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Oil Prices, Fossil-Fuel Stocks and Alternative Energy Stocks

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Abstract

As new alternative energy industries are created and old ones are revised, markets constantly try to interpret and adjust to those changes. The purpose of this study is to shed some light on the inner dynamics of the select outside price-shocks *versus* sector-specific energy companies. This study analyzes the inner dynamics (both short and long-term) of sub-sector energy company portfolios such as petroleum, coal, natural gas, solar, nuclear, wind, and biofuel with respect to each other as well as other asset markets commonly used in literature. In light of outside shocks, we find that some alternative energy companies behave like fossil-fuel companies, while others don't. Interestingly petroleum companies give no significant short-term response to oil-price or exchange-rate shocks. Also, there is a significant relationship between gold price shocks and most energy sub-sectors in the long-run. The same relationship was not observed in the short-run.

Keywords: oil prices, alternative energy

1. Introduction

Recent oil price fluctuations have made the impact of oil shocks on financial markets an interesting topic. Although it has always been one of the driving factors for policy, decreasing the dependency on fossil fuels via concentrating on renewable/alternative energy sources have driven the financial markets to be more diverse. While brand-new sectors are being created, others, which had minimal impact in the past, are being revitalized. While, the dependency on oil is expected to continue in the future, this should keep the oil market as a significant impact factor on the rest of the markets. According to many estimates, oil production, due to skyrocketing demand (especially from emerging markets such as China and India), will reach its highest level between 2016 and 2040 (Appenzeller, 2004).

With the United States utilizing/consuming almost a quarter of the world's entire oil production, and the industries of developed nations consisting largely of energy-demanding sectors, it is only natural to assume that fluctuations in energy prices should have a significant impact on the world's economy. As several previous studies have already suggested, since equity markets also reflect on how companies in a given economy perform, it is not a far leap to expect significant reactions from these markets to energy price shocks.

The energy market is dominated by the fossil-fuel related sources (oil, coal, and natural gas). The scarcity of fossil-fuel reserves, added to the unstable economic and political structure of nations with significant portions of those reserves, make the markets for those energy sources volatile. Fluctuating oil prices, especially recently, have demanded a higher level of attention towards alternative energy sources. Although there is not a true alternative source of energy to oil, decreasing costs associated with the creation of alternative sources are expected to do a significant impact in the long-run. (Woloski, 2006).

It is common for energy commodities to be used as diversification tools for investors, hedging opportunities for users/producers and trading assets for investors. Economical volatility and future uncertainty pushes investors away from currency based bets to commodity based investments (Gormus & Sarkar, 2014). Some studies find that futures on energy commodities are not necessary for an efficient energy stock portfolio (Galvani & Plourde, 2010), others suggest these alternative energy company stocks have a better than expected performance which does not correlate with their size, sector and style (Chia et al., 2009). While traditional energy asset classes such as oil, natural gas and coal are still utilized by investors, alternative classes such as "green" energy is dictating a significant impact in the market. These assets increase the available classes for market participants (Gormus & Sarkar, 2014).

Due to supporting government policies and public initiatives, alternative energy companies appear to be enjoying a positive investment environment. However, how the stocks of these companies fare relative to fossil fuel company stocks in the face of an oil shock still needs to be explored.

Hamilton (1983) was one of the pioneers in analyzing the relationship between oil price shocks and U.S. markets, where his findings indicated oil prices as an important factor contributing to the U.S. recessions; especially after World War II. Several other studies (Uri, 1996; Soytas et al., 2010; Sadorsky, 1999; Oladosu, 2009) have found some relationship between oil price shocks and other macroeconomic variables in the US and other economies. In terms of stock market returns, there are several important studies conducted which find a direct relationship (Ewing, 2007; Sadorsky, 1999, 2001; Park, 2008; Soytas, 2011) between oil price fluctuations and stock market performance. For example, Sadorsky (1999) found symmetric as well as asymmetric effects of oil prices and oil price volatility on the stock market returns.

There is very limited research regarding energy companies at sub-sector level (especially with the inclusion of alternative energy sectors). A significant study conducted by Henriques and Sadorsky (2008), showed that alternative energy companies behave like high-technology companies and shocks to technology stocks impact the alternative energy companies more than oil price shocks. They use a VAR approach to test oil price shocks against a single alternative energy ETF (substituting for all alternative energy companies) as well as a high-technology company index.

Gormus et al. (2014) conducted a volatility spillover study between the energy sub-sectors. Although the data this study uses is similar, we look at a different time frame conduct a short-term and long-term return analysis (compared to the general volatility analysis in their study). Our approach fits the literature on the impact of oil price changes on stock returns; however it distinguishes itself by investigating the interactions between the general asset market and all sub-sectors of energy industry (including fossil and alternative energy related companies). The variables researched in this study include companies in the sub-sectors of petroleum, coal, natural gas, solar, wind, nuclear and biofuel, as well as major drivers commonly used in literature such as oil prices, gold prices, exchange rates, and S&P500 index. Our approach tries to answer several questions: (1) What are the short-term reactions of different type of energy companies to price shocks from the oil, gold and currency markets? (2) How does one sub-sector differ from another and/or which ones behave similarly? (3) Do price movements in oil, gold and currency help explain reactions from any of the sub-sector company performance in the long-run?

2. Literature Review

There are studies that indicate no impact of oil prices on local commodity prices. For example, Soytas et al. (2009) examined the transmissions of information between world oil prices, interest rates (Turkish), exchange rates, and local gold and silver prices in Turkey. They found no evidence of oil prices having any predictive power of precious metal prices, interest rates, or the exchange rates. Authors suggest that in the presence of a threat of devaluations, market participants move towards the precious metal markets. However; they do observe transitory positive impacts of innovations between oil, gold, and silver prices.

