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Oil prices and the stock prices of alternative energy companies

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Abstract

Energy security issues coupled with increased concern over the natural environment are driving factors behind oil price movements. While it is widely accepted that rising oil prices are good for the financial performance of alternative energy companies, there has been relatively little statistical work done to measure just how sensitive the financial performance of alternative energy companies are to changes in oil prices. In this paper, a four variable vector autoregression model is developed and estimated in order to investigate the empirical relationship between alternative energy stock prices, technology stock prices, oil prices, and interest rates. Our results show technology stock prices and oil prices each individually Granger cause the stock prices of alternative energy companies. Simulation results show that a shock to technology stock prices has a larger impact on alternative energy stock prices than does a shock to oil prices. These results should be of use to investors, managers and policy makers.
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1. Introduction

> "In the long run, households and businesses respond to higher fuel prices by cutting consumption, purchasing products that are more efficient, and switching to alternative energy sources. Higher energy prices also encourage entrepreneurs to invest in the research

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> and development of new energy-conserving technologies and alternative fuels, further expanding the opportunities available to households and businesses to reduce energy use and switch to low-cost sources". Economic Report of the President (2006, page 243).

Energy security issues (dwindling global oil supplies in the face of increased global demand, and political insecurity in oil rich countries), coupled with increased concern about the natural environment (climate changes like global warming and local air quality issues), are driving factors behind oil price movements and rising oil prices should help spur greater demand and supply of alternative energy (see for example, Rifkin, 2002; Bleischwitz and Fuhrmann, 2006; McDowall and Eames, 2006; New Energy Finance, 2007).

Concerns about future oil shortages stem from current estimates that predict world oil production will peak somewhere between 2016 and 2040 (Appenzeller, 2004). Oil is a globally traded commodity and the price of oil is determined by global oil demand and global oil supply conditions. Rapidly increasing demand for oil from emerging market economies like China and India, coupled with oil supply shortages will lead to much higher oil prices in the future and eventually a substitution away from oil to alternative energy sources. In the short to medium term, the outlook for oil is complex because the largest consumers of oil are not the countries with the largest reserves. Close to 60% of the world's proved oil reserves are contained in just five countries (Saudi Arabia, Iran, Iraq, Kuwait, and United Arab Emirates) (BP, 2006). The largest oil consuming region, North America (which accounts for approximately 30% of world consumption), has just 5% of the world's proved oil reserves. Moreover, 75% of the world's proved oil reserves are located in the Organization of the Petroleum Exporting Countries (OPEC) and most of the oil reserves in these countries are controlled by national oil companies which give these oil producing countries a disproportional amount of diplomatic leverage in world affairs. The eleven members of OPEC, Algeria, Indonesia, Iran, Iraq, Kuwait, Libya, Nigeria, Qatar, Saudi Arabia, United Arab Emirates, and, Venezuela (www.opec.org), are for the most part, located in geopolitical hot spot regions of the world. Geopolitical uncertainty in regions of the world where large oil deposits are located creates a security issue for the large oil consuming nations. Scarce resources command a price and oil prices respond to the economics of global demand and supply conditions, geopolitics, institutional arrangements (OPEC), and the dynamics of the oil futures market.

Stress on the natural environment is also a major concern. The concentration of CO_2 levels in the atmosphere had remained roughly constant for many thousands of years before taking a sudden upturn which coincides with the development of the modern industrialized economy. Over the past 140 years, atmospheric CO_2 concentrations have risen by approximately 100 parts per million (ppm) from approximately 275 ppm to nearly 375 ppm (Glick, 2004). The increased concentration of CO_2 contributes to global warming and global warming has the very real potential to disrupt the relationship between business and society as we know it (see for example, Duncan, 2006, 2007). According to the United Nations sponsored Intergovernmental Panel on Climate Change (IPCC), a price of carbon in the range of \$20 to \$50 a ton by 2020–30 should stabilize CO_2 concentrations in the atmosphere at an acceptable value of 550 ppm by the end of the century (Duncan, 2007). A carbon price can be established either through a carbon tax or a cap and trade system. With a cap and trade system, companies that hold their emissions below the cap can sell their remaining allowance on a carbon market. Companies that exceed their cap can purchase allowances on the carbon market. The introduction of a cap and trade system increases the costs of producing a carbon intensive good. Producers of carbon based products either cut production or incur abatement costs to reduce carbon emission. In either case, the supply curve for carbon based energy sources shifts to the left, raising price and reducing quantity. A carbon tax is a tax levied on carbon emissions generated from the combustion of fossil fuels (Poterba, 1993; Harris, 2006). A carbon tax is a specific tax determined to be a fixed amount per ton of coal or barrel of oil. The supply curve for carbon based energy sources shifts to the left, raising the price of carbon based energy sources (fuels) and reducing the quantity demanded (Harris, 2006, Fig. 18-7). The tax burden that is shared between producers and consumers of carbon based energy sources depends upon the relative elasticities of demand and supply. The carbon tax would appear to consumers as an energy price increase.

