CAUSALITY AND VOLATILITY SPILLOVER EFFECTS ON SUB-SECTOR ENERGY PORTFOLIOS

by

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ABSTRACT

CAUSALITY AND VOLATILITY SPILLOVER

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During a time of extensive crises related to energy sources, in particular fossil fuels, IPOs for alternative energy-related companies are a common occurrence. As new industries are created or old ones are revised, investors, who constantly are trying to update their portfolios for hedging their risk, face new challenges. The purpose of this study is to aid investors in market anticipation, forecasting, and portfolio diversification through shedding some light on the inner dynamics of the select asset markets *versus* sector-specific energy companies. Although energy companies related to fossil fuels such as oil, coal, and natural gas are previously studied, alternative energy companies have been minimally tested. This study analyzes the inner dynamics 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 asset markets commonly used in literature. The analysis includes Toda-Yamamato Granger Causality Tests, Generalized Impulse Responses and Volatility Spillover models.

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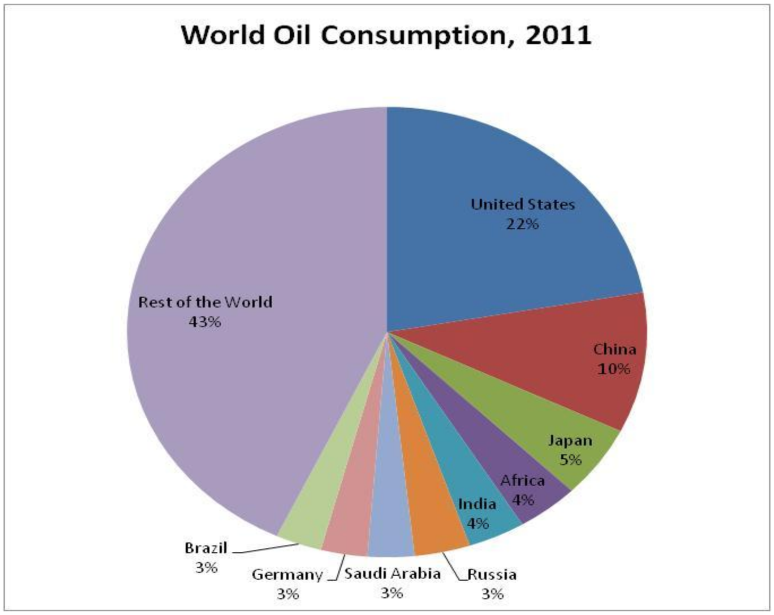
CHAPTER 1

INTRODUCTION

"…as long as I'm president, I will not walk away from the promise of clean energy."
President Barack Obama, 2011

Recent oil price fluctuations have made the impact of oil shocks on financial markets an interesting topic. Although is always been one of the driving factors for policy making processes, increased emphasis on decreasing the dependency on fossil fuels via concentrating on renewable/alternative energy sources, have driven the financial markets to include brand-new sectors as well as revitalize others; which had minimal impact in the past. 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).

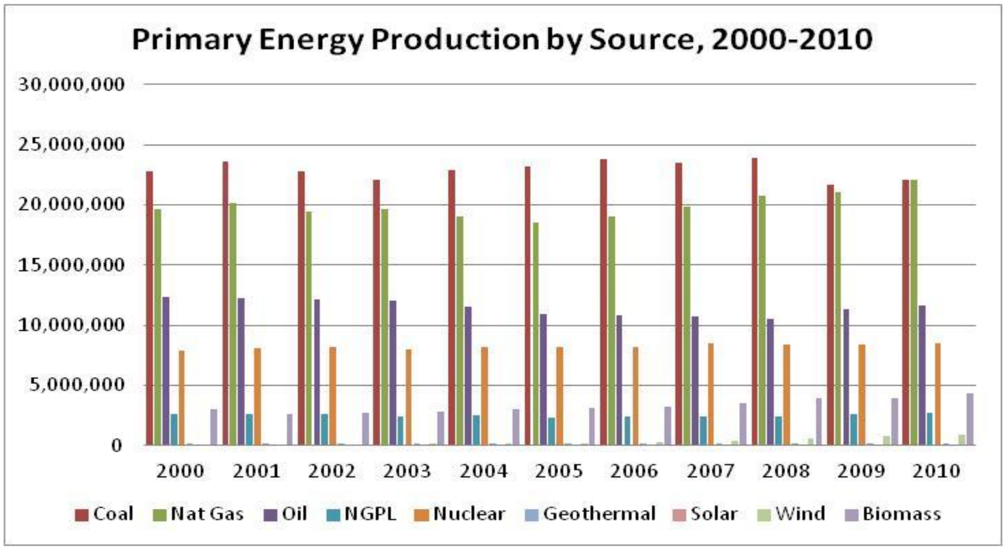


Source: www.eia.gov

Figure 1.1 World Oil Consumption in 2011 per Country

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 economy in general. Since stock markets reflect, to a large extent, how companies operating in an economy are doing in general, it is not a far leap to expect significant reactions from the equity markets to energy price shocks.

The energy market is dominated by the fossil fuel-related sources (oil, coal, and natural gas). The scarcity of these reserves, added to the unstable economic and political structure of nations with larger portion of those reserves, make the markets for those energy sources volatile.



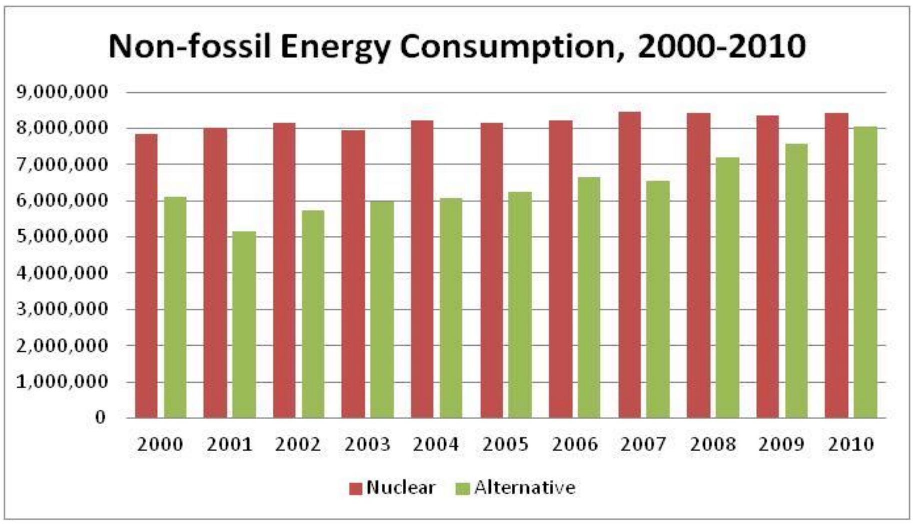
Source: www.eia.gov (In Billion Btu)

Figure 1.2 Primary Energy Production by Source from Year 2000 to 2010

Rocketing oil prices demand a higher level of attention towards alternative energy sources and research. In the short-run, the higher prices and difficulties associated with attaining these alternative sources will outweigh the benefits of energy independence and the decrease in pollution. No alternative energy source is yet a perfect substitute for oil due to limited research and the economics of scale for large production of fossil fuels. This, however, is normal and will change as more and more emphasis is given to alternative energy (Woloski, 2006).

In his State of the Union address in 2011, President Obama proposed a Clean Energy Standard (CES), whereby year 2035, 80 percent of our electricity would come from “clean” energy sources: renewable energy (e.g. wind, solar, biomass, and hydropower), nuclear power, natural gas, and “clean” coal.

It is a fact that consumption (therefore production) of alternative energy sources have increased significantly in the past few years.



Source: www.eia.gov (In Billion Btu)

Figure 1.3 Energy Consumption from Fossil-Fuel Alternatives

Energy commodities such as oil and natural gas provide diversification opportunities for investors, hedging opportunities for users of these hard assets and trading opportunities for speculators. Modern portfolio theory recommends investors to diversify their portfolio in order to reduce any unsystematic risk which is often done using different asset classes, as they are assumed to be not perfectly positively correlated. Commodities are becoming an ever important asset class, as the uncertainty in the general economy increases casting a doubtful shadow on the future of U.S. dollar. While, “old” (oil, natural gas, and coal) energy-related assets are still used fairly heavily, the “new” (green) energy-related assets are causing a large impact and speculation in the market, increasing the available asset classes and choices for the market participants (Gormus and Sarkar, 2012). While some studies suggest that futures on energy commodities do not provide an increased return to an efficient energy stock portfolio **(**Galvani and Plourde 2010), others analyze the green energy stocks and suggest that these companies have a superior performance which is not just explicable by their size, sector and style (Chia et al. 2009).

CHAPTER 2

MOTIVATION

Although it is an accepted notion that increasing oil prices are good for the alternative energy companies, empirical work related to the measurement of those relationships is very limited at best. As new companies for solar, wind, nuclear, and biofuel are created and IPOs for those companies are issued, investors try to create well-balanced portfolios, including these new sectors, while trying to minimize their risk. Portfolios consisting of stocks as well as commodity futures is a common practice; however, as these “alternatives” to well known commodities are created, it becomes that more important to understand the relationship between these commodity markets and sector-specific (including the newly created sectors) energy portfolios.

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 as well as other economies.

In terms of stock market returns, there are several important studies conducted which find a direct relationship (Ewing 2007, Sadorsky 1999 and 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) and the only one available, which came close to this study, was Henriques and Sadorsky's (2008) study. They used 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. Weekly data from 2001 and 2007 were used and they found that shocks to oil prices have a limited impact on the alternative energy ETF tested. Their conclusion was that alternative energy companies behave like high-technology companies and shocks to technology stocks impact the alternative energy companies more than oil price shocks do (Henriques and Sadorsky, 2008).

The study fits the literature on the impact of oil price changes on stock returns; however it distinguishes itself by including a comprehensive comparison of fossil fuel as well as alternative energy companies (as individual sub-sectors) and several of the well-known drivers in the market.

Unlike previous research that was done, this comprehensive study includes several different approaches towards understanding the inner-dynamics of the relationship between sub-sector energy companies such as oil, coal, natural gas, solar, wind, nuclear and biofuel, and the major drivers commonly used in literature such as oil prices, gold prices, exchange rates, and the stock market. Also this study employs a combination of methodologies such as VAR, Granger causality, and volatility spillover models for a complete understanding of the relationships possibly present between each of the variables tested.

Through VAR and Granger causality tests, this study identifies level-causality between the asset markets and the sub-sector company portfolios. This test is significant in that it allows investors to see the reaction of one asset group reacting to the other in the short run as well as long run. For example, impulse responses show how the returns of one market react (in terms of how long it takes to react, how long it takes to die-off as well as the magnitude of reactions) to a shock from another market. From a forecasting perspective, this information could prove significantly valuable. If there are no Granger causality relationships found, this could be interpreted as follows: the asset classes tested can be used at the same time in a portfolio as a diversification tool to minimize risk.

Through the volatility spillover studies, the causality in variance (or risk) can be observed. This information also is important for an investor. Through understanding how historical risk of one asset affects the other, investors can anticipate/forecast the riskiness of an asset through looking at another towards adjusting/minimizing the riskiness of their portfolio.

CHAPTER 3

LITERATURE REVIEW

3.1 Significance of Energy Commodity Markets

Clements and Krolzig (2002) investigated the relationship between oil prices and the business cycle asymmetries. Through a three-state Markov-switching model they found that although some downturns in activity that lead to recessions can be attributed to strong shifts in oil prices, the asymmetries detected in the business cycle in general are not explicable by oil prices.

Brown and Yucel (2008), using an error-correction model, tested different factors that affect the natural gas prices. In their model they tested several factors including crude oil prices, weather, seasonality, storage, and production disruptions. They found that one of the prominent drivers that influence natural gas prices was crude oil prices. Although the relationship between these two "substitutes" has complex short-term dynamics, it is observed to be stable in the long-run.

Soytas et al. (2009) examined the transmissions of information between oil prices (world), interest rates (Turkish), exchange rates, and gold and silver prices. They found no evidence of oil prices having any predictive power of precious metal prices, interest rates, or the exchange rates. Authors suggest that precious metals are considered to be a "safe haven" in developing countries especially when there is a threat of devaluation. 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 (also see articles under "Volatility Spillover Studies"). When testing for the relationship between energy futures prices and exchange rates, Sadorsky (2000) found that co-integration between futures prices for heating, crude oil, gasoline, and a trade-weighted index of exchange rates. Utilizing a VAR and Granger causality framework, he found that there exists a long-run equilibrium relationship between all variables tested. The study also suggests the existence of a transmission effect from exchange rate shocks to energy futures prices.

Li (2011) evaluated the relationship between NYMEX future prices for crude oil, unleaded gasoline, heating oil, and the U.S. trade-weighted exchange rate. Co-integration is detected among all variables but exchange rate. Granger causality tests and impulse response functions strengthen the conclusion that the U.S. exchange rate is not related to energy prices, and has faded across time.

Mohammadi (2011) examined the long-run relations and short-term dynamics among coal, natural gas, and crude oil. His conclusions for the post-1970 period were in line with the view that there is a locational difference between the pricing of energy commodities. He found that oil prices are determined globally, natural gas prices are determined regionally, and long-term contracts were the determining factor for coal prices.