Exchange rates often have been found to be a significant contributor to the movements in the energy sector and vice versa. This is expected because the trading of the most important energy commodity, oil, is conducted in US dollars (Gormus et al., 2014). When testing for the relationship between energy futures prices and exchange rates, Sadorsky (2000) found that there exists co-integration between futures prices for heating, crude oil, gasoline, and a trade-weighted index of exchange rates. Utilizing VAR and Granger causality methodologies, he found that there exists a long-run equilibrium relationship between all of the tested variables. The study also suggests the existence of a transmission effect from exchange rate shocks to energy futures prices.

Utilizing co-integration and Granger causality tests, Li (2011) evaluated the relationship between NYMEX future prices for crude oil, unleaded gasoline, heating oil, and the U.S. trade-weighted exchange rate. While co-integration was found among the entire set of variable with the exception of exchange rate, energy prices were not found to be a significant driver in the U.S. exchange rate.

In an attempt to understand why a certain energy sub-sector grows faster than others, Jenner, Chan, Frankenberger, and Gabel (2012) tested the dynamics behind the states supporting the alternative energy companies. They found that some alternative energy companies have a higher chance of surviving if they concentrate on some sub-sectors compared to others. This suggests that based on the subsector concentration, the stock behaviors of alternative energy companies may show different dynamics.

One line of the literature focuses entirely on the link between energy commodity and financial markets. Sadorsky (2001), tested for the interaction between the exchange rates, oil prices, and interest rates on the Canadian oil and gas industry. The multifactor market model frame-work showed that the oil and gas industry was significantly impacted by the shocks to those variables. Oil prices were found to be positively correlated and the exchange rates were found to be negatively correlated with the Canadian oil and gas industry stock prices.

In a study which supports the findings of Sadorsky (1999), Chiou, Lee, and Lin (2008) examined the relationship between oil prices and S&P 500 using traditional and threshold causality/co-integration testing. Similar to Sadorsky's study (1999), they found that an asymmetric uni-directional relationship exists between oil prices and the stock markets. These findings showed that changes in oil prices affect economic activity but the same is not true in the opposite direction. Evaluating some of the developed markets, Jones and Guatam (1996) tested the stocks markets' reactions to oil price shocks using quarterly data and a standard cash flows/dividends valuation model. The study, which included the United States, Canada, England, and Japan, showed that there is a significant relationship between oil prices and stock market returns. However; when they introduced real cash flows and future industrial production into their model, they found that the oil–price shocks were not significant anymore for the U.S. and Canadian stock prices.

The extant literature mainly focuses on the effect of oil price shocks on stock indexes; however, as suggested by several studies, the impact of an oil price change on sub-sector stock performance may be different. Furthermore, the currency markets may have a confounding effect on the link between oil and stock markets. Hence, using aggregate indexes may ignore sector specific reactions to oil price shocks. This paper aims to fill a gap in the literature by utilizing sub-sector portfolios of energy companies in an attempt to separately examine how fossil fuel and alternative energy company stocks react to changes in oil prices, gold prices, and exchange rate while controlling for the overall market behavior.

3. Data

In this study, we use a similar data set to the study conducted by Gormus et al. (2014). The significant difference between this study and their study lies in the time-frame and the type of analysis conducted. Gormus et al. (2014), evaluates the volatility spillovers between for the sub-sectors within a 5 year period and this study looks at short and long-term stock return relationships within a 3 year window. The data used in this study consist of several value-weighted sub-sector energy indexes as well as test variables commonly used in literature. We created seven indexes including companies in the sub-sectors of petroleum, coal, natural gas, solar, nuclear, wind, and biofuel. The criteria used for creation of these indexes were that each company in the portfolio must have at least 50% of its revenue with the sub-sector it is listed. The outside shock variables used are daily oil price returns, daily gold price returns, daily USD/EUR exchange rate returns, and S&P500 index returns.

For his study we followed the commonly accepted norm that an index needs to have at least ten to 12 companies to be robust. However; this posed some time constraints due to the inception of most alternative companies being fairly recent. The data consists of daily values for 3 years spanning from January 2009 to December 2011. In literature, oil prices, gold prices and exchange rates are commonly used as shock variables, so we followed suit and, in addition, also included the S&P 500 index (to control for market).

The company data are gathered from COMPUSTAT and CRISP data bases, while historical oil prices were obtained from www.eia.gov. Historical gold prices were obtained from www.goldprice.org and USD/EUR prices were obtained from www.oanda.com and the historical prices of S&P 500 Index were obtained from CRISP.

Each index is value weighted and rebalanced daily with a base price of 100. The daily log returns of each asset were calculated and used in both the VAR and Granger Causality frame-works. The largest sizes of portfolios in value (on average) are natural gas, petroleum, and wind.

Below in Table 1, are the descriptive statistics of data used.

Table 1. Descriptive statistics: level index prices

	BIOFUEL (11)	COAL (14)	NAT GAS (16)	NUCLEAR (32)	PETROLEUM (41)	SOLAR (17)	WIND (19)	S&P500	OIL	CURRENCY	GOLD
Mean	111.19573	116.84137	116.97766	104.86435	107.33830	89.08115	101.16719	1116.92897	78.58306	1.37085	1255.06481
Median	111.72639	114.71992	115.70970	105.38581	101.65465	92.05321	102.17403	1127.79000	79.62000	1.37220	1212.50000

St. Dev	12.42254	18.55923	17.19972	15.82164	16.44760	18.79701	14.70360	155.50452	16.38644	0.06803	269.92436
Skewness	0.19985	0.03757	0.08113	-0.40861	0.56460	-1.24089	-0.66536	-0.61532	-0.57562	-0.22001	0.40938
Kurtosis	-0.17571	-0.78233	-0.45733	0.14257	-0.87416	1.68240	0.49121	-0.27291	0.22042	-0.58700	-0.84067
Observations	726	726	726	726	726	726	726	726	726	726	726

The numbers in parentheses indicate number of companies in each index.