Energy security issues coupled with increased concern over the natural environment are driving factors behind oil price movements. While it is widely accepted that rising oil prices are good for the financial performance of alternative energy companies, there has been relatively little statistical work done to measure just how sensitive the financial performance of alternative energy companies are to changes in oil prices. Rising oil prices provide a strong stimulus for substituting from petroleum based energy production and usage to alternative energy based production and usage. Although the alternative energy industry may still be small compared to other more established industries (in 2004, approximately 6% of the total energy used in the United States came from renewable sources (Economic Report of the President, 2006, p.233), investors, consumers, governments and other industries will be seeking alternatives to current energy sources. Although this bodes well for the industry in the long run, a better understanding of the relationship between oil prices and the financial performance of alternative energy companies is critical to understanding the development of the alternative energy industry in the years to come. The purpose of this paper is to provide an empirical analysis of the relationship between oil prices and the stock prices of alternative energy companies. This paper is organized as follows. The following sections discuss the research methodology, data, and results. The final section of the paper presents the concluding comments.

2. Empirical methodology

A vector autoregression (VAR) is used to empirically investigate the relationship between the stock prices of alternative energy companies and oil prices. One of the advantages of using a VAR is that the researcher does not need to provide prior assumptions about which variables are response variables and which variables are explanatory variables because in a VAR all variables are treated as endogenous. This means that in a VAR, each variable depends upon the lagged values of all the variables in the system. This allows for a much richer data structure that can capture complex dynamic properties in the data (Brooks, 2002).

A vector autoregression can be written in the following way.

$$y_t = \sum_{j=1}^{p} B_j y_{t-j} + u_t,$$

In the above equation, variable y is a n vector of endogenous variables and B_j is a $n \times n$ matrix of regression coefficients to be estimated. The error term, u, is assumed to be independent and identically distributed with a zero mean and constant variance. In the above equation for a VAR there are n^2p free parameters. Consequently, the selection of the appropriate lag length, p, is important. If the lag length is set too large relative to the sample size (T), degrees of freedom will be used up and this will lead to large standard errors on the estimated coefficients. If the lag length is set too low, then there may not be enough lags in the VAR to adequately capture the dynamic properties of the data. Ideally the chosen model should also have no serial correlation in the residuals.

Vector autoregressions (VARs) are one of the most popular estimation techniques used in econometrics. If each of the variables in a VAR is integrated of order 1 ($I(1)$) then a VAR in first differences can be estimated and conventional asymptotic theory used for hypothesis testing. If the variables in the VAR are cointegrated of order 1 then an error correction model (ECM) can be used for estimation and hypothesis testing. In general, however, it is not known a priori whether or not a set of variables are cointegrated and consequently, pre-tests for cointegration and unit roots need to be performed before the VAR model is estimated. Moreover, ECMs can only be estimated for models with a data set where each variable has the same order of integration.

Toda and Yamamoto (1995) propose a lag augmented VAR (LA-VAR) testing procedure which is robust to the integration and cointegration properties of the data and avoids the possible pre test bias. As long as the order of the data integration does not exceed the true lag length of the model a usual lag length selection criteria can be used to select the appropriate lag length (k). The researcher then estimates a VAR with $k+d_{\max}$ lags where $d_{\max}$ is the suspected maximum order of integration. Linear or non-linear restrictions on the first k coefficient matrices are tested using standard asymptotic theory. The last coefficient matrices are ignored since they are regarded as zeros. Monte Carlo simulations (for sample sizes of 50, 100 and 200) by Yamada and Toda (1998) find that the LA-VAR approach has better size stability then the ECM approach while the ECM approach has better power then the LA-VAR approach.

Because of the large number of estimated coefficients in a VAR, the coefficients in themselves are not that interesting to look at. VAR models are mostly used to test Granger causality (do lags of one variable help explain the current value of some other variable?) and describe the dynamics of the data (Brooks, 2002). Model dynamics can be studied using impulse response functions. Impulse responses show the impact of a one standard deviation shock or innovation of one variable on the current and future values of another variable. Impulse responses are correlated if two or more of the error terms in the VAR are contemporaneously correlated and this makes impulse responses difficult to interpret. The usual way around this problem is to impose an orthogonality condition (like a Cholesky decomposition) on the positive definite covariance matrix of shocks. This approach forces the innovation from one data series to have no contemporaneous effect on the other data series. The resulting impulse responses may not be robust to the ordering of the variables in the VAR. Our approach uses generalized impulse responses (Pesaran and Shin, 1998) which do not depend upon the ordering of the variables in the VAR.