Zikovic and Vlahinic-Dizdarevic utilized the Value at Risk (VAR) and Expected Shortfall (ES) methodologies on energy commodities (WTI oil, natural gas, and coal) with high confidence levels during the 2008 economic crisis. The authors found that, out of those commodities, natural gas is the most volatile and most prone to extreme movements. On the other hand, coal proved to be the least volatile, mainly because of domestic consumption.

Smistad and Pustylnick (2012) analyzed twelve oil and gas Western Canadian energy firms and their use of financial derivatives to manage price risk. Regardless of size, all firms utilized derivatives to hedge risk. Larger firms, on the other hand, tended to use more hedge accounting than small- or mid-size firms. In spite of the fact that all firms claim that they only use derivatives for hedging, most firms do speculate.

In an attempt to understand why a certain energy sub-sector flourishes faster than others, Jenner, Charf, Frankenberger, and Gabel (2012) tested the mechanics 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 *versus* others. In their study, they show that the existence of a solar energy association increases the probability of a state to adopt regulations (which benefit those companies), as well as solar radiation. Also they show the unemployment rate increases the odds of supporting one sector *versus* another. On the other hand, electricity market concentration decreases the probability of transition.

Ordonez, Sala, and Silva (2011) examined the impact of oil prices to labor market flows in the United States. They concluded that oil shocks are an important driving force of job market flows, the job-finding probability is the main transmission mechanism of the shocks, and they bring a new amplification mechanism for the labor market volatility, and hence should be considered as complementary of labor productivity.

3.2 Volatility Spillover Studies

Thimann et al. (2009) compiled a spillover study which tried to identify the shock *versus* reaction framework between emerging market economies (EME) and global equity markets. They identified fourteen different EMEs affecting the global markets by approximately 0.3%.

Their findings include heterogeneity regarding the responses to shocks, which is important to identify towards having a more robust study.

Bhar and Nikolava (2009) tested for negative conditional volatility spillovers from China and India to the Asia-Pacific region and then the world. The model employed with this study was a bi-variate EGARCH (General Autoregressive Conditional Heteroskedasticity) with time-varying correlations relating equity index returns from BRIC countries (Brazil, Russia, India, and China) both in terms of regional index returns and world index returns. Their findings suggest that there exists a negative volatility spillover from India to the Asia-Pacific region and they suggest the result is due to the low impact of the Asian financial crisis on India.

Steeley (2006) tested for volatility spillovers between bond and stock markets. The methodology he used was GARCH and the results identified spillover between stock and bond markets. This study is important in terms of capturing the volatility spillover effects through identifying and augmenting the conditional variance terms towards explaining the volatility transmission effects. The study shows that extended conditional variance specification of returns can be explained by past innovations and past conditional variance of those returns.

The relationship between exchange rates and stock returns, in a volatility spillover framework, was tested by Kanas (2000). Using a bi-variate EGARCH model, he tested the relationship for six developed countries: the United States, the United Kingdom, Canada, Japan, France, and Germany. The model Kanas used follows the Nelson (1991) bi-variate EGARCH approach:

$$\log h_{S,t} = \omega_S + \sum_{j=1}^{p} \beta_{S,i} \log h_{S,t-j} + \sum_{i=1}^{q} \alpha_{S,i} g(z_{S,t-i}) + \sum_{i=1}^{q} \eta_{E,i} g(z_{S,t-i})$$

$$\log h_{E,t} = \omega_S + \sum_{j=1}^{p} \beta_{E,i} \log h_{E,t-j} + \sum_{i=1}^{q} \alpha_{E,i} g(z_{E,t-i}) + \sum_{i=1}^{q} \eta_{S,i} g(z_{E,t-i})$$

where, the subscripts “E” and “S” represent foreign exchange and stock asset classes respectively. Kanas (2000) found significant evidence to suggest symmetric spillovers between asset classes for all of the countries tested. The results showed a unidirectional spillover where there was a spillover from stock returns to exchange rates, but not vice versa.

Chang et al. (2009) studied the volatility transmission mechanism between exchange rates and the stock market in Vietnam. They found asymmetric effects in spillovers using a bivariate GJR-GARCH model:

$$h_{S,t} = \omega_{S,0} + \delta_S h_{S,t-1} + \alpha_S \varepsilon_{S,t-1}^2 + \beta_S \varepsilon_{S,t-1}^2 I_{S,t-1} + \eta_S \varepsilon_{E,t-1}^2 I_{S,t-1}$$

$$h_{E,t} = \omega_{E,0} + \delta_E h_{E,t-1} + \alpha_E \varepsilon_{E,t-1}^2 + \beta_E \varepsilon_{E,t-1}^2 I_{E,t-1} + \eta_E \varepsilon_{S,t-1}^2 I_{E,t-1}$$

where, the subscript “S” stands for stocks and “E” stands for exchange rate. This study has similar strengths and limitations as Steeley (2006). The main limitation is the consideration of one country (in this case, Vietnam).

Harris and Pisedtasalasai (2006) found, in a UK-based sample, that there are spillover effects for both returns and volatility from large stocks to small stocks. There is also some period-specific evidence of volatility spillover from small to large stock portfolios. Simulations demonstrate that non-synchronous trading explains some of the spillover effects. Findings are consistent with prices of large stocks being affected with new information before prices of small stocks.

Pindyck and Rotemberg (1990) tested, using GARCH methodology, the co-movement of prices for oil and various commodities. They showed that there exists an excess co-movement that goes beyond the impact of common macroeconomic factors. However; Cashin et al. (1999) utilize the same commodities tested in Pindyck and Rotemberg (1990) and found no support for excess co-movement in the prices of unrelated commodities while finding support for related commodities.

Haigh and Holt (2002) utilized a multivariate GARCH methodology to model time variation in hedge ratios of crude oil, heating oil, and unleaded gasoline futures contracts. When considering volatility spillovers between markets, they found that there are significant reductions in uncertainty, even after accounting for trading costs.

3.3 Oil Shocks *versus* Stock Markets

Utilizing a multifactor market model, Sadorsky (2001), estimated the expected returns to Canadian oil and gas industry stock prices. The results included the strong impact of exchange rates, oil prices, and interest rates on the Canadian oil and gas industry. He also found that there is a positive relationship between oil prices and the returns of industries tested, where exchange rates had a negative effect. From a risk perspective, the Canadian oil and gas industry was found to be less risky than the rest of the market and a pro-cyclical relationship is apparent. Since investors try to find ways to hedge their risk, Sadorsky suggests that Canadian oil and gas stocks might not be the best hedging tool against inflation.

Sadorsky (1999) tested the oil prices and oil price volatility against stock returns. The method he employed was a VAR framework. The results indicated that after 1986, oil price movements had a larger contribution to forecast error variance in stock returns then interest rates. In other words, oil price shocks explain a larger portion of stock returns than it did in the past. Furthermore, oil price volatility is found to have an asymmetric effect on the economy.

Chiou, Lee, and Lin (2008) examined the relationship between oil prices and S&P 500 using traditional and threshold causality/co-integration testing. They found that an asymmetric uni-directional relationship exists between oil prices and the stock markets. Their findings are supported by the findings of Sadorsky (1999) which concludes the changes in oil prices affect economic activity but not the other way around.

Through a comprehensive study including the United States, Canada, England, and Japan, Jones and Gautam (1996) studied the stock markets using a standard cash flows/dividends valuation model. Based on quarterly data, Jones and Guatam tested the reaction of stock markets to oil shocks and tried to justify current and future changes in real cash flows or changes in expected returns. They concluded that a relationship between oil prices and stock market returns exists. However; when real cash flows and future industrial production were taken into account, the changes in Canadian and U.S. stock prices were largely explained. It was concluded that oil prices have a strong effect on the countries' real stock returns. Oil volatility and price shocks also have a significant effect on real stock returns in the U.S. market (Sadorsky, 1999).

When examining the United States and thirteen European countries, from an import/export point of view, Park and Ratti (2008) found that the stock markets for oil-importing countries were negatively impacted while the stock markets for oil-exporting countries were positively impacted by an oil price shock.

Using an extended market model, which this study also employs, Faff and Brailsford (1999) found that some industries' stock prices reacted differently to an oil shock in Australia. In their study they found that diverse resource industries were positively affected while industries such as paper and transportation reacted negatively to oil price shocks. Eryigit (2009) used a similar model to the one used by Faff and Brailsford (1999) and found that oil price increases have positive effects on some Turkish sub-sector indices while some indices were not affected.

Mothany (2011) investigated the relationship between oil price movements and stock returns in U.S. transportation companies. The author estimated oil price risk exposures at the firm and industry level by using the Fama-French-Carhart four-factor model. Overall, the study suggests that oil price exposure varies across firms and over time, mainly attributed to the cost structure of firms, their financial policies, diversification activities, and hedging strategies.

Henriques and Sadorsky's (2008) used a VAR approach to test oil price shocks against an alternative energy ETF as well as a high-technology company index. They used weekly data from 2001 and 2007 and found that shocks to oil prices have a limited impact on the alternative energy ETF tested. The conclusion was that alternative energy companies behave like high-technology companies and shocks to technology stocks impact the alternative energy companies more than oil price shocks do.

CHAPTER 4

DATA

The data used in this study consist of several value-weighted sub-sector energy portfolios as well as test variables commonly used in literature. The author 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 daily re-balanced, value-weighted portfolios were that each company in the portfolio must have at least 50% of its revenue from the sub-sector it is listed under. The test variables (from now on "asset markets") used are daily oil price returns, daily gold price returns, daily USD/EUR exchange rate returns, and S&P500 index returns.

In the literature, ten to twelve companies seem to be the accepted minimum for a robust index, so this restriction was followed. This; however, did limit the date span since most of the alternative energy companies were created relatively recently. In other words, although there have been petroleum companies around for many years, since specialized wind companies are a relatively new occurrence, that became the constraint for all other portfolios. The data consists of daily values for three years spanning from January 2009 to December 2011. In literature, oil prices, gold prices and exchange rates are used (most frequently one at a time) as independent variables, so all of those including S&P 500 index are included to control for the 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. Historical USD/EUR exchange rates were obtained from www.oanda.com and the historical daily closing prices of S&P 500 Index were obtained from www.yahoofinance.co .

Each portfolio is value weighted and rebalanced daily with a base price of 100. The daily log returns of each asset were calculated and tested both at level (for VAR and Granger Causality estimations) and as first-differenced series (to establish stability condition for the GARCH models). Below are the descriptive statistics of data used:

Table 4.1 Descriptive Statistics: Company Size in Each Index

	Company	Mean	Median	St. Dev.
BIOFUEL	11	2,018,519	136,128	5,680,153
COAL	14	4,997,700	2,543,518	7,214,104
NAT GAS	16	16,520,311	6,417,573	32,368,136
NUCLEAR	32	10,709,501	2,347,132	30,484,224
PETROLEUM	41	24,801,892	3,377,603	61,348,177
SOLAR	17	1,067,157	218,020	2,590,698
WIND	19	14,001,929	1,937,610	38,407,585
Total	160	--	--	--

Table 4.2 Descriptive Statistics: Level Index Prices

	BIOFUEL	COAL	NAT GAS	NUCLEAR	PETROLEUM	SOLAR	WIND	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

When size of the companies in each portfolio is analyzed, one can see that the largest size of portfolios in value (on average) are natural gas, petroleum, and wind. However; when the median is examined, one can see that, in fact, those portfolios are skewed by large companies.

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. Below is the descriptive statistics of level-log returns (which are used in the tests of this study):

Table 4.3 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
Maximum	0.0741	0.4690	0.2124	0.1962	0.0720	0.1601	0.1262	0.1837	0.1728	0.0462	0.0684
Minimum	-0.1331	-0.2859	-0.2121	-0.1902	-0.0827	-0.1728	-0.0863	-0.2068	-0.1742	-0.0242	-0.0582
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
Sum	0.1690	0.0981	0.0566	0.0540	0.2646	-1.2064	0.2009	0.0391	0.0265	-0.0411	0.5917
Sum Sq. Dev.	0.3021	3.6910	1.8412	1.4977	0.2239	0.7443	0.2765	1.0743	0.9618	0.0409	0.1143
Observations	725	725	725	725	725	725	725	725	725	725	725