According to Table 1, the nuclear and petroleum indexes include the highest number of stocks. The descriptive statistics for the level-price of portfolios show that mean and median of the portfolios as well as other asset markets tested are fairly close to each other. Table 2 shows the descriptive statistics of level-log returns (which are used in the tests of this study):

Table 2. Descriptive statistics: index log-returns

	BIOFUEL	COAL	NAT GAS	NUCLEAR	PETROLEUM	SOLAR	WIND	S&P500	OIL	CURRENCY	GOLD
Mean	0.0002	0.0001	0.0001	0.0001	0.0004	-0.0017	0.0003	0.0001	0.0000	-0.0001	0.0008
Median	0.0013	0.0002	-0.0005	-0.0010	0.0011	-0.0003	0.0009	0.0001	-0.0012	-0.0001	0.0010
Std. Dev.	0.0204	0.0714	0.0504	0.0455	0.0176	0.0321	0.0195	0.0385	0.0364	0.0075	0.0126
Skewness	-0.7159	0.3551	0.0584	0.0509	-0.3346	-0.2072	0.0504	-0.0456	0.1740	0.1797	-0.2295
Kurtosis	7.3827	6.9919	4.9210	5.6996	4.7638	6.6009	7.2406	6.8510	6.2307	4.9572	5.7754
Observations	725	725	725	725	725	725	725	725	725	725	725

Table 2 shows that the log returns are very close to zero and coal, natural gas, and nuclear returns have the three highest standard deviations. Non-normality is clear from the skewness and kurtosis figures for all returns. When we investigate the correlation coefficients between the returns in Table 3, we observe that Gold returns have negative correlations with coal, natural gas, nuclear, and wind stock returns, but the correlations are small in absolute value. All other correlation coefficients are positive ranging between 0.0013 for S&P500 and natural gas returns to 0.8947 for natural gas and coal stock returns. The wide range of correlations suggests that company stocks in different energy sectors may respond differently to outside shocks.

Table 3. Pearson correlations

	BIOFUEL	COAL	CURRENCY	GOLD	NAT GAS	NUCLEAR	OIL	PETRO	S&P500	SOLAR	WIND
BIOFUEL		0.3420	0.3595	0.0625	0.3576	0.3147	0.2961	0.7093	0.3268	0.4649	0.6094
COAL	0.3420		0.1390	-0.0549	0.8947	0.7331	0.4354	0.4344	0.8039	0.2392	0.2531
CURRENCY	0.3595	0.1390		0.2453	0.1339	0.1595	0.2750	0.4524	0.1102	0.3297	0.3965
GOLD	0.0625	-0.0549	0.2453		-0.0450	-0.0287	0.0685	0.0877	0.0013	0.0491	-0.0027
NAT GAS	0.3576	0.8947	0.1339	-0.0450		0.8056	0.4893	0.4743	0.8994	0.2331	0.2842
NUCLEAR	0.3147	0.7331	0.1595	-0.0287	0.8056		0.4006	0.4292	0.8972	0.2303	0.3974
OIL	0.2961	0.4354	0.2750	0.0685	0.4893	0.4006		0.4434	0.3745	0.2414	0.2667
PETRO	0.7093	0.4344	0.4524	0.0877	0.4743	0.4292	0.4434		0.4418	0.5902	0.7456
S&P500	0.3268	0.8039	0.1102	0.0013	0.8994	0.8972	0.3745	0.4418		0.2373	0.3172
SOLAR	0.4649	0.2392	0.3297	0.0491	0.2331	0.2303	0.2414	0.5902	0.2373		0.5270
WIND	0.6094	0.2531	0.3965	-0.0027	0.2842	0.3974	0.2667	0.7456	0.3172	0.5270	

4. Methodology

To understand the long-run relationship between the variables, we followed the Toda-Yamamoto procedure (Toda & Yamamoto, 1995). Unlike commonly used causality models, TY does not require to test for cointegration. This way, a possible pretest bias is avoided. Another important aspect of the TY procedure is that it allows for VAR series to be run in levels. Whether the data have same order of integration or not is irrelevant. This helps with avoiding loss of information related to differencing the series while providing more flexibility with the consideration of arbitrary levels of integration.

With the TY procedure, first, maximum integration order (d) is defined for the series. At this step we utilized

Dickey-Fuller GLS detrended unit root tests by Elliot et al. (1996). Using some information criteria, the optimum lag length (k) is defined in the next step. From the augmented VAR procedure (k+d) perspective, if the common assumptions are satisfied, then a modified Wald test constitutes a long-run causality test. This is achieved through testing the joint significance of the first k lags of each variable in each equation in the system. The distribution followed by the test statistic is Chi-square with k degrees of freedom.

The VAR system allows for flexibility since all variables are treated as dependent variables. This, in return, allows for the direction of causality to be from any set of the variables. Granger causality tests help to understand whether there are any long-run static equilibrium relationships between the variables. However; the model fails to include variables which might respond to innovations from another in the short-run. To address the possible problem of omitted response to innovations in variables, and the aspect of time-persistence, a "generalized" impulse response framework was used. Consider the following VAR representation:

$$g_t = A\sum_{i}^{p} \phi g_{t-i} + \varepsilon_t \tag{1}$$

where g_t is an m x 1 vector of endogenous variables jointly determined, ε are m x m matrices of coefficients to be estimated, A is a vector of constants, t is time, p is the optimal lag length, and ε_t is an m x 1vector well-behaved disturbances with covariance $\varepsilon = \sigma_{ij}$. The term $(S_n\varepsilon e_j)(\sigma_{ij})^{-1}$ represents the generalized impulse response of g_{t+n} with respect to a unit shock to jth variable at time t. Note that $S_n = \varepsilon_1 S_{n-1} + \varepsilon_2 S_{n-2+\dots} \varepsilon_p S_{n-p}$, n = 1, 2, …, $S_0 = 0$ for n<0 and e_j is the m x 1 selection vector with unity as its jth element and zero elsewhere.

In order to capture how shocks to a variable transfer through the VAR system of equations, we employ the generalized impulse responses developed by Koop et al. (1996), and Pesaran and Shin (1998). The traditional approaches to variance decomposition and impulse responses are not used as commonly in literature anymore, due to their shortcomings, and the generalized approach has taken its place. For the results to be robust, the ordering of variables should not matter, which is a problem with the traditional approach. Generalized approach avoids that problem. Using the log-likelihood test one can see that given a diagonal covariance matrix, the results of both methods are very similar. We do not discuss the methodology in detail to conserve space, but the methods employed in this paper are widely used in the literature.