3. Data

The stock market performance of alternative energy companies is measured using the WilderHill Clean Energy Index (ECO). ECO was the first index for tracking the stock prices of clean renewable energy companies and has become a benchmark index. Further details of this index are available at www.wilderhill.com. Individual investors can not directly buy the ECO index but can invest in an exchange traded fund which mirrors the ECO. At the end of February 2005, an exchange traded fund (ETF) with ticker symbol PBW that invests in alternative energy companies began trading on the American Stock Exchange (AMEX). This ETF is managed by PowerShares Capital Management and tracks the WilderHill Clean Energy Index which consists of approximately 40 companies engaged in the alternative energy (hydrogen fuel cells, wind, solar) industry. The WilderHill Clean Energy Index is based on the WilderHill Fuel Cell Index which was initiated on September 13, 1999 in response to the increased interest in the stock prices of publicly traded fuel cell companies.

It may be the case that investors view alternative energy companies as similar to other high technology companies. This is what happened in the late 1990s to a number of publicly traded fuel cell companies (for example, Ballard Power). The stock prices of these fuel cell companies rose quickly as the NASDAQ stock index made new highs. Once the technology stock market bubble burst in early 2000, however, the stock price of fuel cell companies fell very quickly and in line with other technology stock prices. Consequently, a stock market index of technology companies is needed to investigate the relationship between alternative energy stock prices and the broad-based technology sector. The Arca Tech 100 index, which was formally known as The Pacific Stock Exchange (PSE) Technology Index and still retains the sticker symbol PSE, is used to measure the stock market performance of technology firms because the Arca represents a pure play on technology. Unlike NASDAQ, all of the companies in the Arca index are technology related and the index includes companies listed on leading stock exchanges as well as over the counter shares. The Arca Tech 100 Index is a price-weighted, broad-based index which is comprised of 100 listed and over-the-counter stocks from 15 different industries including computer hardware, software, semiconductors, telecommunications, data storage and processing, electronics and biotechnology (http://www.nyse.com/marketinfo/indexes/pse.shtml).

Rising oil prices, which, in the absence of complete substitution effects between the factors of production, increase the costs of producing goods and providing services. Higher production costs dampen cash flows and reduce stock prices. Rising oil prices also impact the discount rate used in the equity pricing formula used to value stocks because rising oil prices are often indicative of inflationary pressures which central banks can control by raising interest rates. Many authors have found a statistically significant relationship between oil price movements and stock prices (see for example, Kaneko and Lee, 1995; Ferson and Harvey, 1995; Jones and Kaul, 1996; Huang et al., 1996; Sadorsky, 1999; Faff and Brailsford, 1999; Sadorsky, 2001; Hammoudeh and Eleisa, 2004; Hammoudeh et al., 2004; Hammoudeh and Huimin, 2005; El-Sharif et al., 2005; Basher and Sadorsky, 2006; Boyer and Filion, 2007). None of these papers has, however, looked at the relationship between oil prices and the stock prices of alternative energy companies. The overall impact of rising oil prices on the stock prices of alternative energy companies should be positive because rising oil prices encourage substitution towards other (non-petroleum based) energy sources. In this paper, oil prices are measured using the closing prices of the nearest contract on the West Texas Intermediate crude oil futures contract. This futures contract trades on the NYMEX and is the most widely traded physical commodity in the world.

Previous business cycle research has highlighted the importance of interest rates in explaining stock price movements (see for example, Chen, 1991; Chen et al., 1986; Sadorsky, 1999, 2001). In this paper, the interest rate variable is the yield on a 3 month U.S. T Bill.

For this study, weekly data on the Wednesday closing prices for ECO, PSE, and oil prices were collected from Datastream over the period January 3, 2001 to May 30, 2007 for a total of 335 weekly observations. Wednesday closing prices were used because in general there are fewer holidays on Wednesdays then Fridays. Any missing data on Wednesday closes was replaced with closing prices from the most recent trading session. Interest rate data were obtained from the Federal Reserve Board of St. Louis (http://research.stlouisfed.org/fred2/). The data set is limited by the fact that data on the ECO is only available from January 2001 to the present. Weekly data provides a good compromise on the use of noisy daily data and a relatively short span of monthly data.