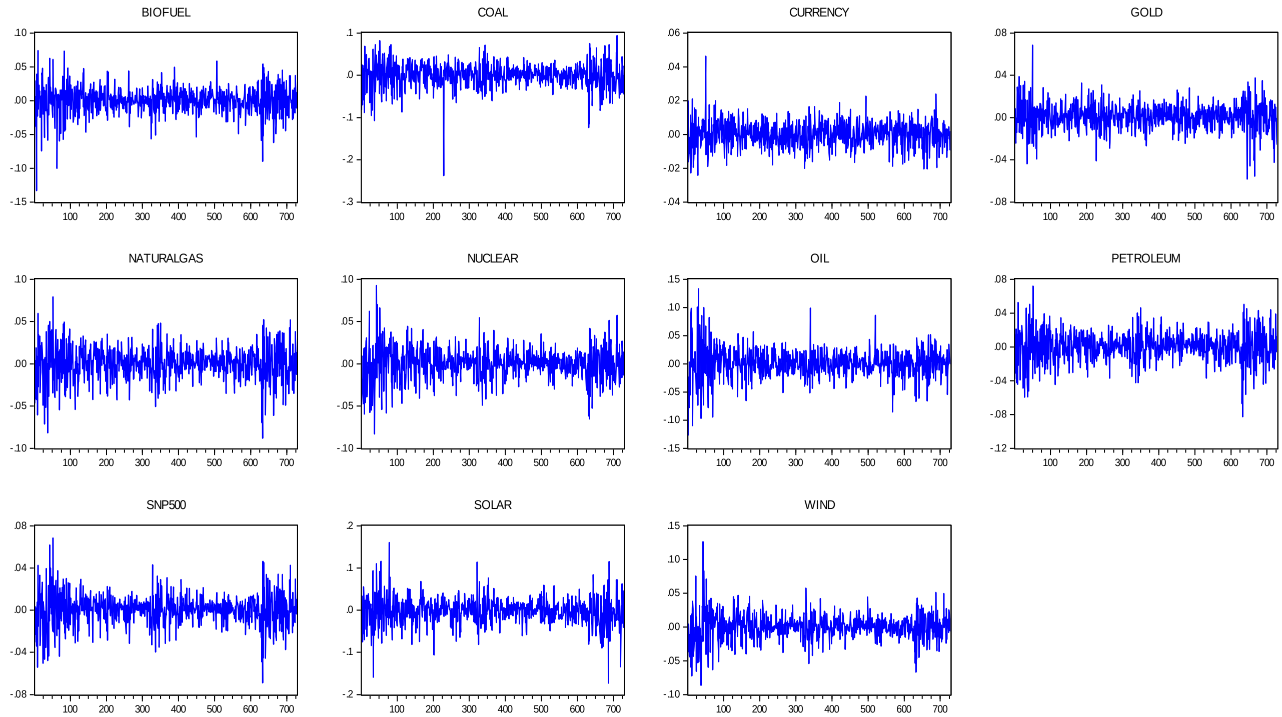


Figure 4.1 Histograms of All Data

Table 4.4 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	

CHAPTER 5

METHODOLOGY

To understand the long-run relationship between the variables, the researcher followed the Toda-Yamamoto procedure (Toda and 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. Using some information criteria, the optimum lag length (k) is defined. From the augmented VAR procedure (k+d) perspective, if the common assumptions are satisfied, then a Wald test constitutes a long-run causality. This is achieved through testing the joint significance of the first k lags of each variable. The distribution followed by the Wald test 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 one variable which might respond to innovations to 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:

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

Where g_t is an *m* x 1 vector of endogenous variables jointly determined, ϕ are m x m matrices of coefficients to be estimated, A is a vector of constants, *t* is linear time trend, *p* is the optimal lag length, and ε_t is an *m* x 1vector well-behaved disturbances with covariance $\Sigma = \sigma_{ij}$. The term $(S_n\Sigma e_j)(\sigma_{ij})^{-1}$ represents the generalized impulse response of g_{t+n} with respect to a unit shock to jth variable at time t. Note that $S_n = \boldsymbol{\phi_1} S_{n-1} + \boldsymbol{\phi_2} S_{n-2+\ldots} \boldsymbol{\phi_p} S_{n-p,}$ 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.

The traditional approaches are not used as commonly in literature anymore, due to its 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.

In order to determine the volatility spillover of biofuel, coal, natural gas, nuclear, petroleum, solar, and wind, portfolios in respect to each other as well as common asset markets, this study uses the causality in variance test developed by Hafner and Herwartz (2006). In literature, it is common to see the causality in variance tests developed by Cheung and Ng (1996) and Hong (2001)--especially for commodity-related estimations. Their test is based on cross-correlation functions (CCF) of standardized residuals which are obtained from univariate GARCH models. However; according to Hafner and Herwartz (2006), the tests are likely to suffer from oversizing effects. This is especially apparent when the samples are small or medium and the volatility processes are leptokurtic. Also, when Cheung and Ng's procedures are used, the CCF-based causality in variance testing approach is affected by the orders of leads and lags. This sensitivity of the robustness of the findings puts this into question. The test developed by Hafner and Herwartz (2006) is based on a Lagrange Multiplier principle. This principle avoids the problems faced by the Cheung and Ng's methodology. Also, in their paper, Hafner and Herwartz used Monte Carlo simulations to test the LM approach. Their findings indicate that their approach is stronger in terms of robustness when leptokurtic innovations in small samples are considered.

Estimation of univariate GARCH models are necessary for the Hafner and Herwartz (2006) approach of testing for causality in variance. The model below describes the null hypothesis of non-causality in variance between the two return series:

$$H_0 : Var\left(\varepsilon_{it} \middle| F_{t-1}^{(j)}\right) = Var\left(\varepsilon_{it} \middle| F_{t-1}\right) \qquad j = 1,\ldots,N,\ i \neq j \tag{q}$$

where $F_t^{(j)} = F_t \setminus \sigma(\varepsilon_{j\tau}, \tau \leq t)$ and ε_{it} is the residuals from GARCH model. The following model is considered to test for the null hypothesis.

$$\varepsilon_{it} = \xi_{it} \sqrt{\sigma_{it}^2 g_t}, \qquad g_{it} = 1 + z'_{jt}\pi, \quad z_{jt} = \left(\varepsilon_{t-1}^2, \sigma_{t-1}^2\right)' \tag{f}$$

where conditional variance $\sigma_{it}^2 = \omega_i + \alpha_i \varepsilon_{it-1}^2 + \beta_i \sigma_{it-1}^2$ and ξ_{it} denotes the standardized residuals of GARCH model**.** In equation (f), the sufficient condition for equation (q) is $\pi = 0$ which ensures that the null hypothesis of non-causality in variance $H_0 : \pi = 0$ is tested against the alternative hypothesis $H_1 : \pi \neq 0$. The score of the Gaussian log-likelihood function of ε_{it} is given by $x_{it}\left(\xi_{it-1}^2\right)/2$ where the derivatives $x_{it} = \sigma_{it}^{-2}(\partial \sigma_{it}^2 / \partial \theta_i)$ that $\theta_i = (\omega_i, \alpha_i, \beta_i)'$. Hafner and Herwartz (2006) give the following LM test in order to determine the volatility transmission between the series:

$$\lambda_{LM} = \frac{1}{4T}\left(\sum_{t=1}^{T}(\xi_{it}^2 - 1)z'_{jt}\right)V(\theta_i)^{-1}\left(\sum_{t=1}^{T}(\xi_{it}^2 - 1)z_{jt}\right) \tag{z}$$

where

$$V(\theta_i) = \frac{\kappa}{4T}\left(\sum_{t=1}^{T} z_{jt} z'_{jt} - \sum_{t=1}^{T} z_{jt} x'_{it}\left(\sum_{t=1}^{T} x_{it} x'_{it}\right)^{-1} \sum_{t=1}^{T} x_{it} z'_{jt}\right), \quad \kappa = \frac{1}{T}\sum_{t=1}^{T}(\xi_{it}^2 - 1)^2$$

Misspecification indicators in z_{jt} will be the determinants of the distribution of the test statistic (asymptotic) in equation (z). Since there are two misspecification indicators in λ_{LM}, chi-square distribution with two degrees of freedom is the best fitting distribution for this type of model.

CHAPTER 6

RESULTS

Table 6.1 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*

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

The data used in the studies were not all stationary. Although, the methodology utilized for the VAR models as well as causality models did not require them to be, the volatility spillover models would have been biased if nonstationary data were utilized. While the researcher used the level-returns for the VAR and causality studies, the GARCH models utilized differenced series. Dickey-Fuller tests show that differenced series are stationary with at least 10% significance-level; while most are significant at 1% level. As table 6.1 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.

Table 6.2   Breusch-Godfrey Serial Correlation LM Test

Dependant	F- Statistic	Probability F	Obs*R Squared	Probability C
Biofuel	0.1843	0.8317	0.3777	0.8279
Coal	2.2983	0.1012	4.7166	0.0946
Natural Gas	1.7191	0.1800	3.5088	0.1730
Nuclear	0.6290	0.5334	1.2971	0.5228
Petroleum	3.0078	0.0500	6.0742	0.0480
Solar	2.6759	0.0695	5.4088	0.0669
Wind	1.3255	0.2663	2.7473	0.2532

Table 6.3 Heteroskedasticity--White Test

Dependant	F- Statistic	Probability F	Obs*R Squared	Probability C
Biofuel	4.0214	0.0000	347.7355	0.0000
Coal	1.0731	0.2607	241.5463	0.2875
Natural Gas	3.2236	0.0000	308.0613	0.0000
Nuclear	4.0867	0.0000	474.9104	0.0000
Petroleum	3.7655	0.0000	196.4030	0.0000
Solar	2.1889	0.0000	128.7548	0.0000
Wind	6.4432	0.0000	620.6238	0.0000

In order to test for serial correlation and heteroskedasticity, Breusch-Godfrey and White tests were employed, respectively. With the Breusch-Godfrey test, the null hypothesis is that there is no serial correlation. As table 6.2 shows; with all series except petroleum, one cannot reject that there is no serial correlation within the series tested.

Table 6.3 shows the heteroskedasticity test results. The null hypothesis with this test is that there is no heteroskedasticity. All series except coal were found to show a heteroskedasticity problem. Through White Coefficient Covariance Matrix, the standard errors were adjusted to make the series suitable for testing for the Toda-Yamamoto methodology.

6.1 Vector Autoregressions

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 below show the results of these tests. Each graph demonstrates how a series reacts to a 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 s.d. 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 duration of the response before it dies off.

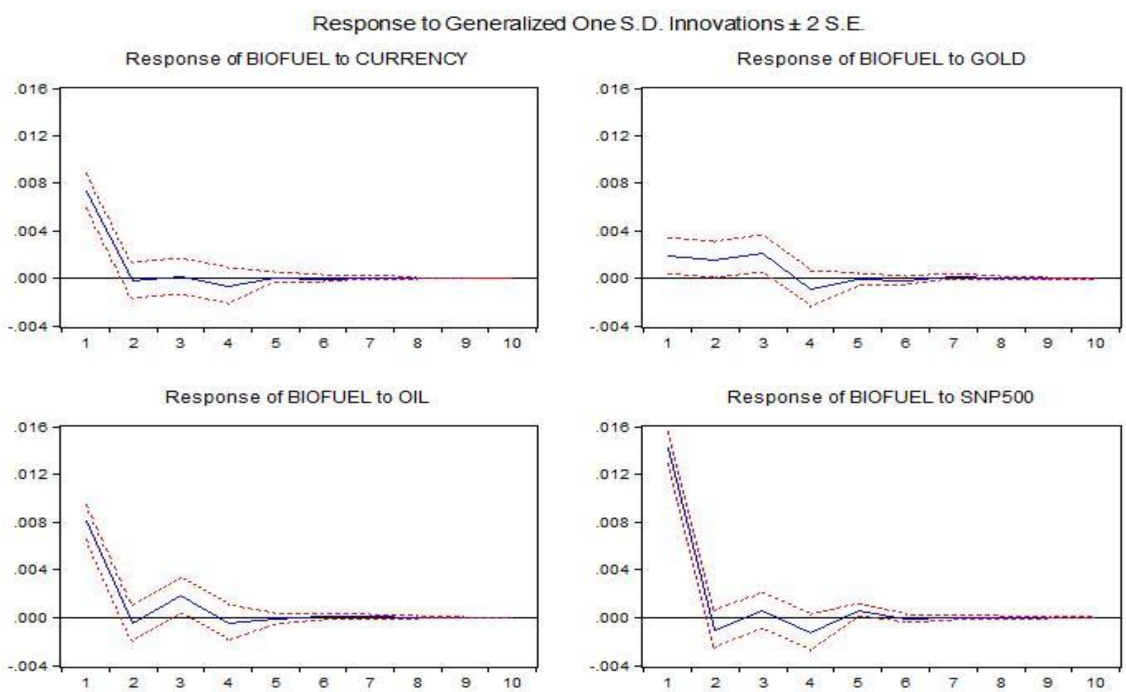


Figure 6.1 Impulse Response--Biofuel

In figure 6.1 one 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.

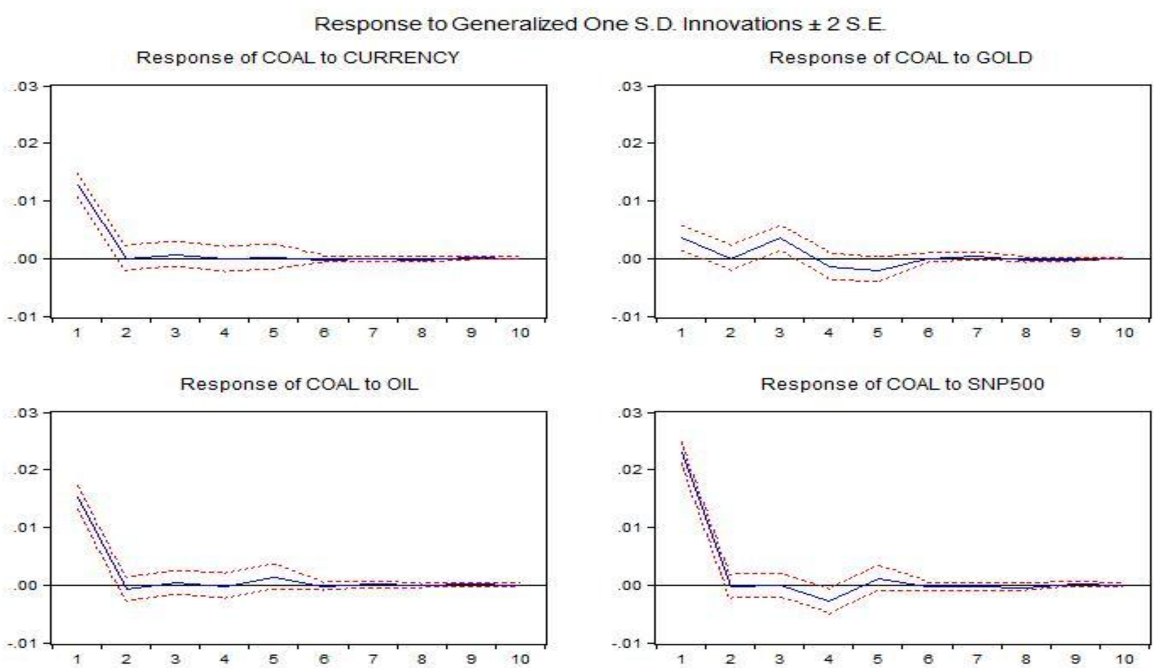


Figure 6.2 Impulse Response--Coal

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 6.2 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.