5. Results

The first step of the TY procedure is to check for the maximum integration order of the series that will enter the VAR system. Table 4 summarizes the DF-GLS unit root test results.

Table 4. Unit-root tests

	DF-GLS	FD DF-GLS
Biofuel	-30.6975***	-30.6975***
Coal	-2.1933	-3.8452***
Currency	-2.7113*	-2.7113*
Gold	-26.2470***	-26.2470***
Natural Gas	-2.4708	-3.3165***
Nuclear	-2.1738	-2.8190**
Oil	-2.1243	-16.6443***
Petroleum	-3.3015**	-3.3015**
S&P500	-2.4193	-3.6836***
Solar	-2.8590**	-2.8590**
Wind	-2.7843*	-2.7843*

Note. *** Significant at 1%, ** Significant at 5%, * Significant at 10% level.

Table above tests for the order of the variables used in the study. DF-GLS refers to the Dickey-Fuller type unit-roots tests done on the log-returns of indexes, while FD DF-GLS refers to the first-differenced log-return series.

The variables used in the study do not seem to have a common integration order. Although, the methodology utilized for the VAR models as well as Toda-Yamamato Granger Causality models did not require them to be, we still looked at the first-differenced series to see if they were of the same order. Dickey-Fuller tests show that differenced series are stationary with at least 10% significance-level; while most are significant at 1% level. As Table 4 illustrates, coal, natural gas, nuclear, oil, and S&P 500 series are not stationary when level log-returns are tested, while all are found to be stationary when differenced series are tested.

The VAR constructed according to the Toda-Yamamoto procedure is then subjected to a battery of diagnostic tests. Test results suggest that there is no serial correlation in any of the equations. On the other hand, all series except coal show a heteroskedasticity problem where the standard errors were White adjusted to make the series suitable for testing. Diagnostic test results are available from the authors upon request.

5.1 Generalized Impulse Responses

To investigate the short-run relationships among different sub-sector energy portfolios as well as oil, gold, exchange rates, and S&P 500, vector autoregressions were employed. As previously mentioned, this methodology is flexible in the sense that all variables can be tested as depended variables. In this study, generalized impulse responses were used to demonstrate the shot-run relationships between variables due to its avoidance of short-comings (especially in terms of ordering of variables) possibly apparent with traditional methods. Graphs 6.1 to 6.7 below show the results of these tests. Each graph demonstrates how a series reacts to a generalized one-standard deviation shock (change) to another series. In other words, the graphs show how much of a response a series gives (in terms of returns) to a one standard deviation change in another series (i.e. oil, gold, S&P500, and exchange rates). The response can be positive or negative and, since the data used are daily, it also demonstrates the daily duration of the response before it dies off. The common deduction from all 7 graphs is that shocks in oil, S&P 500, gold and exchange rate returns are transitory and do not appear to have permanent effects on any of the energy company portfolios.

In Figure A1 we can see the generalized impulse responses of biofuel portfolio to the asset markets tested. The strongest response observed is between S&P 500 and biofuel. This is probably due to two things: first, S&P 500 represents the entire market and as previous research shows, there is a lead-lag type relationship between different sectors and the market itself. Second, there are some large energy companies in the S&P 500 index and the positive relationship between the energy portfolio and S&P 500 is expected. Since, the market variable is mainly used as a control variable in this study, the relationships between the portfolios and other asset markets (other than S&P 500) become that much more important. Biofuel portfolio gives strong (and almost identical) responses to exchange rate (from now on “currency”) and oil price returns. The portfolio does a positive jump of approximately 0.8% to a one standard deviation shock to oil and currency returns. The response dies off in approximately two to two and a half days.

When the short-term relationships between the coal, a common fossil fuel, sub-sector portfolio and asset markets were tested, very strong relationships were observed. As Figure A2 shows, coal gave approximately 1.5% response to oil and 1.3% response to currency. The response to a shock in gold prices was minimal. The impacts are short lied and die off within 2 days.

When the natural gas portfolio is analyzed, one can see that the high positive response to a shock in S&P 500 is still apparent. As Figure A3 above illustrates, the second strongest response is given to oil with 1.3% and the third strongest to currency with 0.9%. As with most portfolios tested, the responses die off in approximately two days. Again, as with other portfolios, short-term responses to gold price returns are negligible. Granger causality results will shed more light on these phenomena since it tests for long-term relationships.

Figure A4 show the generalized impulse responses of the nuclear portfolio to the asset markets tested. Aside from the high response to S&P 500 index, the nuclear portfolio showed the strongest response to oil with 0.9% and second strongest to currency with 0.8%.

Some interesting results were found when the petroleum portfolio was tested against the asset markets. While initial intuition suggested that these tests would show the strongest relationships with oil and currency, the results were surprisingly different. The portfolio, comparatively, showed minimal, if any, response to both oil and currency shocks. The response to oil price shocks was at 0.3% and the response to currency price shocks was not significant. Response to gold prices was not significant as well. These results (as seen in Figure A5) suggest that petroleum companies (or traders who trade their stocks) have some information about the shocks to both oil and currency prices before the actual shock happens. This way, they adjust to those shocks preemptively. In other words, the petroleum companies are more efficient in terms of information compared to other energy companies tested.

Figure A5 shows the responses of the solar stock portfolio to the asset markets in concern. The results are similar to other portfolios where oil and currency shocks triggered the second and third highest responses. Solar stocks gave an initial impulse response of 1.1% to currency shocks and 1.0% response to oil shocks where all responses died off within two days. Responses to gold price shocks were not significant.

Wind company portfolio proved similar relationships to other non-fossil fuel related energy company portfolios where it gave a 0.8% response to currency and 0.6% response to oil. Response to gold price shocks was not significant.