A time series plot of the WilderHill Clean Energy Index (ECO), the Arca Technology Index (PSE), and oil prices is shown in Fig. 1. For ease of comparison each series is set equal to 100 on January 3, 2001. Notice the similar pattern between the stock prices of alternative energy

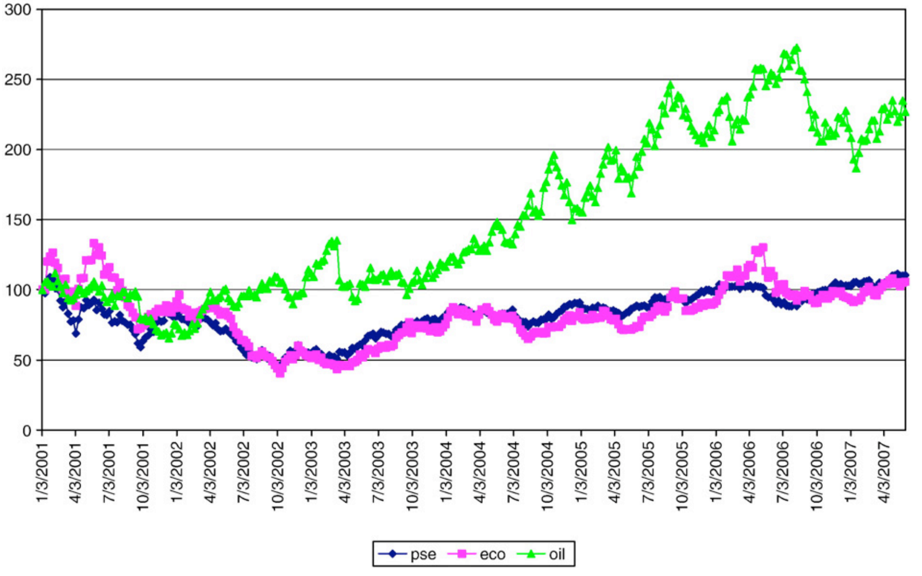

Fig. 1. ECO, PSE, and oil prices.

companies and the stock prices of technology companies. The share prices of alternative energy companies and technology companies each lost half of their value between January 2001 and October 2002. The ECO correlates very highly with the PSE as the correlation coefficient between the two series is 0.83. The correlation between ECO and oil prices is 0.43. Notice that while share prices of alternative energy companies and technology companies have struggled to regain their highs, oil prices have easily doubled between 2002 and 2006.

The annual average returns, obtained by multiplying the average weekly continuously compounded returns reported in Table 1 by a factor of 52, of the ECO and PSE were 0.84% and 1.52% respectively. In comparison, the annualized average returns on the S&P 500 were 1.98% and the average annualized returns on three month U.S. T bills were 2.69%. The average annualized

Table 1
Summary statistics for weekly returns

	ECO	PSE	SP500	OIL
Mean	0.02	0.03	0.04	0.25
Median	0.20	0.09	0.10	0.55
Maximum	18.18	13.54	10.18	10.62
Minimum	−13.79	−12.77	−7.84	−23.59
S.D.	4.31	3.48	2.20	4.40
Skewness	−0.03	0.03	0.21	−0.72
Kurtosis	4.14	4.60	5.76	5.35
Jarque-Bera	18.25	35.51	108.60	105.28
Probability	0.00	0.00	0.00	0.00
Nobs	334	334	334	334
Sharpe ratio	−0.06	−0.05	−0.05	0.32

Summary statistics are shown for continuously compounded weekly returns (January 3, 2001 to May 30, 2007). Sharpe ratios calculated using annual returns.

Table 2
Market risk comparisons from estimating a multifactor model

	ECO	ECO	PSE	PSE
Constant	0.00	0.00	0.00	0.00
	−0.22	−0.35	−0.33	−0.37
Market	1.40	1.39	1.40	1.41
	15.06***	14.83***	16.80***	17.06***
Oil		0.11		0.00
		3.12***		0.09
Rate		0.01		−0.03
		1.03		−1.26
Rbar2	0.51	0.52	0.78	0.78
DW	2.02	2.02	2.15	2.16
$F(p)$	0.00	0.00	0.00	0.00

The first cell for each variable contains the coefficient estimate and the second cell contains the heteroskedasticity and autocorrelation robust t statistic.