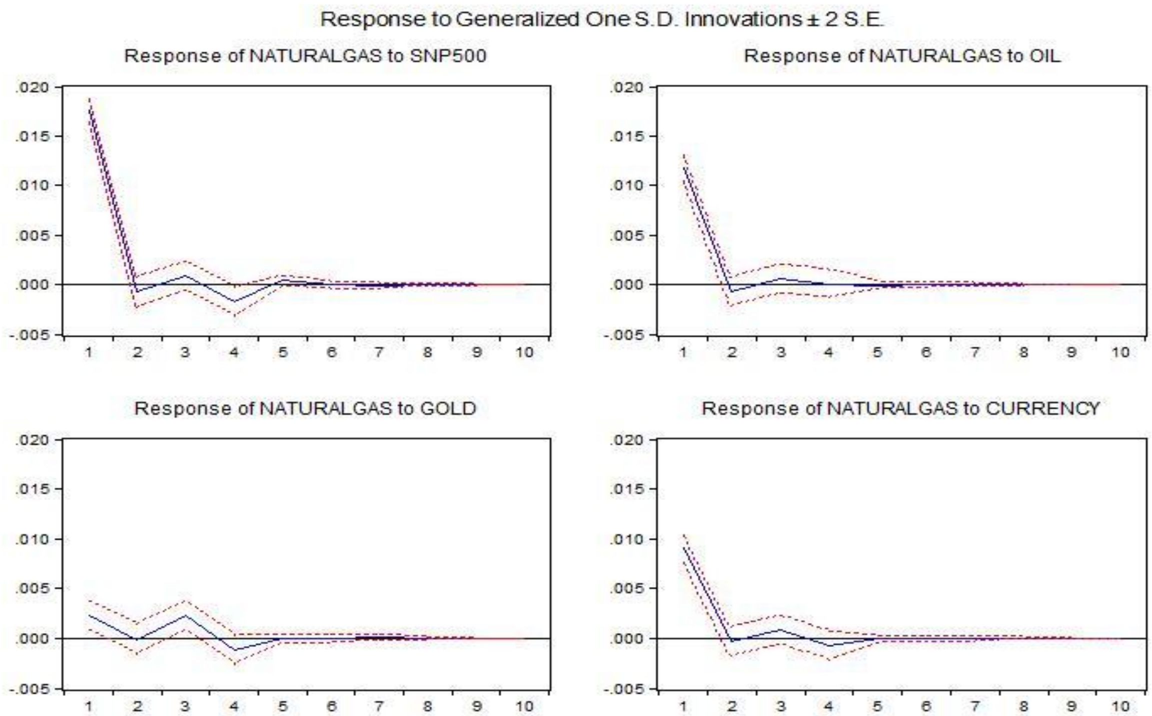


Figure 6.3 Impulse Response--Natural Gas

When the natural gas portfolio is analyzed, one can see that the high positive relationship with S&P 500 is still apparent. As figure 6.3 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 6.4 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%.

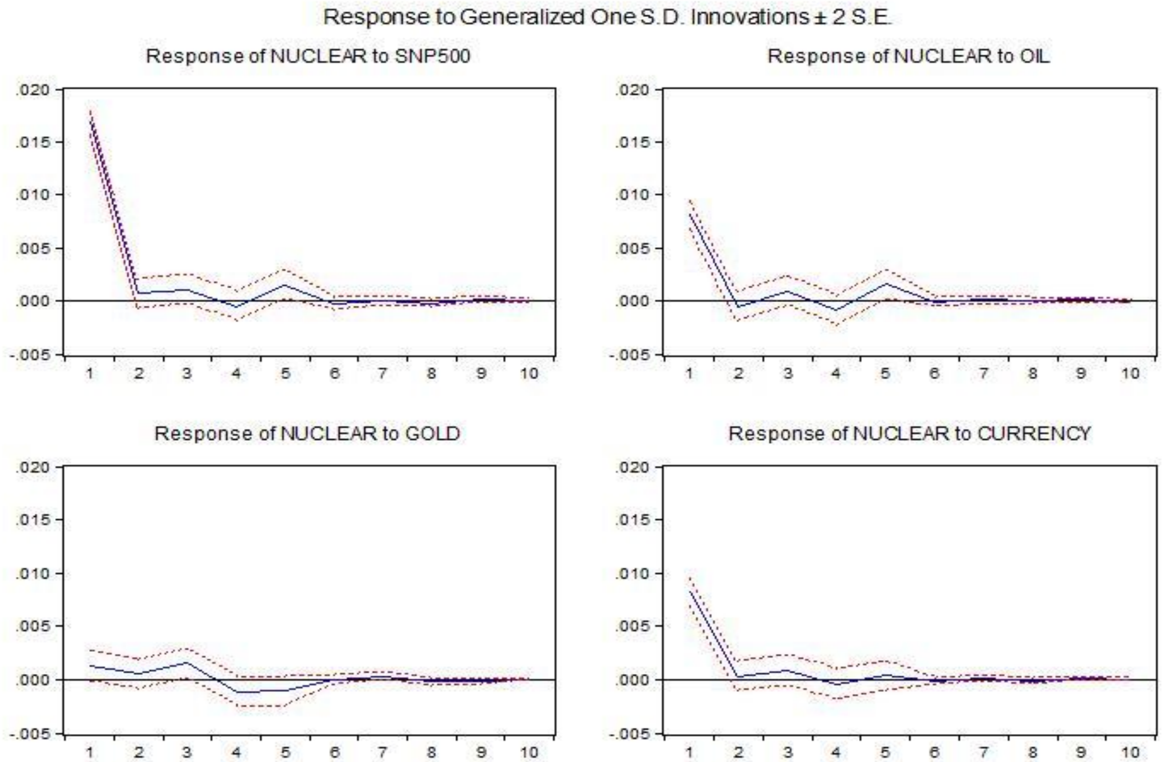


Figure 6.4 Impulse Response--Nuclear

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 returns. 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 6.5) 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.

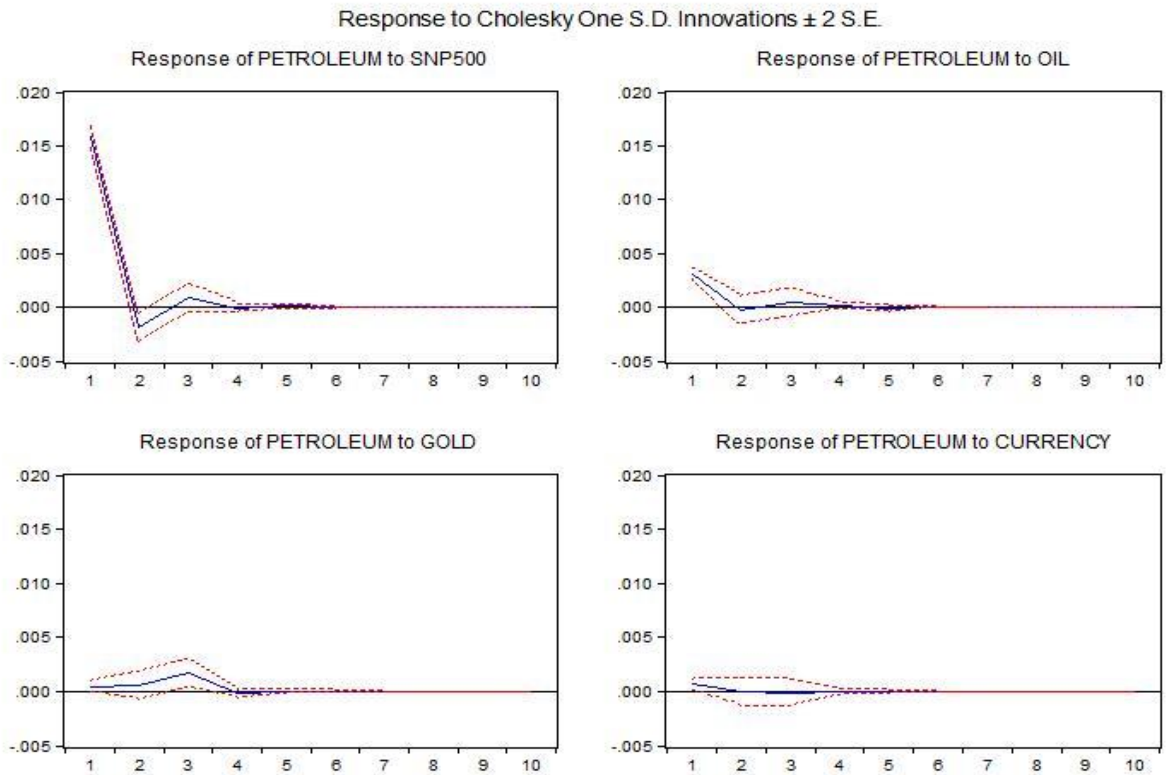


Figure 6.5 Impulse Response--Petroleum

Figure 6.5 shows the responses of the solar stock portfolio to the asset markets tested. 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.

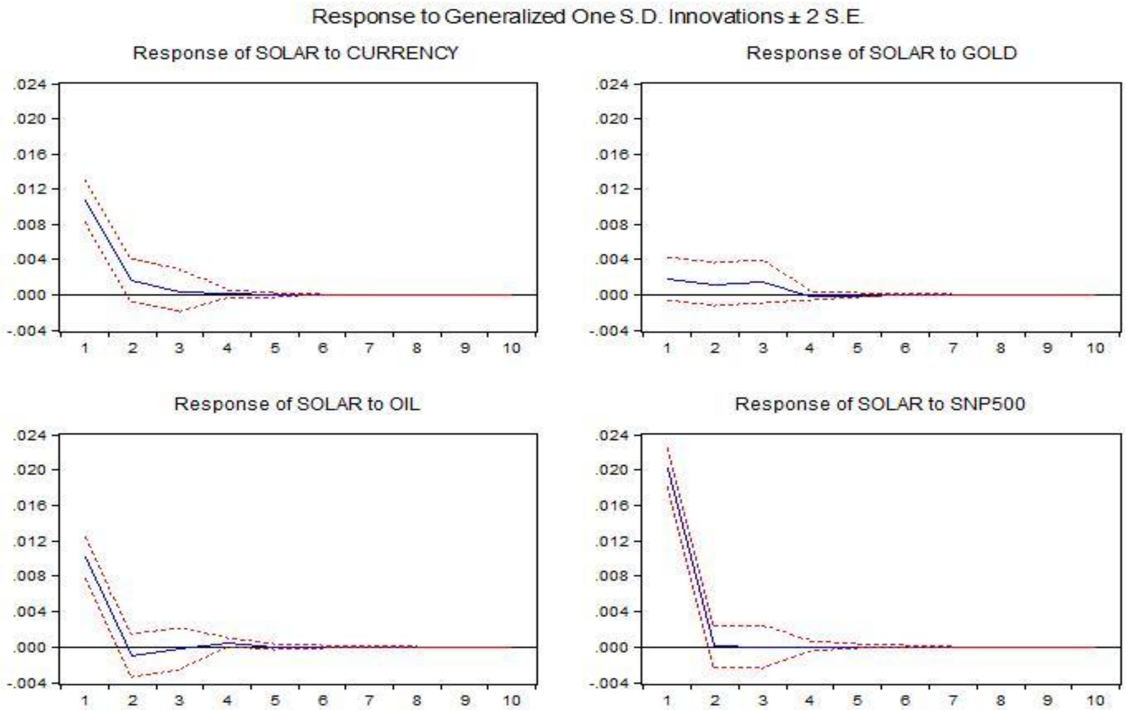


Figure 6.6 Impulse Response--Solar

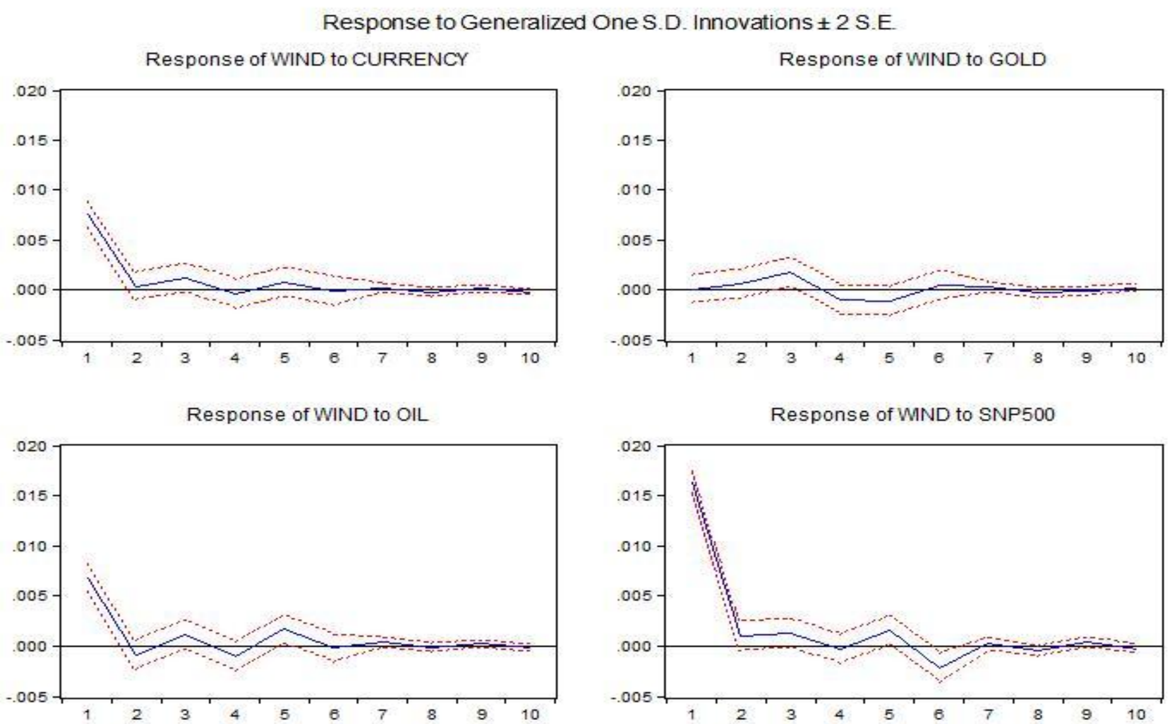


Figure 6.7 Impulse Response--Wind

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.