5.1.1 Summary of Generalized Impulse Response Results

The strongest responses to oil price shocks were given by companies related to other fossil fuels; where coal portfolio gave an initial response of 1.5%, and natural gas gave an initial response of 1.3%. The strongest response to oil price shocks from the non-fossil fuel group was by the solar portfolio, where it gave a response of 1.1% in returns to a one standard deviation shock to the oil prices.

The petroleum company portfolio, however, did not give any response to either currency or oil price shocks. As previously mentioned, this could be due to the information efficiency in that market, where investors trading petroleum stocks could have additional information related to future oil and currency price shocks. This, in return, results in those company stock prices adjusting to shocks before they actually happen, thus not giving any response at the time of the shocks themselves.

None of the portfolios tested gave any significant responses to gold price shocks in the short-run. As Granger causality results are discussed in the later part of the study, it will shed some light on why that is the case.

5.2 Granger Causality

Through the Toda-Yamamoto methodology, the vector autoregressions were employed; however, since the standard errors of those regressions were adjusted using the White Coefficient Covariance Matrix, the stability of the regressions needed to be tested before the Granger causality tests were utilized. Common practice in literature is to use CUSUM and CUSUM Square tests for verifying the stability of these types of regression models, while also testing for consistency of the coefficients in those models. Originally developed by Brown et al. in 1975, CUSUM and CUSUM squares tests, in terms of serial correlation, endogeneity, and lack of structural invariance perform better from the perspective of a dynamic model of the ADL type. These tests are not affected by serial correlation or regressors which are not predetermined even if over-specified (Caporale et al., 2004). All of the CUSUM and CUSUM square tests showed stability of the regression models tested (Results available upon request).

In order to determine long-run Granger causality relationships between the asset markets and the sub-sector energy portfolios, Wald tests were conducted. Wald tests employ coefficients of previous vector autoregression models at the optimum lag structure determined by the lag order selection criteria tests (i.e., Akaike Information Criterion, Schwarz Information Criterion, and Hannan-Quinn Information Criterion). The null hypothesis with these tests is that there is no Granger causality. Therefore, any rejection of this hypothesis implies the existence of a long-run Granger causality between the variables tested.

Table 5. Long run granger causality test results

	Currency	Oil	S&P 500	Gold
Biofuel	0.4883	0.2509	0.3342	0.0081
Coal	0.7298	0.6738	0.2141	0.0388
Natural Gas	0.9996	0.6735	0.5851	0.0870
Nuclear	0.9803	0.6349	0.8581	0.2270
Petroleum	0.9700	0.5556	0.0881	0.4885
Solar	0.1340	0.2214	0.5425	0.4741
Wind	0.9903	0.2496	0.5646	0.0257

Table 5 shows the results of Wald tests modeling a unidirectional Granger causality from the 4 asset market returns to the seven sub-sector energy portfolios. As the results show, it cannot be rejected that there is no long-run Granger causality running from currency markets to any of the portfolio returns. In other words, there is no significant evidence to support the currency prices having any long-run effects on the portfolios tested. A similar picture emerges with the Oil prices. As table 5 shows, oil prices have no significant long-run effects on the sub-sector energy portfolios tested. This is another interesting finding since, in literature, speculations and debates concerning the long-run effects of oil prices on stock markets have been plenty. Findings below support the line of literature which argues against the possibility of a long-term relationship between oil prices and stock markets. However; it is important to note that this study only tests for the sub-sector energy companies, not the entire stock market.

Table above summarizes the p-values of the modified Wald test statistics for long run Granger non-causality.

Similar to currency and oil prices, the market (represented by the S&P 500 index) does not have any long-run effects on the portfolios. The results show a rejection of non-causality at 10% level between S&P 500 and the petroleum portfolio. It is, however, difficult to derive any conclusions from this result since rejection is not achieved for any other portfolio. Further testing would be necessary to identify/establish the possibility of any relationships. The most interesting results among all Granger causality tests were found between gold prices and the seven energy portfolios. As table 5 shows, there were some significant relationships suggested by the results. The null hypothesis was rejected at 1% level for the biofuel portfolio, at 5% level for the coal and wind portfolios, and at 10% level for the natural gas portfolios. Unlike the Generalized Impulse Response results which showed no short-term relationships between gold prices and any of the portfolios, Granger causality tests suggest long-run relationships. Gold returns can improve the return forecasts for bio-fuel, coal, natural gas and wind portfolios.

In summary, with the exception of gold prices, Granger causality tests could not find much (if any) long-run relationships between the asset markets and the sub-sector energy portfolios tested in this study. From an investor's perspective, the results suggest that currency, oil, and S&P 500 markets could be used as diversification tools in a portfolio since there are no long-run effects of any of these asset markets on the energy stocks. However; the same cannot be said about gold. Investors need to understand that gold prices do have a long-run effect on most of the energy companies and, unlike the common perception among novice investors, and they should be careful when including gold in their portfolios.

6. Conclusions

In light of volatile energy prices, alternative sources of energy (i.e., renewable and "green" energy) have been gaining more traction. Increased interest from citizens and incentives from the governments helped create brand new sectors while revitalizing others. Due to its nature of being relatively new, however, those sectors have been minimally studied. The goal of this study is to understand some of the inner dynamics of the sub-sectors energy companies (both fossil-and alternative energy-related), in the light of some asset markets frequently studied in literature. The study makes an attempt in providing answers to questions like: Do these sub-sectors behave uniformly or do they differ in terms of their susceptibility to energy price shocks? What are the short- and long-run relationships between these sectors and the major asset markets?

Aside from servicing a gap in the literature, this study has significant information for professional investors. The Generalized Impulse Responses and Granger causality tests identify level-Granger causality between the asset markets and the sub-sector company portfolios. These tests are significant in allowing investors to see the reaction of one asset group to the other in the short run as well as long run. The results of this study confirmed some of the previously untested speculations while shedding some light on other very interesting phenomena. The generalized impulse response tests show the strongest responses to oil price shocks were given by companies related to other fossil fuels. Coal portfolio gave an initial response of 1.5% positive returns, and natural gas gave an initial response of 1.3% to a one standard deviation shock to the oil prices. The strongest response to oil price shocks from the non-fossil fuel group was by the solar portfolio; it gave a response of a 1.1% in returns. All of the impulse responses died off within two to three days.