***, **, *, denote a test statistic is statistically significant at the 1%, 5%, or 10% level of significance.

Rbar2 refers to the adjusted R-squared value, DW is the Durbin–Watson statistic, $F(p)$ is the probability value for a F test of all slope coefficients equal to zero.

return of oil futures prices were 12.75% reflecting the strong oil market over this time period. Risk adjusted returns are measured using the Sharpe ratio (Table 1). Higher values of the Sharpe ratio are preferred to lower values. Sharpe ratios for ECO, PSE, SP500, and OIL were −0.06, −0.05, −0.05, and 0.32 respectively. On a risk adjusted basis, the oil futures market was a better investment then technology stocks or the broad-based stock market. Notice that the Sharpe ratios for ECO, PSE, and S&P 500 where each very similar indicating that on a risk adjusted basis there was not much to choose between them.

Market risk comparisons are investigate using a multifactor model (Sadorsky, 2001) that relates stock returns on either ECO or PSE to stock market returns (measured by the S&P 500) and risk factors for the oil price returns and interest rate changes. These models are estimated using ordinary least squares (OLS) (Table 2). Heteroskedasticity and autocorrelation robust t statistics are reported. The estimated coefficient on the market return variable indicates that the ECO index is approximately 40% riskier than the broad-based market (S&P 500). The estimated coefficient on the market risk variable indicates that the PSE index is also approximately 40% riskier than the S&P 500. The interest rate variable is not a significantly priced risk factor for either the ECO index or the PSE index. Oil price returns are a statistically significant risk factor for the ECO index at the 1% level. Oil price returns are not a significant risk factor for the PSE index. The multifactor models are useful for explaining the risk/return relationship between macroeconomic variables and stock prices when all variables are measured contemporaneously. Dynamic relationships between stock prices and macroeconomic variables are explored using vector autoregressions.

4. VAR results and discussion

The VAR model consists of four variables, the WilderHill Clean Energy Index (ECO), the Arca Technology Index (PSE), U.S. West Texas Intermediate crude oil futures prices (OIL), and the interest rate (RATE). To reduce unwanted variability (heteroskedasticity) in the data, natural logarithms are taken of each data series (LECO, LPSE, LOIL, LRATE).

Table 3
Unit root tests

	Levels			First differences		
	ADF(lags)	PP(NWBW)	KPSS(NWBW)	ADF(lags)	PP(NWBW)	KPSS(NWBW)
LECO	−1.494(0)	−1.707(8)	0.548(15)**	−17.904(0)***	−18.015(7)***	0.157(7)
LPSE	−1.334(0)	−1.410(6)	1.129(15)***	−19.454(0)***	−19.418(6)***	0.258(5)
LOIL	−0.845(0)	−0.828(5)	2.203(15)***	−18.139(0)***	−18.144(5)***	0.068(5)
LRATE	−0.881(0)	−1.017(11)	0.874(15)***	−17.290(0)***	−18.064(11)***	1.137(11)***

Unit roots are tested using the Augmented Dickey and Fuller (ADF), Phillips and Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) unit root tests. The Schwarz information criterion is used to select the lag length in the ADF regression. The Barlett kernel for the PP and KPSS regressions are determined using the Newey–West bandwidth (NWBW). All unit root tests regressions include an intercept. The numbers in parentheses are the optimal lag lengths. ***, **, *, denote a test statistic is statistically significant at the 1%, 5%, or 10% level of significance.

In order to apply the Toda and Yamamoto (1995) lag augmented VAR (LA-VAR) testing procedure it is necessary to determine the order of integration of each data series. The integration (unit root) properties of the data are investigated using Augmented Dickey-Fuller (ADF) tests, Phillips and Perron (PP) tests, and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) unit root tests. The null hypothesis for the ADF and PP tests is that the data series has a unit root. The null hypothesis for the KPSS test is that the data series is stationary. The results of applying these unit root tests to each data series are shown in Table 3. For each of the ECO index, PSE index, and oil price series, the maximum order of integration was one. The ADF and PP tests indicate the interest rate series is integrated of order 1 ($I(1)$), but the KPSS test provides evidence against this. Second differencing the LRATE series produces a KPSS test of 0.090 which indicates stationarity.

Likelihood ratio statistics select a VAR lag length (k) of eight. The VAR was estimated using ten lags (a lag length of eight from the above mentioned lag length selection criteria and two lags to allow for data integration of order 2).

