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Graduate School of Environmental Studies, Tohoku University, Graduate School of International Corporate Strategy, Hitotsubashi University

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Shunsuke Managi[1*,2] and Tatsuyoshi Okimoto[3]

[1] Graduate School of Environmental Studies, Tohoku University
6-6-20 Aramaki-Aza Aoba, Aoba-Ku, Sendai 980-8579, Japan
Tel: 81- 22-795-3216/ Fax: 81- 22-795-4309, managi.s@gmail.com
(*Corresponding author)

[2] Graduate School of Public Policy, The University of Tokyo

[3] Graduate School of International Corporate Strategy, Hitotsubashi University
tokimoto@ics.hit-u.ac.jp

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Abstract

In this paper, we analyze the relationships among oil prices, clean energy stock prices, and technology stock prices, endogenously controlling for structural changes in the market. To this end, we apply Markov-switching vector autoregressive models to the economic system consisting of oil prices, clean energy and technology stock prices, and interest rates. The results indicate that there was a structural change in late 2007, a period in which there was a significant increase in the price of oil. In contrast to the previous studies, we find a positive relationship between oil prices and clean energy prices after structural breaks. There also appears to be a similarity in terms of the market response to both clean energy stock prices and technology stock prices.

Key Words: clean energy; stock prices; oil price; Markov-switching VAR

JEL Classification: Q42, Q43

1. Introduction

Increases in oil price negatively affect economic activity and stock prices (Hamilton, 2003; Kilian, 2009). For example, most U.S. recessions are preceded by large oil shocks. There have been extensive studies analyzing the effects of oil price changes on the real economy, as well as their transmission mechanisms (e.g., Hamilton, 2003, 2009a; Kilian, 2008, 2009) [1]. The previous literature suggests a positive association between rising oil prices and inflationary pressures on the economy (e.g., Fama, 1981; Darby, 1982; Cunado and Perez, 2005). Furthermore, many studies indicate a negative relationship between rising oil prices and stock prices (e.g., Hamilton, 1983; Huang and Masulis, 1996; Jones and Gautam, 1996; Sadorsky, 1999, 2001; Henriques and Sadorsky, 2008, Park and Ratti, 2008; Kilian and Park, 2009).

Although the aforementioned studies suggest a negative effect on stock prices from rising oil prices, there are several industries that benefit from higher oil prices. One such example might be the clean, or alternative, energy industry[2]. As oil prices increase, people are motivated to seek out alternative energy sources, albeit via imperfect substitutes, causing a surge in the price of alternative energy stocks. It is therefore worthwhile to examine the connection between clean energy stock prices and oil prices.

Once we consider the economic incentives related to the stock prices of green energy firms, there are a few applicable studies to examine. For example, Linn (2006) and Bushnell et al. (2009) examine changes in the stock prices of green energy firms as a function of external shocks, such as price changes in the carbon market and environmental regulations. To date, however, there exist very few studies examining the relationship between clean energy stock prices and oil prices. One such study is conducted by Henriques and Sadorsky (2008), who analyze the relationship between clean energy stock prices and oil prices from January 3, 2001, through May 30, 2007 by using the vector autoregression (VAR) approach. They find that the stock prices of alternative energy companies are impacted by shocks to technology stock prices, but they also find that shocks to oil prices have little significant impact on the stock prices of alternative energy companies. Thus, the previous literature fails to provide evidence of a positive effect on clean energy stock prices from rising oil prices

[1] It is also important to note that an increase in oil price has long-term effects on the economy. For example, a high growth rate in energy-saving technologies is observed when oil prices increase (e.g., Kumar and Managi, 2009).

[2] See Narayan and Sharma (2011) for evidence regarding the positive effect on the energy industry.

(see also Sadorsky, 2012). However, extending the data up to 2008 and applying the VAR in line with Henriques and Sadorsky (2008), Kumar et al. (2012) show a positive relationship between oil prices and the stock prices of alternative energy companies. Therefore, how changes in the data affect the relationship is the remaining research question.

The main contribution of this paper is its further examination of the relationships among oil prices, clean energy stock prices, and technology stock prices. To this end, we extend Henriques and Sadorsky's (2008) study into the Markov-switching (MS) framework. The MS model provides a powerful tool for investigating an economic system with possible structural changes and asymmetric effects, which is arguably the case in our analysis, as discussed below. We note here none of the previous studies consider possible structural changes in order to understand the relationships among oil prices, clean energy stock prices, and technology stock prices.

Because oil prices have most likely had structural breaks in their time series data over the past 40 years, as pointed out by Hamilton (1983), it is not unreasonable to consider the possibility of structural breaks in the effects of oil prices on the economy. Moreover, there may be examples of significant changes in the interactions within the economic system that are causally related to oil prices. For instance, Kapetanios and Tzavalis (2010) analyze structural breaks in economic relationships, which are assumed to be driven by large economic shocks, such as oil shocks. They show that the first oil shock, at the end of 1973, had a large and long-term negative effect on economic activity, though the effect might not be large as was widely thought. If this is the case, the economic system may have been significantly altered as a result of the increase in oil prices during 2008. It is therefore crucial to use a model that can incorporate a possible structural change, such as the MS model employed by our study.