In summary, 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.

6.2 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). Figures 6.8 through 6.18 illustrate these results.

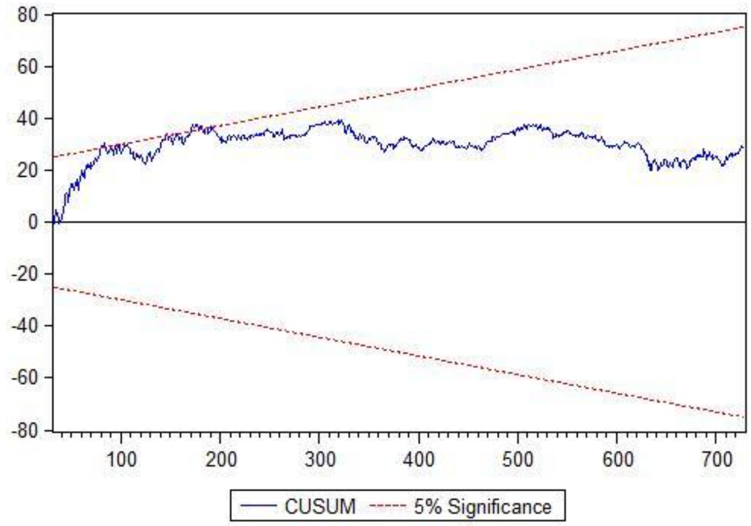


Figure 6.8 CUSUM Test--Wind

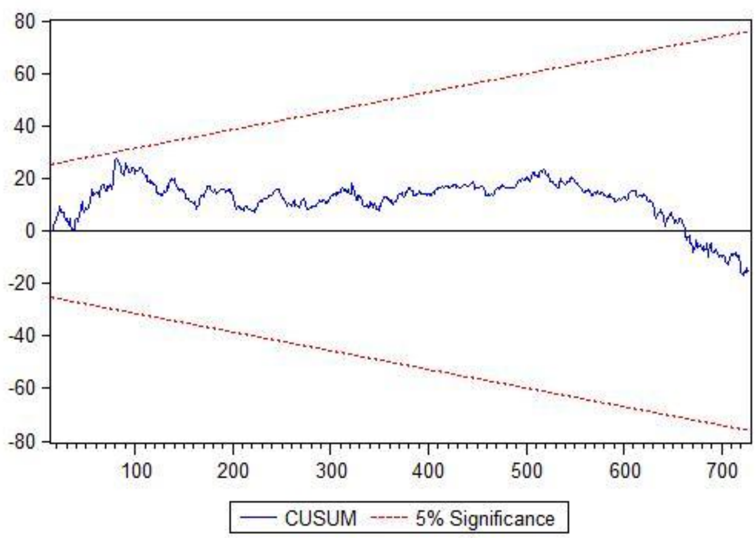


Figure 6.9 CUSUM Test--Solar

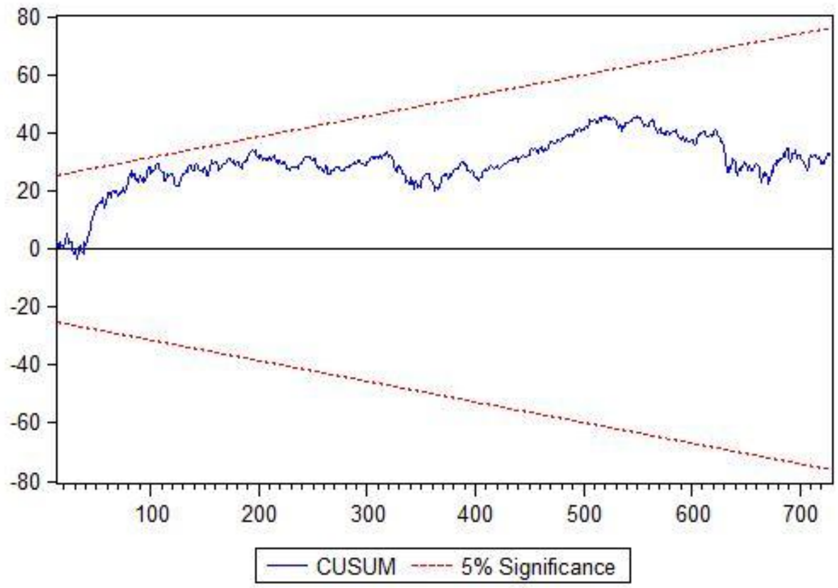


Figure 6.10 CUSUM Test--Petroleum

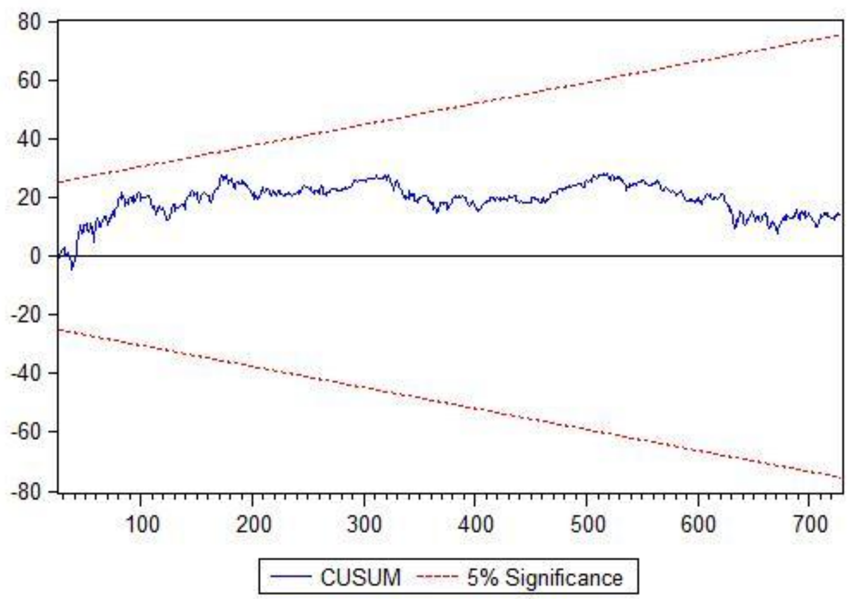


Figure 6.11 CUSUM Test—Nuclear

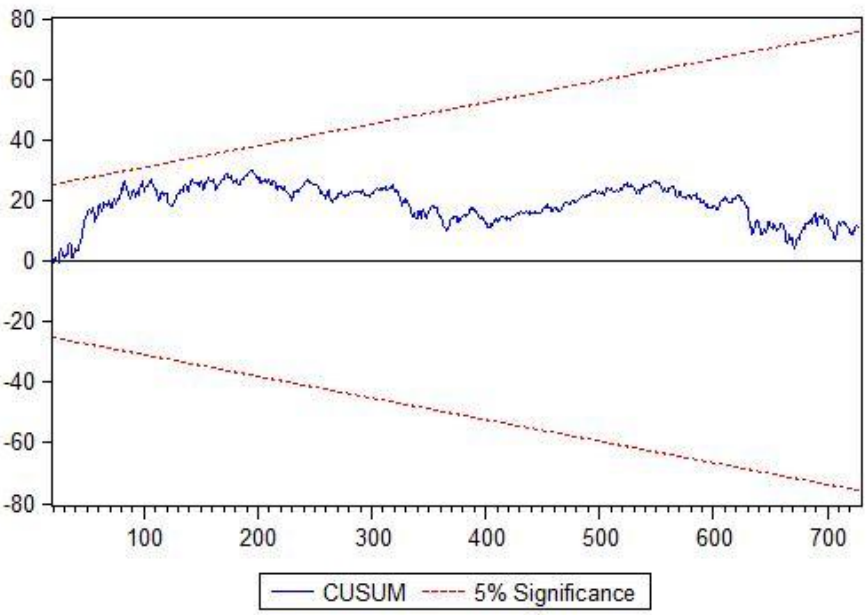


Figure 6.12 CUSUM Test--Natural Gas

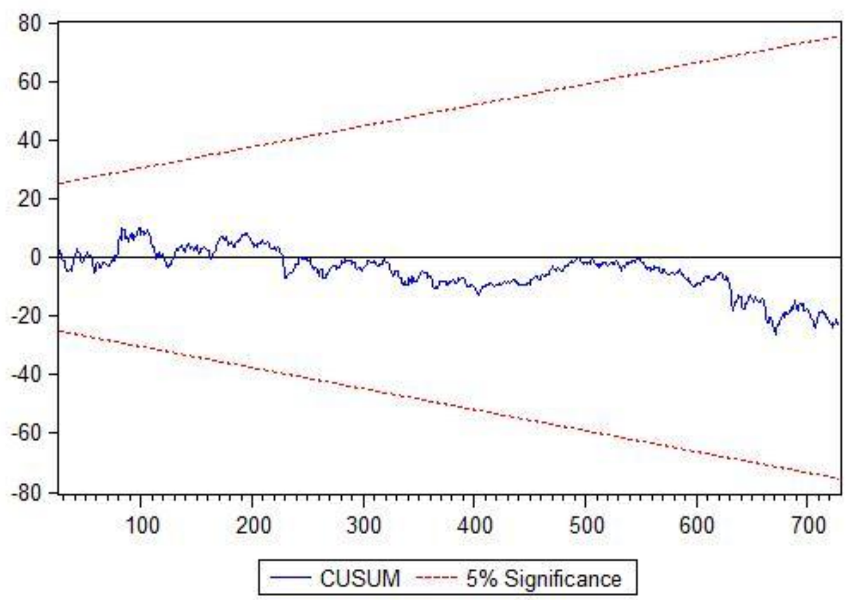


Figure 6.13 CUSUM Test--Coal

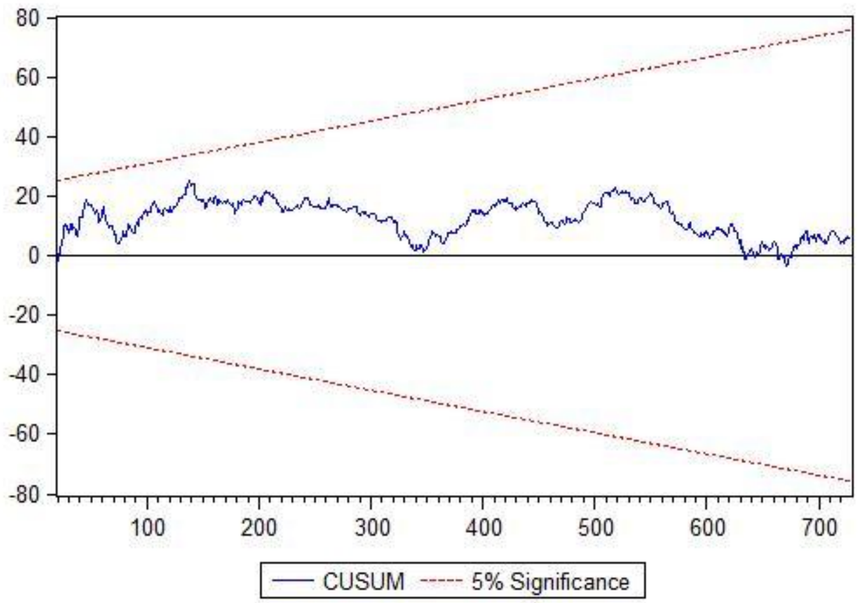


Figure 6.14 CUSUM Test--Biofuel

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 possible existence of a long-run Granger causality between the variables tested.

Table 6.4 shows the results of Wald tests modeling a unidirectional Granger causality from currency to the seven sub-sector energy portfolios. For consistency and accuracy, the results were evaluated using both F and Chi-square distributions. As the results show, it cannot be rejected that there is no long-run Granger causality between any of the pairs. In other words, there is no significant evidence to support the currency prices having any long-run effects on the portfolios tested.