Model fit tests show that the VAR fits well. Adjusted R-squared values range from 0.976 for the LECO equation to 0.996 for the LRATE equation (Table 4). These values are very high and demonstrate a good fitting model. The standard error of the equation provides a measure of how different the predicted values of the dependent variable are from the actual values. In general, smaller values are better because they indicate a tighter fitting model (less dispersion about the regression line). The standard error of the equation expressed as a percentage of the mean of the dependent variable shows that each equation fits very well. The residuals from the LPSE equation have the least amount of variation on average and the residuals from the interest rate equation have the most amount of variation on average (Table 4). For each equation, the reported F statistic

Table 4
VAR model fit

	LECO	LPSE	LOIL	LRATE
R-squared	0.979	0.980	0.990	0.997
Adjusted R-squared	0.976	0.977	0.988	0.996
S.E. equation	0.039	0.032	0.043	0.036
F-statistic	328.847	345.714	677.115	2225.252
Mean dependent	5.046	6.530	3.681	0.792
S.D. dependent	0.249	0.208	0.393	0.603
S.E. (%)	0.767	0.482	1.160	4.582

Table 5
Lagrange multiplier (LM) tests for serial correlation

Lags	LM-stat	Probability
1	17.51	0.35
4	19.16	0.26
12	16.37	0.43

Probabilities calculated from a chi-square distribution with 16 degrees of freedom.

(testing all slope coefficients equal to zero) is statistically significant at the 1% level indicating the importance of the explanatory variables in each regression equation. Lagrange multiplier (LM) tests for residual serial correlation (the null hypothesis is no serial correlation) show no evidence of serial correlation at the 5% level of significance (Table 5). Overall, the VAR fits well and can be used for hypothesis testing and studying the dynamic properties of the data.

Granger causality tests calculated using Toda and Yamamoto (1995) LA-VAR Wald tests show that alternative energy stock prices are explained by past movements in oil prices, technology stock prices, and interest rates (Table 6). These results are important in establishing that, at least from a Granger causality perspective, oil prices are not the only variable impacting the stock prices of alternative energy companies.

Technology stock prices are influenced by lagged oil prices and lagged interest rates. Notice that as expected, interest rates Granger cause stock prices (either alternative energy stock prices or technology stock prices). Also notice that oil prices impact both measures of stock prices. The result that oil price movements have a statistically significant impact on technology stock prices is consistent with the previously mentioned literature in Section 3 of this paper that finds broad support for a relationship between oil prices and stock prices.

Granger causality tests indicate that lagged interest rates do have some statistically significant impact on current oil prices. Since interest rates are a lagging economic indicator, this result is consistent with the view that increased economic growth leads to higher interest rates.

Neither stock prices (of alternative energy companies or technology companies), nor oil prices have a Granger causal impact on interest rates. This is consistent with the U.S. Federal Reserve's view that interest rate changes in either the discount rate or the federal funds rate are set with an eye towards economic growth and inflation. During the time period under study in this present paper, oil prices were rising but overall inflation rates were generally low (less than 3%).

Fig. 2 shows the response of each variable in the system to a one standardized innovation of each variable in the system. Analytically calculated standard errors are used to construct confidence intervals which are shown to gauge the significance of each impulse response. Initially, the stock prices of alternative energy companies responds positively to a shock to itself and this effect is positive and significant for up to at least ten weeks into the future. The most dramatic

Table 6
Toda and Yamamoto (1995) LA-VAR Wald tests

Dependent variable				
	LECO	LPSE	LOIL	LRATE
LECO	–	7.833	3.863	7.283
LPSE	26.140***	–	8.559	8.821
LOIL	18.457***	16.068**	–	11.310
LRATE	21.004***	30.133***	17.280**	–