There are also a number of studies reporting the asymmetric effects of oil prices on economic activities (e.g., Hamilton, 1983, 1996; Mork, 1989; Jones and Leiby, 1996; Mork and Olsen, 1994). Although rising oil prices negatively affect economic activities, declining oil prices do not stimulate the economy. There are also several previous studies that report an asymmetric dependence in the stock market (Maheu and McCurdy, 2000; Ang and Bekaert, 2002; Okimoto, 2008). Because one of the main purposes of this paper is to examine the interactions among oil prices, clean energy stock prices, and technology stock prices, it is of great importance to consider the possibility of certain asymmetric effects among these three variables by using the MS model.

This study applies the Markov-switching vector autoregressive (MSVAR) models to the economic system consisting of oil prices, clean energy and technology stock prices, and interest rates. The results indicate that there is a structural change in late 2007, a period in which there was a significant increase in the price of oil. Although our results are entirely consistent with those of Henriques and Sadorsky (2008) before the structural break, we find that oil prices have positively impacted clean energy stock prices after the structural break, forming a striking contrast to the results of Henriques and Sadorsky (2008).

The paper is organized as follows: Section 2 describes the methodology of the MSVAR model. In Section 3, we present the data and discuss the empirical results. Concluding remarks are offered in Section 4.

2. Methodology

The main purpose of this paper is to examine the dynamic relationships among oil prices, technology stock prices, and clean energy stock prices, along with possible structural changes and asymmetric effects. To this end, we employ the MSVAR model. The VAR model can serve as a convenient tool for examining the interactions among variables, while the Markov-switching framework provides natural and tractable models for processes with switching regimes. By combining these two techniques, we can model regime switching interrelations with sufficient flexibility.

2.1 MSVAR model

The basic model used in this study is the recursive structural VAR model. To briefly illustrate the recursive structural VAR model, let $\mathbf{y}$ be an $n \times 1$ vector consisting of n variables for examining dynamic relations. A reduced-form VAR model can be written as[3]

$$\mathbf{y}_t = \Phi_1 \mathbf{y}_{t-1} + \Phi_2 \mathbf{y}_{t-2} + \Lambda + \Phi_p \mathbf{y}_{t-p} + \varepsilon_t \tag{1}$$

where p is the lag length necessary to describe the dynamics of the system, Φ_j $(j = 1, \ldots, p)$ are $n \times n$ coefficient matrices, and ε_t is a disturbance term. We also assume that ε_t is a Gaussian vector white noise with $E(\varepsilon_t) = 0$ and $E(\varepsilon_t \varepsilon_t') = \Omega$.

One problem associated with the use of the VAR model (1) is the identification of structural shocks. To identify the structural shocks, we assume that the variables in the

[3]The constant term is omitted for notational simplicity. However, all estimated models include a constant term.

system have a recursive structure or are to be ordered according to their degrees of exogeneity, as proposed by Sims (1980). Under this recursive structural VAR assumption, the Cholesky decomposition can be used to identify the structural shocks. Once the structural shocks are identified, we can calculate the impulse response functions in order to analyze the interactions among the variables.

To capture the possible time variation in the interrelations between oil and stock markets, we introduce the MS framework into the recursive structural VAR model according to Sims and Zha (2006) and Inoue and Okimoto (2008). With this specification, the reduced-form VAR model (1) is expressed as

$$\mathbf{y}_t = \Phi_1(s_t)\mathbf{y}_{t-1} + \Phi_2(s_t)\mathbf{y}_{t-2} + \cdots + \Phi_p(s_t)\mathbf{y}_{t-p} + \varepsilon_t,$$

where s_t is a latent variable taking the value of either 1 or 2. Moreover, $E(\varepsilon_t\varepsilon_t') = \Omega(s_t)$ is also assumed to be a function of s_t. In other words, this MSVAR model allows us to specify different VAR models for different regimes.

For the stochastic process of s_t, the MS model employs the Markov chain, as suggested by Hamilton (1989). The Markov chain is a simple model that describes the dynamics of a discrete random variable. The law of state evolution is governed by a transition probability matrix $\mathbf{P}$, where the (i, j) element of $\mathbf{P}$ indicates $Pr\left(s_t = i \mid s_{t-1} = j\right)$:

$$\mathbf{P} = \begin{pmatrix} p_{11} & 1-p_{22} \\ 1-p_{11} & p_{22} \end{pmatrix}$$

Although the model has a simple structure, it can characterize various types of state evolutions that depend on the elements of matrix $\mathbf{P}$. For example, the regime is very transitive if p_{ii} is small, whereas it is highly persistent if p_{ii} is close to 1 because the expected duration of each regime can be calculated by $1/(1-p_{ii})$. Another interesting example is given by the following transition matrix:

$$\mathbf{P} = \begin{pmatrix} p_{11} & 0 \\ 1-p_{11} & 1 \end{pmatrix} \tag{3}$$

Because the $(1,2)$ element of this transition matrix is zero, once a state moves from Regime 1 to Regime 2, it will never return to Regime 1. In other words, once the model reaches Regime 2, it will continue in Regime 2 for the remainder of the sample period. Therefore, the MS model with transition probability matrix (3) can be used to capture a permanent structural change within the sample period.