Table 6.4 Granger Causality, Wald Test--Currency

	F- Statistic	Probability F	Chi-square	Probability C
Biofuel	0.7175	0.4883	1.4351	0.4879
Coal	0.4324	0.7298	1.2974	0.7297
Natural Gas	0.0004	0.9996	0.0008	0.9996
Nuclear	0.0609	0.9803	0.1828	0.9803
Petroleum	0.0014	0.9700	0.0014	0.9700
Solar	2.2502	0.1340	2.2502	0.1336
Wind	0.0732	0.9903	0.2926	0.9903

A similar picture emerges when Wald tests are conducted using the Oil prices. As table 6.5 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 6.5 Granger Causality, Wald Test--Oil

	F- Statistic	Probability F	Chi-square	Probability C
Biofuel	1.3855	0.2509	2.7710	0.2502
Coal	0.5125	0.6738	1.5376	0.6736
Natural Gas	0.3954	0.6735	0.7909	0.6734
Nuclear	0.5700	0.6349	0.7100	0.6347
Petroleum	0.3476	0.5556	0.3476	0.5554
Solar	1.4979	0.2214	1.4979	0.2210
Wind	1.3507	0.2496	5.4030	0.2484

Table 6.6 shows the results for Wald tests between S&P 500 and the energy company portfolios. 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. Under both the Chi-square distribution and the F-distribution, the results show a rejection at 10% level between S&P 500 and the petroleum

portfolio. It is, however, difficult to derive any conclusions from this result since under neither of the distributions, rejection is not achieved under for any other portfolio. Further testing would be necessary to identify/establish the possibility of any relationships.

Table 6.6 Granger Causality, Wald Test--S&P 500

	F- Statistic	Probability F	Chi-square	Probability C
Biofuel	1.0978	0.3342	2.1956	0.3336
Coal	1.4969	0.2141	4.4908	0.2131
Natural Gas	0.5363	0.5851	1.0727	0.5849
Nuclear	0.2546	0.8581	0.7638	0.8581
Petroleum	2.9165	0.0881	2.9165	0.0877
Solar	0.3712	0.5425	0.3712	0.5423
Wind	0.7403	0.5646	2.9615	0.5643

The most interesting results among all Granger causality tests were found between gold prices and the seven energy portfolios. As table 6.7 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.

Table 6.7 Granger Causality, Wald Test--Gold

	F- Statistic	Probability F	Chi-square	Probability C
Biofuel	4.8525	0.0081	9.7051	0.0078
Coal	2.8077	0.0388	8.4231	0.0380
Natural Gas	2.4501	0.0870	4.9002	0.0863
Nuclear	1.4501	0.2270	4.3502	0.2260
Petroleum	0.4804	0.4885	0.4804	0.4882
Solar	0.5130	0.4741	0.5130	0.4738
Wind	2.7884	0.0257	11.1536	0.0249

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.

6.3 Volatility Spillover

In the third part of this study, the possibility of any risk spillovers among the energy portfolios and the asset markets was tested. As mentioned in the methodology section, this study utilizes the Hafner and Herwartz (2006) approach of causality in variance tests. The tests utilize Lagrange multiplier principles employing univariate GARCH models.

The results of the GARCH tests can be found from table 6.8 through table 6.18. The model below refers to those tests:

$$\sigma_{it}^2 = \omega_i + \alpha_i \varepsilon_{it-1}^2 + \beta_i \sigma_{it-1}^2 \tag{1}$$

A quick check of the GARCH(1,1) estimated coefficients reveals that the stability requirements $\omega > 0, 0 \le \alpha, 0 \le \beta, \alpha + \beta < 1$ are met in all models.

Table 6.8 GARCH (1,1) Results—Biofuel

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.0002	0.0007	0.2613	0.7939
Variance Equation				
C	0.0000	0.0000	5.2401	0.0000
RESID(-1)^2	0.0321	0.0057	5.6162	0.0000
GARCH(-1)	0.9463	0.0069	137.6084	0.0000
R-squared	0.0000	Mean dependent var		0.0002
Adjusted R-squared	0.0000	S.D. dependent var		0.0204
S.E. of regression	0.0204	Akaike info criterion		-5.1146
Sum squared resid	0.3021	Schwarz criterion		-5.0893
Log likelihood	1860.5830	Hannan-Quinn criter.		-5.1048
Durbin-Watson stat	2.2687			

Table 6.9 GARCH (1,1) Results—Coal

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.0011	0.0015	0.7207	0.4711
Variance Equation				
C	0.0012	0.0001	8.5000	0.0000
RESID(-1)^2	0.5839	0.0788	7.4117	0.0000
GARCH(-1)	0.2014	0.0507	3.9753	0.0001
R-squared	-0.0003	Mean dependent var		-0.0001
Adjusted R-squared	-0.0003	S.D. dependent var		0.0716
S.E. of regression	0.0716	Akaike info criterion		-2.7935
Sum squared resid	3.7177	Schwarz criterion		-2.7682
Log likelihood	1018.0340	Hannan-Quinn criter.		-2.7837
Durbin-Watson stat	3.3571			

Table 6.10 GARCH (1,1) Results—Currency

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.0000	0.0003	-0.1316	0.8953
Variance Equation				
C	0.0000	0.0000	4.3262	0.0000
RESID(-1)^2	0.0012	0.0056	0.2141	0.8304
GARCH(-1)	0.9780	0.0052	186.6035	0.0000
R-squared	0.0000	Mean dependent var		-0.0001
Adjusted R-squared	0.0000	S.D. dependent var		0.0075
S.E. of regression	0.0075	Akaike info criterion		-6.9702
Sum squared resid	0.0411	Schwarz criterion		-6.9449
Log likelihood	2534.1840	Hannan-Quinn criter.		-6.9604
Durbin-Watson stat	1.9897			

Table 6.11 GARCH (1,1) Results—Gold

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.0010	0.0004	2.5540	0.0107
Variance Equation				
C	0.0000	0.0000	1.9710	0.0487
RESID(-1)^2	0.0638	0.0159	4.0040	0.0001
GARCH(-1)	0.9212	0.0205	44.9959	0.0000
R-squared	-0.0002	Mean dependent var		0.0008
Adjusted R-squared	-0.0002	S.D. dependent var		0.0126
S.E. of regression	0.0126	Akaike info criterion		-6.0418
Sum squared resid	0.1144	Schwarz criterion		-6.0165
Log likelihood	2197.1660	Hannan-Quinn criter.		-6.0320
Durbin-Watson stat	2.0490			

Table 6.12 GARCH (1,1) Results--Natural Gas

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.0010	0.0011	0.9635	0.3353
Variance Equation				
C	0.0003	0.0001	4.6517	0.0000
RESID(-1)^2	0.4536	0.0704	6.4422	0.0000
GARCH(-1)	0.4384	0.0546	8.0278	0.0000
R-squared	-0.0004	Mean dependent var		0.0000
Adjusted R-squared	-0.0004	S.D. dependent var		0.0505
S.E. of regression	0.0505	Akaike info criterion		-3.4758
Sum squared resid	1.8486	Schwarz criterion		-3.4506
Log likelihood	1265.7250	Hannan-Quinn criter.		-3.4661
Durbin-Watson stat	3.4121			

Table 6.13 GARCH (1,1) Results—Oil

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.0005	0.0009	0.5211	0.6023
Variance Equation				
C	0.0002	0.0000	5.9856	0.0000
RESID(-1)^2	0.2845	0.0396	7.1832	0.0000
GARCH(-1)	0.6075	0.0344	17.6491	0.0000
R-squared	-0.0001	Mean dependent var		0.0000
Adjusted R-squared	-0.0001	S.D. dependent var		0.0364
S.E. of regression	0.0364	Akaike info criterion		-4.0373
Sum squared resid	0.9619	Schwarz criterion		-4.0121
Log likelihood	1469.5580	Hannan-Quinn criter.		-4.0276
Durbin-Watson stat	2.9614			

Table 6.14 GARCH (1,1) Results--S&P 500

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.0007	0.0007	1.0610	0.2887
Variance Equation				
C	0.0000	0.0000	3.8320	0.0001
RESID(-1)^2	0.4237	0.0639	6.6273	0.0000
GARCH(-1)	0.5957	0.0423	14.0798	0.0000
R-squared	-0.0004	Mean dependent var		0.0000
Adjusted R-squared	-0.0004	S.D. dependent var		0.0386
S.E. of regression	0.0386	Akaike info criterion		-4.1502
Sum squared resid	1.0781	Schwarz criterion		-4.1250
Log likelihood	1510.5350	Hannan-Quinn criter.		-4.1405
Durbin-Watson stat	3.4164			

Table 6.15 GARCH (1,1) Results—Nuclear

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.0005	0.0010	0.5745	0.5656
Variance Equation				
C	0.0001	0.0000	3.6400	0.0003
RESID(-1)^2	0.3178	0.0456	6.9713	0.0000
GARCH(-1)	0.6605	0.0285	23.1589	0.0000
R-squared	-0.0001	Mean dependent var		0.0001
Adjusted R-squared	-0.0001	S.D. dependent var		0.0455
S.E. of regression	0.0455	Akaike info criterion		-3.6939
Sum squared resid	1.4979	Schwarz criterion		-3.6686
Log likelihood	1343.0490	Hannan-Quinn criter.		-3.6842
Durbin-Watson stat	3.3914			

Table 6.16 GARCH (1,1) Results—Petroleum

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.0010	0.0006	1.8842	0.0595
Variance Equation				
C	0.0000	0.0000	2.4730	0.0134
RESID(-1)^2	0.0746	0.0134	5.5682	0.0000
GARCH(-1)	0.9080	0.0163	55.7187	0.0000
R-squared	-0.0017	Mean dependent var		0.0003
Adjusted R-squared	-0.0017	S.D. dependent var		0.0176
S.E. of regression	0.0176	Akaike info criterion		-5.4201
Sum squared resid	0.2252	Schwarz criterion		-5.3949
Log likelihood	1971.5100	Hannan-Quinn criter.		-5.4104
Durbin-Watson stat	2.1544			

Table 6.17 GARCH (1,1) Results—Solar

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.0007	0.0010	-0.6745	0.5000
Variance Equation				
C	0.0000	0.0000	2.8622	0.0042
RESID(-1)^2	0.0506	0.0113	4.4845	0.0000
GARCH(-1)	0.9383	0.0124	75.9568	0.0000
R-squared	-0.0009	Mean dependent var		-0.0016
Adjusted R-squared	-0.0009	S.D. dependent var		0.0321
S.E. of regression	0.0321	Akaike info criterion		-4.2030
Sum squared resid	0.7456	Schwarz criterion		-4.1777
Log likelihood	1529.6890	Hannan-Quinn criter.		-4.1932
Durbin-Watson stat	2.0501			

Table 6.18 GARCH (1,1) Results--Wind

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.0008	0.0005	1.5081	0.1315
Variance Equation				
C	0.0000	0.0000	3.2711	0.0011
RESID(-1)^2	0.0675	0.0111	6.1005	0.0000
GARCH(-1)	0.9140	0.0139	65.5382	0.0000
R-squared	-0.0008	Mean dependent var		0.0003
Adjusted R-squared	-0.0008	S.D. dependent var		0.0195
S.E. of regression	0.0195	Akaike info criterion		-5.3125
Sum squared resid	0.2769	Schwarz criterion		-5.2873
Log likelihood	1932.4500	Hannan-Quinn criter.		-5.3028
Durbin-Watson stat	1.8895			

In order to determine causality in variance (or volatility spillover) between all variables, individual regression models were tested for each and every portfolio as well as asset markets. These models were tested both ways. For example; the volatility spillover from oil prices to the biofuel portfolio was tested separately then the volatility spillover from the biofuel portfolio to oil prices. Although, intuitively, one might think that risk could spillover from asset markets to companies in a given portfolio yet the reverse is unlikely, these results indicate otherwise. Though some expected spillovers from asset markets to the subsector energy portfolios were suggested by the results, some unidirectional spillovers from portfolios to asset markets were also found.

As previously mentioned in the methodology section, the tests employ the derivatives and the GARCH variance series of the independent variable against the residuals squared minus one of the dependant variable. The R-squared of that regression is then multiplied by the number of observations and arrive at the Lagrange multiplier test statistic. This statistic is then compared to the significance results according to the Chi-square distribution. A rejection implies a spillover from the independent variable to the dependent variable.

Table 6.19 shows the results of volatility spillover tests modeling causality in variance from the biofuel portfolio to all other portfolios as well as the asset markets. The results show a spillover from the biofuel portfolio to the coal portfolio, natural gas portfolio, nuclear portfolio, and oil prices at 1% level. There is also a spillover from the biofuel portfolio to S&P 500 at the 10% level. These results are unidirectional. In other words, spillovers from the biofuel portfolio to these other portfolios were found but not vice versa. One might speculate that biofuel companies produce products which are used as substitutes to gas produced from oil and similar to spillover results from petroleum companies to other portfolios (later discussed), biofuel companies have risk influence on other energy-type companies. These results may imply the dominance of gas related companies and their substitutes on the rest of the energy related companies. However; later results will show that this hypothesis might not be true.