***, **, *, denote a test statistic is statistically significant at the 1%, 5%, or 10% level of significance.

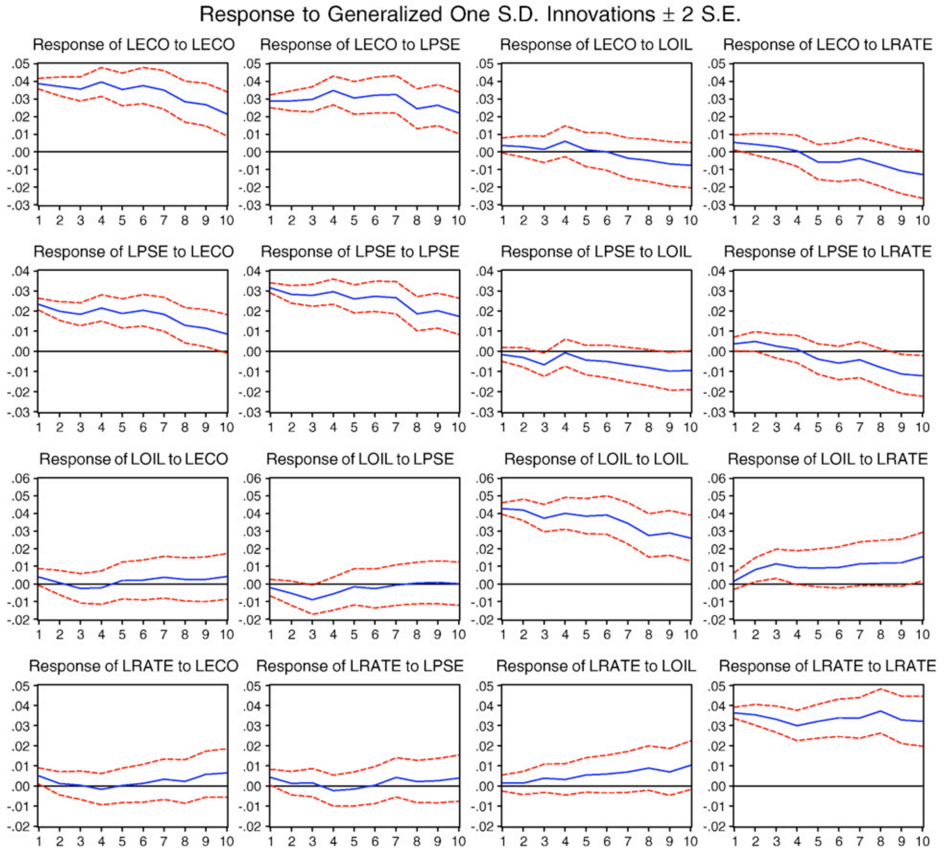

Fig. 2. Impulse response functions.

effect is the response of the alternative energy stock prices to a one standard deviation shock of the technology stock price index. This effect is positive and statistically significant up to at least ten weeks into the future. This result is consistent with the idea that investors view investments in alternative energy stocks as being more closely related to general movements in the technology sector rather than movements in the energy sector. More specifically, a one standard deviation shock to the natural logarithm of technology stock prices raises the natural logarithm of the ECO index by 0.03, or 1.03 points on the ECO index, in the first week. Surprisingly, a one standard deviation oil price shock has no statistically significant impact on alternative energy stock prices which suggests that oil prices shocks are not as important as shocks to technology stock prices. A one standard deviation shock to the interest rate variable has a positive and significant impact on alternative energy stock prices for a period of two weeks. After two weeks, however, this impact quickly diminishes and by week ten the interest rate shock has (as expected) a negative and significant impact on the stock prices of alternative energy companies.

A one standard deviation shock to alternative energy stock prices has a positive and significant impact on technology stock prices over a ten week time horizon. While no statistically significant Granger causal relationship was found running from LECO to LPSE (Table 6), it appears that a one standard deviation shock to LECO does have a dynamic impact on LPSE although it is not

