.688	-0.1260832	0.0832353
L6D.	-0.059152	0.0527408	-1.12	0.262	-0.162522	0.0442181
L7D.	-0.1908117	0.0530087	-3.6	0	-0.294707	-0.0869165
OIL						
LD.	0.1247058	0.0794504	1.57	0.117	-0.0310141	0.2804256
L2D.	-0.0955257	0.079544	-1.2	0.23	-0.251429	0.0603775
L3D.	0.0301318	0.0797261	0.38	0.705	-0.1261286	0.1863921
L4D.	0.1042958	0.0792008	1.32	0.188	-0.0509349	0.2595265
L5D.	0.0341365	0.0796681	0.43	0.668	-0.1220101	0.1902831
L6D.	0.2586243	0.0789826	3.27	0.001	0.1038213	0.4134273
L7D.	0.1132844	0.0789846	1.43	0.151	-0.0415225	0.2680913
TECH						
LD.	-0.0348395	0.0575009	-0.61	0.545	-0.1475392	0.0778603
L2D.	0.0920139	0.0575924	1.6	0.11	-0.0208652	0.2048929
L3D.	-0.0181419	0.0577013	-0.31	0.753	-0.1312344	0.0949506
L4D.	0.0293477	0.0577167	0.51	0.611	-0.083775	0.1424704
L5D.	0.0868154	0.057939	1.5	0.134	-0.0267429	0.2003737
L6D.	-0.0784935	0.0576485	-1.36	0.173	-0.1914825	0.0344955
L7D.	0.0550836	0.0578376	0.95	0.341	-0.0582759	0.1684431
RATE						
LD.	-0.0559133	3.268723	-0.02	0.986	-6.462493	6.350666
L2D.	1.698083	3.205988	0.53	0.596	-4.585537	7.981704
L3D.	1.788968	3.254415	0.55	0.583	-4.589568	8.167504
L4D.	0.0511222	3.198504	0.02	0.987	-6.21783	6.320075
L5D.	-11.01708	3.190405	-3.45	0.001	-17.27016	-4.764005
L6D.	9.624637	3.184587	3.02	0.003	3.38296	15.86631
L7D.	-2.855623	3.257656	-0.88	0.381	-9.240512	3.529267
_cons	-0.4308562	0.282316	-1.53	0.127	-0.9841853	0.122473

Crude oil price (with first differencing)						
	Coef.	**Std. err.**	**z**	**P>|z|**	**[95% Conf. interval]**	
ENERGY						
LD.	0.0480969	0.0303901	1.58	0.114	-0.0114666	0.1076604
L2D.	0.0045823	0.0310302	0.15	0.883	-0.0562359	0.0654004
L3D.	0.0709115	0.0308634	2.3	0.022	0.0104204	0.1314026
L4D.	0.0453007	0.0307077	1.48	0.14	-0.0148852	0.1054866
L5D.	-0.0000839	0.0308688	0	0.998	-0.0605855	0.0604178
L6D.	0.0331483	0.0304885	1.09	0.277	-0.0266081	0.0929047
L7D.	-0.0796243	0.0306434	-2.6	0.009	-0.1396844	-0.0195643
OIL						
LD.	-0.0001624	0.0459289	0	0.997	-0.0901813	0.0898565
L2D.	-0.0535241	0.045983	-1.16	0.244	-0.1436491	0.0366008
L3D.	0.0314618	0.0460883	0.68	0.495	-0.0588696	0.1217931
L4D.	0.0701578	0.0457846	1.53	0.125	-0.0195784	0.1598939
L5D.	0.0510459	0.0460547	1.11	0.268	-0.0392198	0.1413115
L6D.	0.0132719	0.0456584	0.29	0.771	-0.076217	0.1027608
L7D.	0.0988143	0.0456596	2.16	0.03	0.0093232	0.1883055
TECH						
LD.	-0.044517	0.0332403	-1.34	0.18	-0.1096667	0.0206328
L2D.	0.0335295	0.0332932	1.01	0.314	-0.0317238	0.0987829
L3D.	0.0192618	0.0333561	0.58	0.564	-0.0461149	0.0846386
L4D.	-0.0316954	0.033365	-0.95	0.342	-0.0970896	0.0336988
L5D.	-0.0233507	0.0334935	-0.7	0.486	-0.0889967	0.0422954
L6D.	-0.0582237	0.0333256	-1.75	0.081	-0.1235406	0.0070933
L7D.	0.0732228	0.0334349	2.19	0.029	0.0076917	0.138754
RATE						
LD.	-6.371416	1.889592	-3.37	0.001	-10.07495	-2.667885
L2D.	6.182173	1.853325	3.34	0.001	2.549722	9.814624
L3D.	-1.012192	1.88132	-0.54	0.591	-4.699512	2.675128
L4D.	3.687539	1.848999	1.99	0.046	0.0635672	7.31151
L5D.	-2.071292	1.844317	-1.12	0.261	-5.686088	1.543503
L6D.	1.772633	1.840954	0.96	0.336	-1.83557	5.380837
L7D.	-0.4061603	1.883194	-0.22	0.829	-4.097153	3.284832
_cons	-0.0027845	0.1632019	-0.02	0.986	-0.3226544	0.3170854