Table 6.19 Volatility Spillover from Biofuel

	R-Squared	LM Test Statistic
COAL	0.0221	16.0249***
CURRENCY	0.0003	0.2468
GOLD	0.0033	2.3806
NATURAL GAS	0.0202	14.6347***
NUCLEAR	0.0205	14.9149***
OIL	0.0190	13.7598***
PETROLEUM	0.0004	0.3122
S&P500	0.0080	5.808*
SOLAR	0.0002	0.1561
WIND	0.0044	3.1617

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

When the volatility spillovers from coal related company portfolio to all other variables are tested, a different picture can be seen. As table 6.20 shows, there was no significant spillover found from the coal portfolio to any other portfolios or the asset classes tested. Again, these results are unidirectional. Coal company portfolios do face risk spillovers from other portfolios but seem to not have a reverse effect. It is important to note that the coal portfolio represents coal companies, not coal prices. Therefore, coal price volatility could spillover to energy companies, but that hypothesis is not tested in this study.

Table 6.20 Volatility Spillover from Coal

	R-Squared	LM Test Statistic
BIOFUEL	0.0014	1.0179
CURRENCY	0.0000	0.0029
GOLD	0.0004	0.3238
NATURAL GAS	0.0028	2.0241
NUCLEAR	0.0003	0.2098
OIL	0.0003	0.2011
PETROLEUM	0.0000	0.0029
S&P500	0.0001	0.1016
SOLAR	0.0003	0.2447
WIND	0.0042	3.0586

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

Table 6.21 shows the volatility spillover test from currency to all other assets and sub-sector energy portfolios. Spillovers at 1% were found from currency to the coal portfolio, natural gas portfolio, nuclear portfolio, and oil prices. This was a somewhat expected result. Exchange rates are known to have risk effects on energy companies in general. All of the large fossil fuels (oil, natural gas, and coal) are known to interact heavily with exchange rate fluctuations. The interesting result here was that exchange rate risk was spilling over to natural gas and coal companies but not petroleum. In other words, the risk was spilling over to the oil prices but not petroleum companies. One might speculate that, possibly petroleum companies are affected by volatility spillover from oil prices not directly from exchange rates; however, as the later part of the study will show, there was no evidence found to support that hypothesis. A separate discussion can be found under those results. Aside from the major fossil fuel-related companies, exchange rate risk was found to spillover to nuclear companies as well. This, however, was not the same for other type of alternative companies tested. Although nuclear energy is considered to be an alternative energy due to being cleaner than fossil fuels, it is not a renewable energy source. Extremely high costs related finding and production of raw materials as well as production itself, nuclear energy can be seen as another scarce resource; similar to fossil fuels. As the rest of the results will show, solar, wind, and biofuel companies act/react differently than nuclear companies, while nuclear companies are treated/behave similar to companies related to fossil fuels.

Table 6.21 Volatility Spillover from Currency

	R-Squared	LM Test Statistic
BIOFUEL	0.0000	0.0196
COAL	0.0177	12.8378***
GOLD	0.0009	0.6186
NATURAL GAS	0.0152	11.0627***
NUCLEAR	0.0151	10.9626***
OIL	0.0201	14.6027***
PETROLEUM	0.0004	0.2788
S&P500	0.0059	4.3139
SOLAR	0.0002	0.1474
WIND	0.0045	3.2430

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

When the results for volatility spillovers from gold prices to all other variables are analyzed (table 6.22), one sees that there is a spillover at 1% level from gold prices to coal and natural gas portfolios. Spillovers were also found at 10% to oil prices and S&P 500 index. None of the fossil fuel alternative companies were affected by the riskiness of gold prices.

Gold prices were found to have a long-term effect at level prices from the previous Granger causality study results. Results for the volatility spillover tests show that gold prices not only affect large energy companies in the long-run, but those companies also are affected by the risk spillover from the gold prices.

Table 6.22 Volatility Spillover from Gold

	R-Squared	LM Test Statistic
BIOFUEL	0.0002	0.1721
COAL	0.0327	23.7198***
CURRENCY	0.0038	2.7682
NATURAL GAS	0.0237	17.1902***
NUCLEAR	0.0057	4.1520
OIL	0.0064	4.6754*
PETROLEUM	0.0002	0.1234
S&P500	0.0064	4.6616*
SOLAR	0.0019	1.3917
WIND	0.0001	0.0937

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

A similar picture to coal portfolio was found when natural gas companies were analyzed. As table 6.23 shows, there was no significant volatility spillovers found from natural gas companies to other portfolios or asset markets tested. Again, it is important to note that these are not natural gas prices, but natural gas companies. Therefore, although there could possibly be a spillover from natural gas prices to other energy companies, there was no spillovers found from natural gas companies to other asset groups.

Table 6.23 Volatility Spillover from Natural Gas

	R-Squared	LM Test Statistic
BIOFUEL	0.0013	0.9351
COAL	0.0002	0.1692
CURRENCY	0.0000	0.0007
GOLD	0.0032	2.2942
NUCLEAR	0.0004	0.3173
OIL	0.0020	1.4723
PETROLEUM	0.0001	0.1038
S&P500	0.0000	0.0044
SOLAR	0.0008	0.5706
WIND	0.0032	2.3174

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

Table 6.24 shows the tests results for volatility spillovers from nuclear company portfolio to all other variables tested. The only significant spillover found is from the nuclear energy portfolio to oil prices. As previously explained, nuclear energy companies behave similarly to fossil fuel companies with the exception of petroleum companies (later explained). These portfolios are affected by the spillover from other asset markets and renewable energy companies but not vice versa. An interesting finding with these results is that oil prices are affected by the riskiness of the nuclear energy companies. This finding makes the argument of oil prices being susceptible to the riskiness of energy companies stronger. As previous research and short-run tests in this study found, there is a significant relationship between oil prices and the stock market. This study, however, shows that there is also a unidirectional risk spillover from those companies to the oil prices.

Table 6.24 Volatility Spillover from Nuclear

	R-Squared	LM Test Statistic
BIOFUEL	0.0003	0.2468
COAL	0.0006	0.4429
CURRENCY	0.0009	0.6846
GOLD	0.0055	4.0046
NATURAL GAS	0.0003	0.2047
OIL	0.0294	21.3531***
PETROLEUM	0.0002	0.1590
S&P500	0.0004	0.2904
SOLAR	0.0018	1.3300
WIND	0.0004	0.3216

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

Table 6.25 shows the risk spillovers from oil prices to the portfolios and asset markets tested. The results indicate a spillover from oil price risk to natural gas and coal companies at a 1% level. As most all results show, natural gas and coal companies are affected by the riskiness of other portfolios but not vice versa. Although, one might speculate that oil prices volatility should indeed spillover to all of the energy portfolios, table 30 shows that petroleum companies behave like the representatives of oil prices and their risk spillover to all other energy portfolios except renewable energy.

Table 6.25 Volatility Spillover from Oil

	R-Squared	LM Test Statistic
BIOFUEL	0.0003	0.1917
COAL	0.0179	13.0222***
CURRENCY	0.0004	0.3100
GOLD	0.0006	0.4276
NATURAL GAS	0.0193	14.0343***
NUCLEAR	0.0012	0.8407
PETROLEUM	0.0013	0.9561
S&P500	0.0056	4.1012
SOLAR	0.0044	3.1661
WIND	0.0003	0.2243

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

Table 6.26 Volatility Spillover from Petroleum

	R-Squared	LM Test Statistic
BIOFUEL	0.0005	0.3492
COAL	0.0303	22.0036***
CURRENCY	0.0010	0.7318
GOLD	0.0125	9.1076**
NATURAL GAS	0.0355	25.7526***
NUCLEAR	0.0121	8.8063**
OIL	0.0114	8.3119**
S&P500	0.0115	8.3156**
SOLAR	0.0018	1.2821
WIND	0.0014	1.0237

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

Table 6.26 results show that there is a spillover from petroleum companies to coal companies and natural gas companies at a 1% level. There is also a spillover from petroleum companies to gold prices, nuclear companies, oil prices, and S&P 500 at a 5% level. These results suggest that the riskiness of the petroleum companies have a significant effect on most of the other markets including the stock market they are a part of. A part of this reason could be because these companies are typically very large and, as generalized impulse response results showed, internalize information from the oil market faster than the rest of the market. Therefore, the rest of the energy companies follow their lead, including being affected by their volatility.

Table 6.27 shows the volatility spillover test results from S&P 500 to the portfolios and asset markets tested. There is a spillover to oil prices at a 10% level. Since there are no other significant spillovers identified, this relationship of low significance should be further tested before any conclusions can be drawn.

Table 6.27 Volatility Spillover from S&P 500

	R-Squared	LM Test Statistic
BIOFUEL	0.0005	0.3514
COAL	0.0000	0.0015
CURRENCY	0.0003	0.2490
GOLD	0.0033	2.3827
NATURAL GAS	0.0002	0.1459
NUCLEAR	0.0002	0.1212
OIL	0.0072	5.2388*
PETROLEUM	0.0000	0.0015
SOLAR	0.0005	0.3470
WIND	0.0029	2.0873

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

Tables 6.28 and 6.29 represent the remaining renewable energy company portfolios. These results, combined with the spillover results of the biofuel portfolio, make the argument previously suggested of biofuel companies being similar to petroleum companies, irrelevant. All of the renewable energy companies significantly affect the fossil fuel prices (to an extent, represented by oil prices), natural gas companies, coal companies, nuclear companies and the stock market in terms of risk. Volatility spillovers from solar companies to coal and natural gas were found at a 1% level, while spillovers to nuclear companies, oil prices, and S&P 500 were found at a 5% level.

On the other hand, spillovers from wind companies to coal companies, nuclear companies, natural gas companies, and oil prices were found at a 1% level. These results are important and unexpected. Risks from renewable energy companies seem to be the drivers of risk in fossil fuel-related companies with the exception of petroleum companies. However; there is no risk spillover among those renewable energy companies.

One possible explanation could be that most of these renewable energy companies are relatively new and are created due to a combination of a need in the market and government incentives. Governments around the world have recently been adamant about creating policy supporting and encouraging the renewable energy sectors. The macroeconomic volatility of those countries could very well directly impact their policies and funding of such incentives. Assuming those renewable energy companies are highly susceptible to macroeconomic fluctuations, risk could first spillover to those companies and then to the rest of the market. Further discussions and future research extensions towards testing these ideas are discussed in the conclusion section.

Table 6.28 Volatility Spillover from Solar

	R-Squared	LM Test Statistic
BIOFUEL	0.0023	1.7054
COAL	0.0308	22.3745***
CURRENCY	0.0061	4.4192
GOLD	0.0032	2.2913
NATURAL GAS	0.0313	22.7521***
NUCLEAR	0.0118	8.5471**
OIL	0.0073	5.2649*
PETROLEUM	0.0003	0.1917
S&P500	0.0088	6.3953**
WIND	0.0029	2.1032

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

Table 6.29 Volatility Spillover from Wind

	R-Squared	LM Test Statistic
BIOFUEL	0.0000	0.0065
COAL	0.0251	18.2349***
CURRENCY	0.0024	1.7395
GOLD	0.0066	4.7589*
NATURAL GAS	0.0288	20.9421***
NUCLEAR	0.0196	14.2187.***
OIL	0.0194	14.1141***
PETROLEUM	0.0001	0.0682
S&P500	0.0118	8.5784**
SOLAR	0.0007	0.4842

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

Table 6.30, below, gives a summary of the significant findings previously presented at each category. Also, the chart in figure 6.15 gives a graphical representation of those findings:

Table 6.30 Volatility Spillover Summary

FROM	TO	R-Squared	LM Test Statistic
BIOFUEL	COAL	0.0221	16.0249***
BIOFUEL	NATURAL GAS	0.0202	14.6347***
BIOFUEL	NUCLEAR	0.0205	14.9149***
BIOFUEL	OIL	0.0190	13.7598***
BIOFUEL	S&P500	0.0080	5.808*
CURRENCY	NATURAL GAS	0.0152	11.0627***
CURRENCY	COAL	0.0177	12.8378***
CURRENCY	NUCLEAR	0.0151	10.9626***
CURRENCY	OIL	0.0201	14.6027***
GOLD	COAL	0.0327	23.7198***
GOLD	NATURAL GAS	0.0237	17.1902***
GOLD	OIL	0.0064	4.6754*
GOLD	S&P500	0.0064	4.6616*
NUCLEAR	OIL	0.0294	21.3531***

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

Table 6.30 Volatility Spillover Summary Cont'd

FROM	TO	R-Squared	LM Test Statistic
OIL	COAL	0.0179	13.0222***
OIL	NATURAL GAS	0.0193	14.0343***
PETROLEUM	COAL	0.0303	22.0036***
PETROLEUM	GOLD	0.0125	9.1076**
PETROLEUM	NATURAL GAS	0.0355	25.7526***
PETROLEUM	NUCLEAR	0.0121	8.8063**
PETROLEUM	OIL	0.0114	8.3119**
PETROLEUM	S&P500	0.0115	8.3156**
S&P500	OIL	0.0072	5.2388*
SOLAR	COAL	0.0308	22.3745***
SOLAR	NATURAL GAS	0.0313	22.7521***
SOLAR	NUCLEAR	0.0118	8.5471**
SOLAR	OIL	0.0073	5.2649*
SOLAR	S&P500	0.0088	6.3953**
WIND	COAL	0.0251	18.2349***
WIND	GOLD	0.0066	4.7589*
WIND	NATURAL GAS	0.0288	20.9421***
WIND	NUCLEAR	0.0196	14.2187***
WIND	OIL	0.0194	14.1141***
WIND	S&P500	0.0118	8.5784**