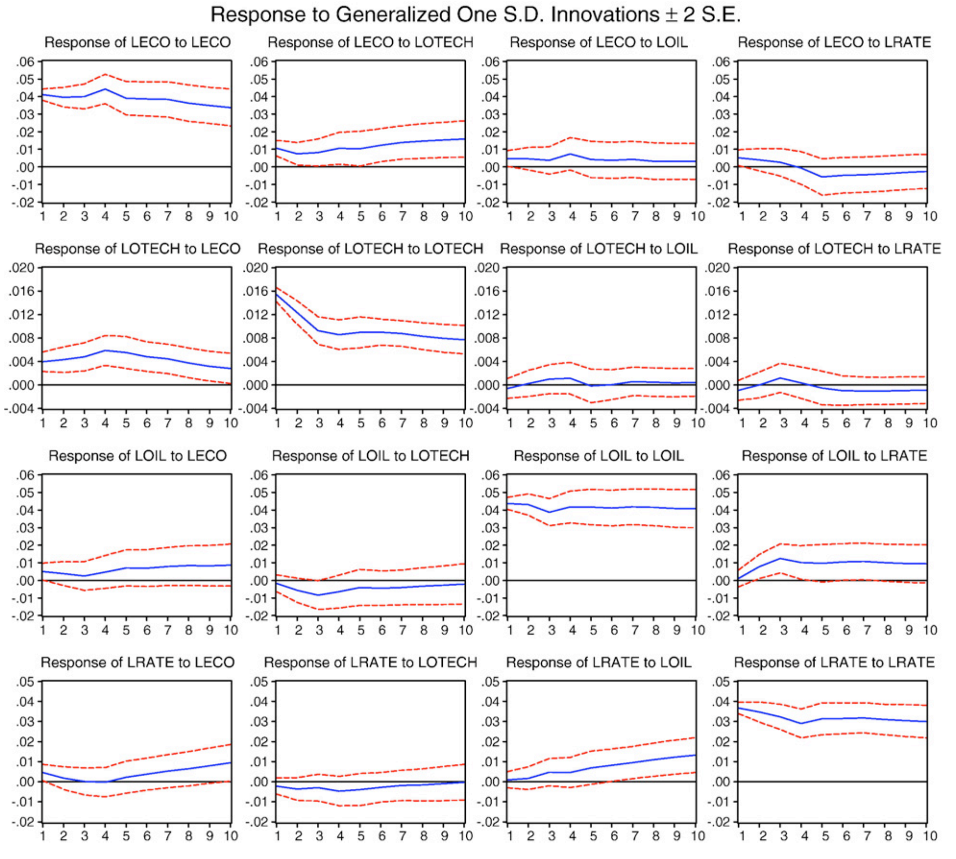

Fig. 3. Impulse response functions using LOTECH.

clear how important this result is given the lack of statistical evidence supporting Granger causality from LECO to LPSE. A one standard deviation shock to technology stock prices has a positive and significant impact on technology stock prices over at least a ten week time horizon. A one standard deviation shock to oil prices has a negative and significant impact on technology stock prices in the third week broadly consistent with the view that rising oil prices dampen technology stock prices because rising oil prices cut into the cash flows of technology oriented companies (Sadorsky, 2003). A shock to the interest rate variable has a positive and statistically significant impact on technology stock prices for two weeks. This impact, however, quickly diminishes after two weeks and by week nine the interest rate shock has (as expected) a negative and significant impact on the stock prices of technology companies.

Oil prices respond positively and significantly to a shock to itself. This effect lasts for at least ten weeks. Oil prices respond positively and significantly to a shock from interest rates. Increases in interest rates usually occur near the top of a business cycle when oil prices are also rising rapidly. Shocks to the other variables, however, have no statistically significant impact on oil prices. In a similar manner, the interest rate variable responds positively and significantly to shocks to itself but shocks to the other variables have no statistically significant impact on the interest rate spread variable.

To check the robustness of the impulse response function results, the VAR model was re-estimated using orthogonalized technology stock prices (Fig. 3). Orthogonalized technology stock prices, denoted as LOTECH, were calculated as the residuals from a regression of the natural logarithm of technology stock prices on the natural logarithm of the S&P 500. Orthogonalized technology stock prices are the technology stock price effect that remains after controlling for general stock market movements. Qualitatively, the results shown in Figs. 2 and 3 are fairly similar. In each of Figs. 2 and 3, shocks to technology stock prices have a greater impact on alternative energy stock prices than do shocks to oil prices.

5. Conclusions

There are several important factors, like energy security issues and environmental concerns, shaping the interaction between business, society and the environment which should generate a positive business environment for companies engaged in the production and distribution of alternative energy. Although this bodes well for the industry in the long run, a better understanding of the relationships between oil prices and financial performance of the alternative energy industry is critical to understanding the development of the alternative energy industry in the years to come.

In this paper, a four variable vector autoregression model is developed and estimated in order to investigate the empirical relationship between stock prices of alternative energy companies, technology stock prices, oil prices, and interest rates. Granger causality tests show that even though the model is estimated over a relatively short time period, movements in oil prices, technology stock prices, and interest rates each have some power in explaining the movements of the stock prices of alternative energy companies.

Simulation results show the stock prices of alternative energy companies to be impacted by shocks to technology stock prices but shocks to oil prices have little significant impact on the stock prices of alternative energy companies. These results add to a small but growing literature showing that oil price movements are not as important as once thought because investors may view alternative energy companies as similar to other high technology companies. These results should be of use to investors, managers and policy makers.

Investors in technology have a wide array of products to choose to invest in from entertainment oriented devices that easily appeal to large numbers of consumers to new energy supply products. One day alternative energy companies could be seen as mainstream energy companies but at the present mass adoption of alternative energy is still too far off and uncertain. In the case of electricity generation in the United States, for example, 71% of energy sources come from fossil fuels (50% coal, 18% natural gas, and 3% petroleum), 20% from nuclear power, 7% from hydroelectric, and 2% from renewable sources (wind, solar, biomass) (Economic Report of the President, 2006, page 252). Consequently, alternative energy companies are seen by investors as potential disruptive technology providers and while the potential returns from investing in the alternative energy industry are high so are the associated risks. Governments can help to bring alternative energy products to market by having a clear and supportive alternative energy policy, and a fiscal policy that taxes carbon and subsidizes alternative energy. Government can also boost demand by being early purchasers of alternative energy related products.

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