Petroleum company portfolio, however, did not give any response to either currency or oil price shocks in the short-run. This could be due to the information efficiency (possibly strong-form) in that market, where investors trading petroleum stocks could have additional information related to short-run future oil and currency price shocks. This, in return, results in those company stock prices adjusting to shocks before they actually happen, thus not giving any response at the time of the shocks themselves. There were no short-term responses by any of the portfolios to gold price shocks. However; the long-term Granger causality tests revealed a long-run relationship between gold prices and most of the sub-sectors. Since there were no other long-run relationships found, the results suggest that all of the portfolios and asset markets tested can be used as diversification tools with the exception of gold.

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Appendix A

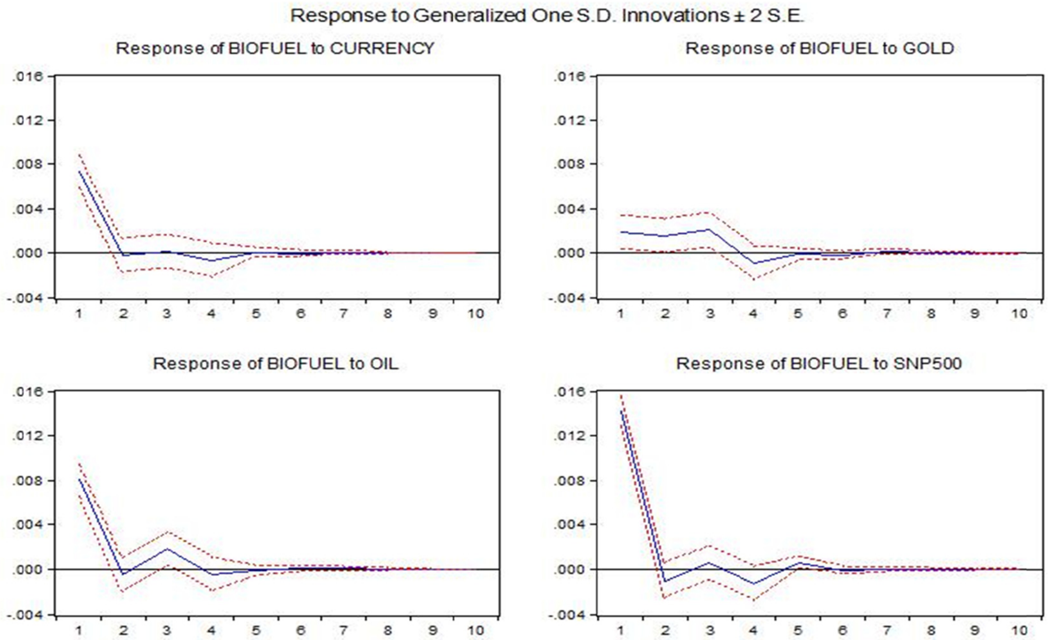