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

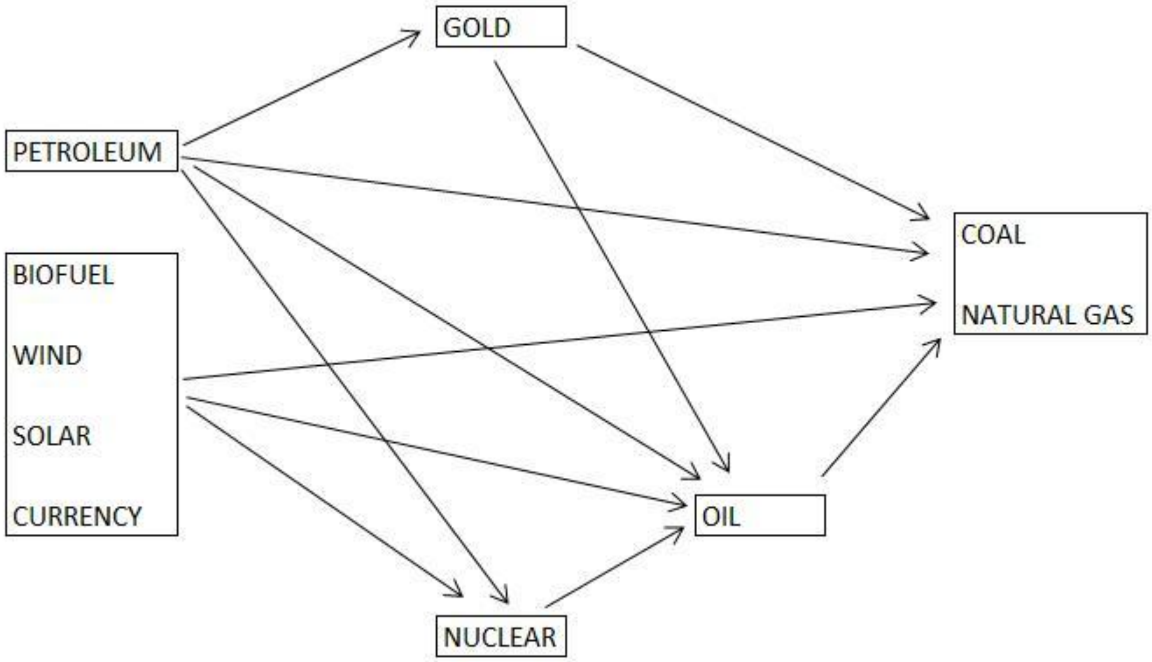


Figure 6.15 Spillover Direction

CHAPTER 7

CONCLUSIONS

Increasing world energy demand has always been a problem. However; recent large fluctuations in oil prices attracted more attention from policy makers and investors. Research related to energy prices affecting the macroeconomy and stock markets is abundant. While governments started paying even more attention to those energy prices, alternative sources of energy (i.e., renewable and "green" energy) gained 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. 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? From a risk perspective, which sub-sector influences the other, or do they all get affected by the riskiness of other asset markets?

This study conducted three different types of approaches towards answering questions above. The first was Vector Autoregressions. These regressions allowed the study to identify any short-term directional reactions from a sub-sector energy portfolio to price shocks in the asset markets which were included in this study. The second approach was the Granger causality tests. These tests allowed the study to identify any long-term relationships between the sub-sector energy portfolios and the asset markets. The third approach was the volatility spillover (causality in variance) tests. This approach allowed the study to identify any risk spillovers between the different energy portfolios as well as the asset markets.

Aside from servicing a gap in the literature, this study has significant information for professional investors. The Vector Autoregression 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. For example, impulse responses show how the returns of one market react (in terms of how long it takes to react, how long does it take to die off as well as the magnitude of reaction) to a shock from another market. From a forecasting perspective, this information could prove strongly valuable. If there are no Granger causality relationships found, this could be interpreted as the asset classes tested can be used at the same time in a portfolio as a diversification tool to minimize risk . Through the volatility spillover studies, the causality in variance (or risk) can be observed. This information is also important for an investor. Through understanding how historical risk of one asset affects the other, investors can anticipate/forecast the riskiness of an asset through looking at another towards adjusting/minimizing the riskiness of their portfolio.

The seven different portfolios created in this study (biofuel, nuclear, solar, wind, petroleum, coal, and natural gas) contain firms which conduct the majority of their business from those sub-sectors. The study also includes four asset markets frequently used in research: oil prices, gold prices, USD/EUR exchange rates, and the S&P 500 index.

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, where 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, where 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. 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.

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.

Volatility spillover tests revealed an unexpected risk relationship between the variables tested. Coal and natural gas portfolios were affected by the riskiness of most of the other variables tested, and these results were unidirectional. In other words there was no spillover from these portfolios to any of the other variables. The variables which were not affected by risk spillover from any of the other variables were petroleum, biofuel, solar, wind, and currency.

However; all of those variables had significant effects on the rest of the portfolios. As previously mentioned, petroleum companies are typically large and could be more efficient in terms of capturing information in the market. This, in turn, could result in their leadership of brokering risk information to the rest of the market. The "renewable" alternative energy companies were also the starting point in brokering risk information to the rest of the energy companies and asset markets (with the exception of petroleum companies and currency prices). However; there was no risk spillover between those portfolios. In other words, they not only influenced the rest of the markets, they behaved uniformly. One possible explanation could be that most of these renewable energy companies are relatively new and are created due to a combination of a need in the market and government incentives. Governments around the world have recently been adamant about creating policy supporting and encouraging the renewable energy sectors. The macroeconomic volatility of those countries could very well directly impact their policies and funding of such incentives. Assuming those renewable energy companies are highly susceptible to macroeconomic fluctuations, risk could first spillover to those companies and then to the rest of the market.

Some of the future extensions of this study could include testing above assumption with the inclusion of macroeconomic variables. If there is any evidence of risk spillover from those macroeconomic variables to renewable energy companies found, this could complete the picture. Also, natural gas and coal commodity prices are not included in this study and could be added as a future extension.

REFERENCES

Barberis, N and A. Shleifer, 2003. "Style Investing," *Journal of Financial Economics* 26, 161-199.

Bhar Ramaprasad and Biljana Nikolava, 2009. "Return, Volatility Spillovers and Dynamic Correlation in BRIC Equity Markets: An Analysis Using Bivariate EGARCH Framework." *Global Finance Journal*, Vol. 19, No.1, 203-218.

Brown, R. L., J. Durbin, J. M. Evans, 1975. "Techniques for Testing the Constancy of Regression Relationships over Time." *Journal of the Royal Statistical Society* B 37, 149- 163.

Brown, S. P. and M. K. Yucel, 2002. "Energy Prices and Aggregate Economic Activity: An Interpretative Survey," *Quarterly Review of Economics and Finance* 42, 193-208.

Chang Hsu-Ling, Chi-Wei Su and Yi-Chu Lai, 2009. "Asymmetric Price Transmission between the Exchange Rate and Stock Market in Vietnam." *International Research Journal of Finance and Economics*, Vol. 23, 104-113.

Caporale, Guglielmo Maria and Pittis, Nikitas, 2004. "Robustness of the CUSUM and CUSUM-of-Squares Tests to Serial Correlation, Endogeneity and Lack of Structural Invariance. Some Monte Carlo Evidence," *Economics Series* 157, Institute for Advanced Studies.

Cashin, P., C. McDormott, and A Scott, 1999. "The Myth of Co-Moving Commodity Prices." Discussion Paper # G99/9, Reserve Bank of New Zealand.

Cheung, Y. W. and L. K. Ng, 1998. "International Evidence on the Stock Market and Aggregate Economic Activity." *Journal of Empirical Finance*,Vol. 5, 281-296.

Chiou, J., Y. Lee, and C. Lin, 2008. "Existence of a Long-Run Equilibrium between the S&P 500 and Oil Prices." *International Research Journal of Finance & Economics*, Issue 21, 68-75.

Clements, M. P. and H. M. Krolzig, 2002. "Can Oil Shocks Explain Asymmetries in the U.S. Business Cycle," *Empirical Economics* 27:185-204.

Cunado, J. and G. F. Perez, 2005. "Oil Prices, Economic Activity and Inflation: Evidence for Some Asian Countries," *Quarterly Review of Economics and Finance* 45, 65-83.

Eryigit, M., 2009. "Effects of Oil Price Changes on the Sector Indices of Istanbul Stock Exchange" *International Research Journal of Finance & Economics*, Issue 25, 209-216.

Faff R. W. and T. J. Brailsford, 1999. "Oil Price Risk and the Australian Stock Market," *Journal of Energy and Finance Development* 4, 69-87.

Gormus, N. Alper and Salil Sarkar, 2012. "Stock Performance of Renewable Energy Companies and the Carbon Markets." *Empirical Economics Letters.* Forthcoming.

Haigh, M. S. and M. T. Holt, 2002. Crack Spread Hedging: Accounting for Time-Varying Volatility Spillovers in The Energy Futures Markets. *Journal of Applied Econometrics*, 17, 269-289.

Harris, R. D. F. and A. Pisedtasalasai, 2006. Return and Volatility Spillovers between Large and Small Stocks in the UK. *Journal of Business Finance & Accounting*, 33, 1556-1571.

Henriques I and P. Sadorsky, May 2008. "Oil Prices and the Stock Prices of Alternative Energy Companies." *Energy Economics*, Volume 30-3, 998-1010.

Jenner, S., G. Charf, R. Frankenberger, and M. Gabel, 2012. What Drives States to Support Renewable Energy? *The Energy Journal*, 33, 1-12.

Jones, C. M. K. and Gautam, 1996. "Oil and the Stock Markets," *Journal of Finance* 51, 463-491.

Kanas Angelos, 2000. "Volatility Spillovers between Stock and Exchange Rate Changes: International Evidence." *Journal of Business Finance and Accounting*, Vol. 27, No. 3-4, 447-467.

Li, R., 2011. Energy Futures Prices and the U.S. Dollar Exchange Rate. *Australian Economic Paper*, September 2011, 62-73.

Mohammadi, H., 2011. Long-Run Relations and Short-Run Dynamics among Coal, Natural Gas, and Oil Prices. *Applied Economics*, 43, 129-137.

Mazraati, M. and H. Shelbi, 2011 . Impact of Alternative Fuels and Advanced Technology Vehicles on Oil Demand in the United States up to 2030. *OPEC Energy Review*, March 2011, 70-89.

Mohanty, S .K., 2011 . Oil Shocks and Equity Returns: An Empirical Analysis of the U.S. Transportation Sector. *Review of Pacific Basin Financial Markets and Policies*, 14, 101-128.

Ordonez, J., H. Sala, and J. I. Silva, 2011. Oil Price Shocks and Labor Market Fluctuations. *The Energy Journal*, 32, 89-118.

Owen, A. D., 2004. "Environmental Externalities, Market Distortions and the Economics of Renewable Energy Technologies." *Energy Journal*, Vol. 25 Issue 3, 127-156.

Park, J., R. A. Ratti, 2008. "Oil Price Shocks and Stock Markets in the U.S. and Thirteen European Countries. Energy Economics," in press, doi:10.1016/j.eneco.2008.04.003.

Pindyck, R. S. and D. L. Rubinfeld, 1998. *Econometric Models and Economic Forecasts* (4th ed.). Boston, Mass.: Irwin/McGraw-Hill.

Pindyck, R. and J. Rotemberg, 1990. "The Excess Co-Movement of Commodity Prices." *Economic Journal* 100, 1173-1189.

Sadorsky, P., October 1999. "Oil Price Shocks and Stock Market Activity." *Energy Economics*, Volume 21-5, 449-469.

Sadorsky, P., January 2001. "Risk Factors in Stock Returns of Canadian Oil and Gas Companies." *Energy Economics*. Volume 23-1, 17-28.

Sadorsky, P., April 2000. "The Empirical Relationship between Energy Futures Prices and Exchange Rates." *Energy Economics*. Volume 22-2, 253-266.

Smistad, R. and I. Pustylnick, 2012. Hedging, Hedge Accounting, and Speculation: Evidence from Canadian Oil and Gas Companies. *Global Journal of Business Research*, 6, 49-62.

Soytas U, Sari Ramazan, S. Hammoudeh, and E. Hacihasanoglu, 2009. "World Oil Prices, Precious Metal Prices and Macroeconomy in Turkey," *Energy Policy* 37, 5557-5566.

Soytas U &Dogrul, H. G, 2010. "Relationship between oil prices, interest rate, and unemployment: Evidence from an emerging market," *Energy Economics*, Elsevier, vol. 32(6), pages 1523-1528, November

Soytas, U & Sari, R & Hacihasanoglu, E, 2011. "Do global risk perceptions influence world oil prices?," *Energy Economics*, Elsevier, vol. 33(3), pages 515-524, May.

Steeley James M., 2006. "Volatility Transmission between Stock and Bond Markets," *International Financial Markets, Institutions and Money*, Vol. 16. No. 1, 71-86.

Thimann Christian, Lucia Cuadro-Saez, Marcel Fratzscher, 2009. "The Transmission of Emerging Market Shocks to Global Equity Markets," *Journal of Empirical Finance*, Vol. 16, No. 1, 2-17.

Uri, N.O. and R. O. Boyd, 1997. "Economic Impact of the Energy Price Increase in Mexico," *Environmental and Resource Economics* 10, 101-107.

Zikovic, S. and N. Vlahinic-Dizdarevic, 2003. Similarities between Expected Shortfall and Value at Risk: Application to Energy Markets. *International Journal of Management Cases*, 386-399.

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