Technology stock price (with first differencing)						
	Coef.	Std. err.	z	P>|z|	[95% Conf. interval]	
ENERGY						
LD.	0.0318126	0.0474937	0.67	0.503	-0.0612734	0.1248986
L2D.	0.0338529	0.0484941	0.7	0.485	-0.0611938	0.1288996
L3D.	-0.0265567	0.0482333	-0.55	0.582	-0.1210924	0.0679789
L4D.	-0.0470701	0.04799	-0.98	0.327	-0.1411287	0.0469886
L5D.	-0.0334546	0.0482418	-0.69	0.488	-0.1280067	0.0610976
L6D.	-0.0112261	0.0476475	-0.24	0.814	-0.1046135	0.0821614
L7D.	-0.0381486	0.0478896	-0.8	0.426	-0.1320106	0.0557133
OIL						
LD.	0.0450671	0.0717777	0.63	0.53	-0.0956147	0.1857489
L2D.	-0.0453124	0.0718623	-0.63	0.528	-0.1861599	0.0955351
L3D.	-0.0150982	0.0720269	-0.21	0.834	-0.1562682	0.1260718
L4D.	0.089578	0.0715522	1.25	0.211	-0.0506618	0.2298178
L5D.	0.0551416	0.0719744	0.77	0.444	-0.0859257	0.1962089
L6D.	0.0914778	0.0713551	1.28	0.2	-0.0483757	0.2313312
L7D.	0.0409857	0.0713569	0.57	0.566	-0.0988713	0.1808427
TECH						
LD.	-0.0226541	0.051948	-0.44	0.663	-0.1244702	0.0791621
L2D.	0.0667284	0.0520306	1.28	0.2	-0.0352497	0.1687066
L3D.	-0.0527925	0.052129	-1.01	0.311	-0.1549634	0.0493785
L4D.	-0.1010256	0.0521429	-1.94	0.053	-0.2032239	0.0011727
L5D.	0.0614836	0.0523437	1.17	0.24	-0.0411082	0.1640754
L6D.	-0.0562339	0.0520813	-1.08	0.28	-0.1583114	0.0458436
L7D.	-0.03587	0.0522521	-0.69	0.492	-0.1382822	0.0665422
RATE						
LD.	3.98635	2.953058	1.35	0.177	-1.801537	9.774237
L2D.	1.705482	2.896381	0.59	0.556	-3.971321	7.382284
L3D.	3.971866	2.940131	1.35	0.177	-1.790685	9.734418
L4D.	8.138706	2.88962	2.82	0.005	2.475155	13.80226
L5D.	-4.587878	2.882303	-1.59	0.111	-10.23709	1.061333
L6D.	8.393625	2.877047	2.92	0.004	2.754716	14.03253
L7D.	-1.213587	2.94306	-0.41	0.68	-6.981879	4.554704
_cons	-0.056496	0.2550523	-0.22	0.825	-0.5563893	0.4433973

Interest rate (with first differencing)						
	Coef.	**Std. err.**	**z**	**P>|z|**	**[95% Conf. interval]**	
ENERGY						
LD.	0.0034343	0.0007345	4.68	0	0.0019946	0.0048739
L2D.	0.0017228	0.00075	2.3	0.022	0.0002528	0.0031927
L3D.	-0.0001817	0.000746	-0.24	0.808	-0.0016438	0.0012804
L4D.	-0.0014736	0.0007422	-1.99	0.047	-0.0029283	-0.0000189
L5D.	-0.001192	0.0007461	-1.6	0.11	-0.0026543	0.0002704
L6D.	-0.0023941	0.0007369	-3.25	0.001	-0.0038384	-0.0009498
L7D.	0.0003635	0.0007407	0.49	0.624	-0.0010881	0.0018152
OIL						
LD.	-0.0014036	0.0011101	-1.26	0.206	-0.0035794	0.0007721
L2D.	-0.0020481	0.0011114	-1.84	0.065	-0.0042264	0.0001302
L3D.	-0.0025071	0.001114	-2.25	0.024	-0.0046904	-0.0003238
L4D.	0.0042384	0.0011066	3.83	0	0.0020694	0.0064073
L5D.	0.0003644	0.0011131	0.33	0.743	-0.0018173	0.0025461
L6D.	0.0014204	0.0011036	1.29	0.198	-0.0007426	0.0035833
L7D.	0.0015577	0.0011036	1.41	0.158	-0.0006053	0.0037207
TECH						
LD.	-0.0008716	0.0008034	-1.08	0.278	-0.0024463	0.000703
L2D.	0.0008871	0.0008047	1.1	0.27	-0.0006901	0.0024643
L3D.	0.0021377	0.0008062	2.65	0.008	0.0005576	0.0037179
L4D.	-0.0006162	0.0008064	-0.76	0.445	-0.0021968	0.0009644
L5D.	0.0011996	0.0008095	1.48	0.138	-0.0003871	0.0027863
L6D.	0.0000946	0.0008055	0.12	0.907	-0.0014841	0.0016733
L7D.	-0.0000852	0.0008081	-0.11	0.916	-0.0016691	0.0014986
RATE						
LD.	0.0496174	0.0456715	1.09	0.277	-0.039897	0.1391319
L2D.	-0.1025929	0.0447949	-2.29	0.022	-0.1903894	-0.0147965
L3D.	-0.016096	0.0454716	-0.35	0.723	-0.1052186	0.0730266
L4D.	0.0715868	0.0446904	1.6	0.109	-0.0160047	0.1591783
L5D.	-0.0513513	0.0445772	-1.15	0.249	-0.138721	0.0360184
L6D.	0.2731618	0.0444959	6.14	0	0.1859514	0.3603722
L7D.	-0.0668118	0.0455168	-1.47	0.142	-0.1560232	0.0223995
_cons	-0.0061801	0.0039446	-1.57	0.117	-0.0139114	0.0015512