Figure A1. Impulse response–biofuel

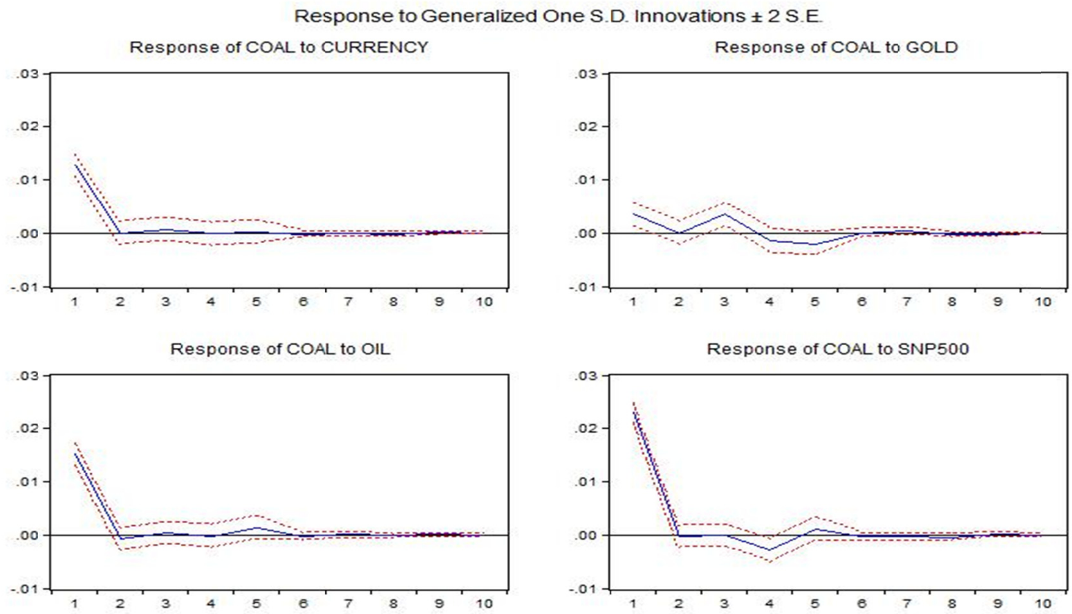

Figure A2. Impulse response–coal

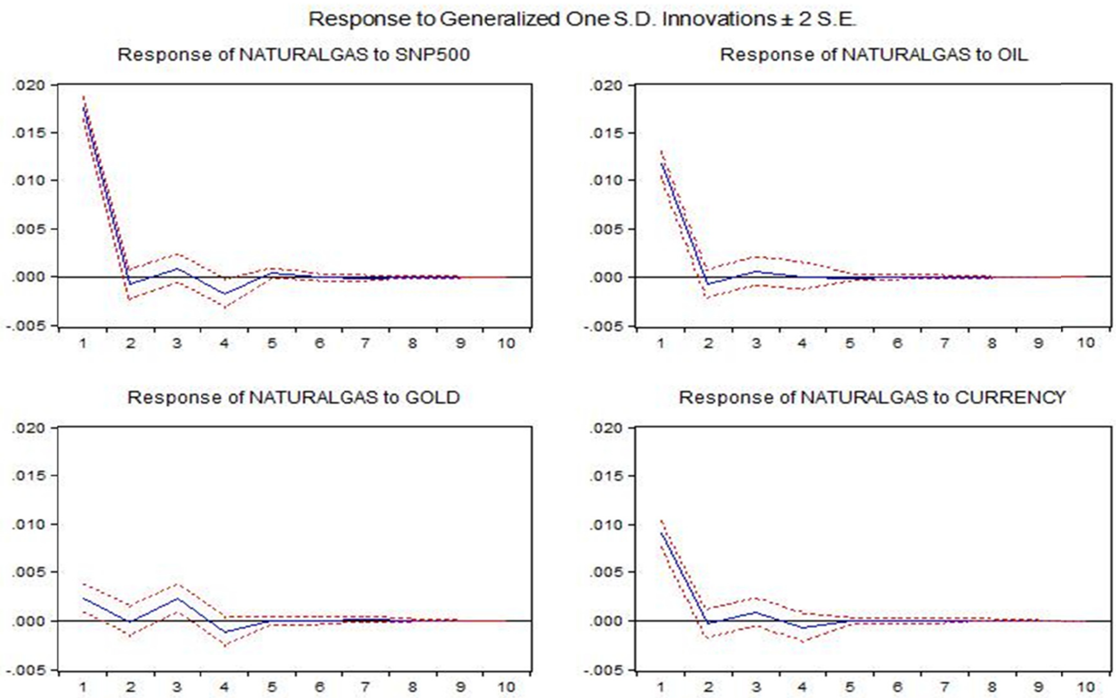

Figure A3. Impulse response–natural gas

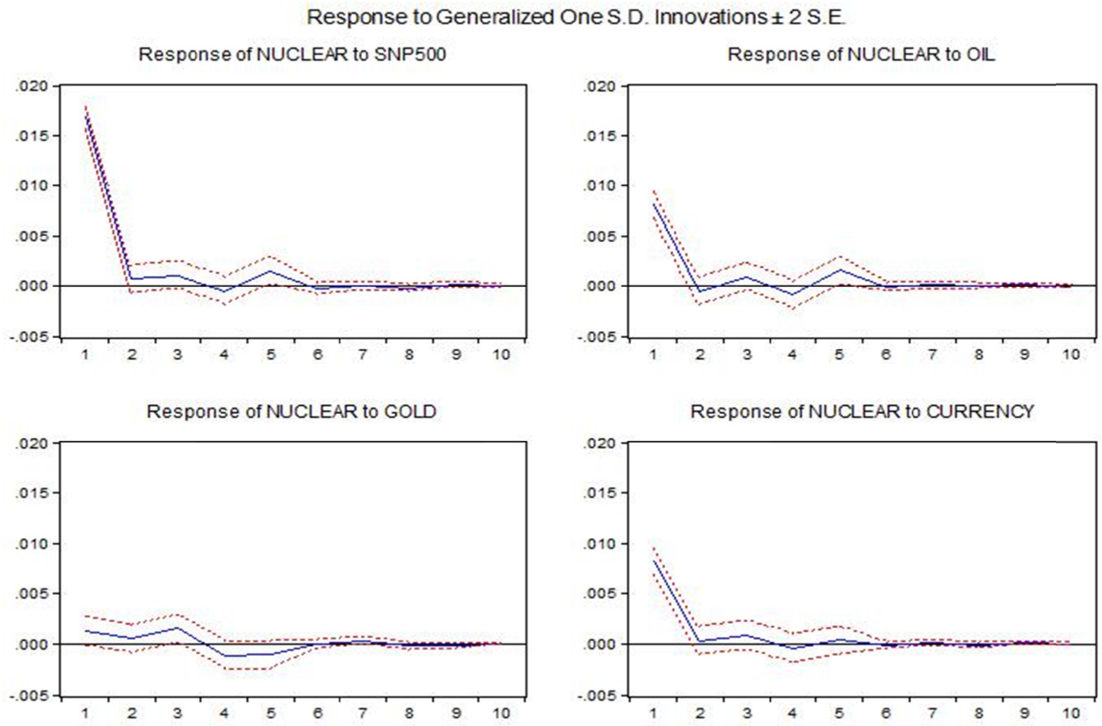

Figure A4. Impulse response–nuclear

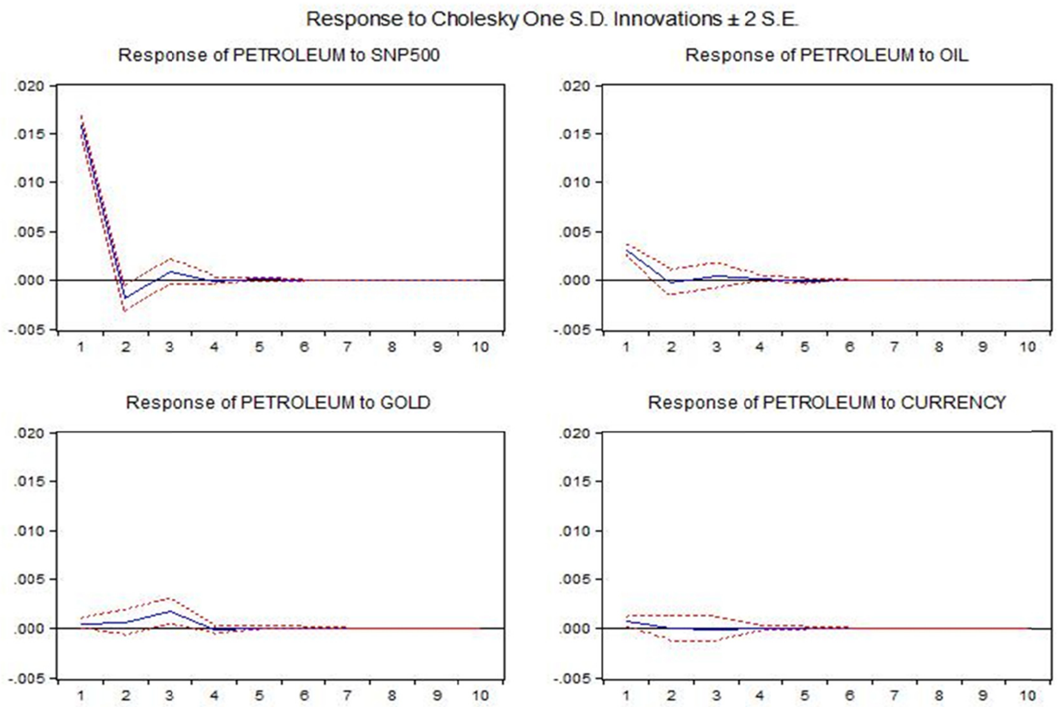

Figure A5. Impulse response–petroleum

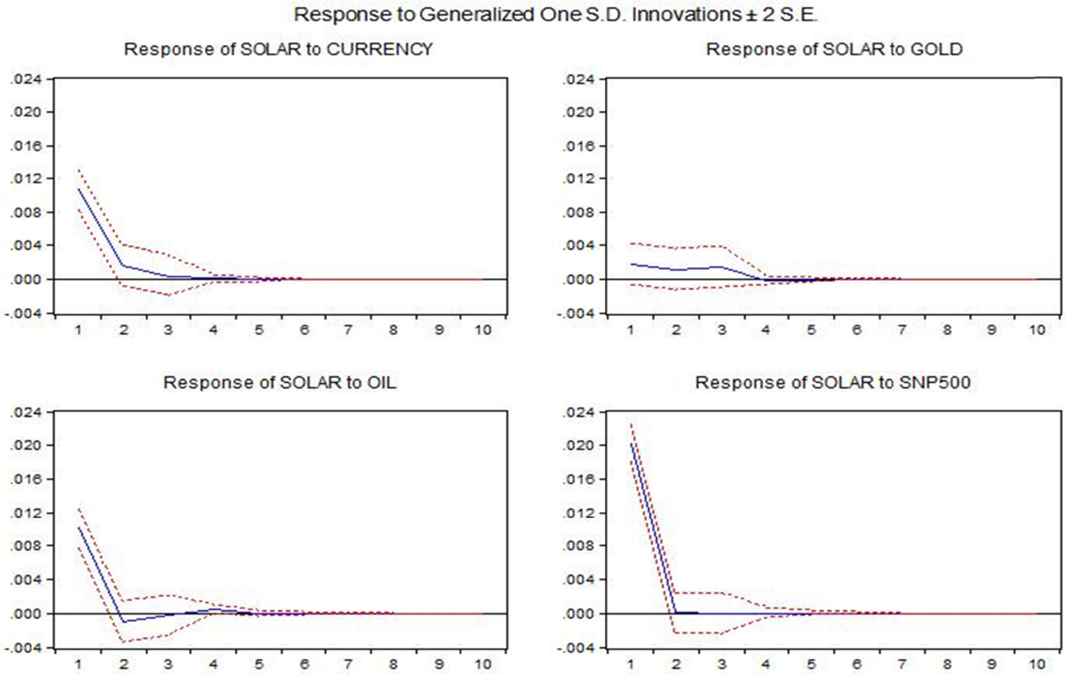

Figure A6. Impulse response–solar

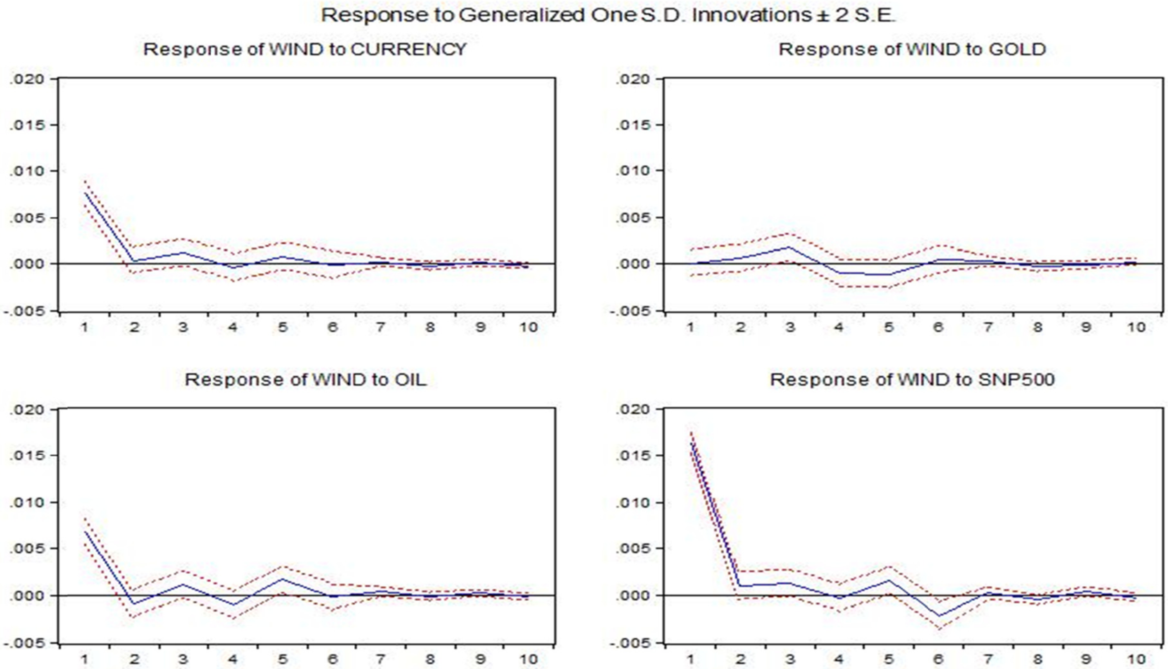

Figure A7. Impulse response–wind