Thus, the VAR model provides us a convenient tool for examining dynamic relationships among the economic/financial variables in each regime, whereas the MS model can describe various types of regime dynamics. By estimating the MSVAR model, we can find the appropriate interactions among variables in each regime via the suitable state evolution, which is very attractive for the purposes of this paper.

2.2 MCMC estimation for the MSVAR model

The MS model is usually estimated via the maximum likelihood estimation (MLE). For instance, Hamilton (1990) reports that by using the expectation-maximization (EM) algorithm (Dempster, Laird, and Rubin, 1977), one can obtain maximum likelihood estimates that are relatively robust with respect to the parameters' starting values. However, if a model contains too many parameters, we often encounter some difficulty in maximizing the log-likelihood function. For example, the four-variable, two-state MSVAR model with four lags that is used in this paper has more than 150 parameters. Not surprisingly, it is difficult to obtain reasonable maximum likelihood estimates for such a large model.

To overcome this difficulty, we employ the Bayesian Markov Chain Monte Carlo (MCMC) approach. The Bayesian method calculates the posterior distribution of the parameters from the prior distribution and the observed data for statistical inferences. Even when the analytical calculation of the posterior distribution is formidable, the MCMC methods can provide feasible algorithms with which to sample from the posterior distribution by constructing a Markov chain that has the desired posterior distribution as its stationary distribution. The state of the chain obtained after the completion of numerous steps is then used as a sample from the desired posterior distribution in order to make statistical inferences.

Among the many MCMC methods available, we adopt the Gibbs sampler in this paper. In what follows, we briefly explain the Gibbs-sampling procedure for the two-state MSVAR model (for algorithm details, see Chib, 1996, 1998; and Kim and Nelson, 1999)

Let θ, T, and $\mathbf{y}_t$ denote a set of unknown parameters, the number of observations, and the observation at time t, respectively. To conduct the Gibbs sampler, we divide the parameters into four blocks, i.e., a set of latent state variables (θ_1), a set of transition probabilities (θ_2), a set of covariance matrices (θ_3), and a set of VAR coefficients (θ_4).[4]

[4]Strictly speaking, $\{s_t\}_{t=1}^{T}$ are the latent state variables, not the parameters. However, because they are estimated from the data, they are usually treated as unknown parameters in the Bayesian framework.

Thus, we can write $\theta = [\theta_1', \theta_2', \theta_3', \theta_4']'$, with each θ_i ($i = 1,2,3,4$) defined as: $\theta_1 = [s_1, s_2, \ldots, s_T]'$, $\theta_2 = [p_{11}, p_{22}]'$, $\theta_3 = [vech(\Omega(1))', vech(\Omega(2))']'$, and $\theta_4 = [\beta(1)', \beta(2)']'$, where $\beta(j) = [vec(\Phi_1(j))', \ldots, vec(\Phi_p(j))']'$. Furthermore, let $p(\theta \mid \tilde{\mathbf{y}}_T)$ be the desired posterior distribution, where $\tilde{\mathbf{y}}_t = \{\mathbf{y}_{-p+1}, \mathbf{y}_{-p+2}, \ldots, \mathbf{y}_t\}$. Then, the Gibbs sampler allows us to generate random samples following $p(\theta \mid \tilde{\mathbf{y}}_T)$, as follows:

1. Set initial values $\theta^{(0)}$ and set $j = 0$.
2. Draw $\theta_1^{(j+1)}$ from $p\left(\theta_1 \middle| \theta_2^{(j)}, \theta_3^{(j)}, \theta_4^{(j)}, \tilde{\mathbf{y}}_T\right)$.
3. Draw $\theta_2^{(j+1)}$ from $p\left(\theta_2 \middle| \theta_1^{(j+1)}, \theta_3^{(j)}, \theta_4^{(j)}, \tilde{\mathbf{y}}_T\right)$.
4. Draw $\theta_3^{(j+1)}$ from $p\left(\theta_3 \middle| \theta_1^{(j+1)}, \theta_2^{(j+1)}, \theta_4^{(j)}, \tilde{\mathbf{y}}_T\right)$.
5. Draw $\theta_4^{(j+1)}$ from $p\left(\theta_4 \middle| \theta_1^{(j+1)}, \theta_2^{(j+1)}, \theta_3^{(j+1)}, \tilde{\mathbf{y}}_T\right)$.
6. Set $\theta^{(j+1)} = \left[\left(\theta_1^{(j+1)}\right)', \left(\theta_2^{(j+1)}\right)', \left(\theta_3^{(j+1)}\right)', \left(\theta_4^{(j+1)}\right)'\right]'$.
7. If $j+1 = N$, stop the algorithm. Otherwise, set $j = j+1$, and repeat the algorithm from Step 2.

Here, N is the number of iterations, and the first N_0 samples are discarded. Thus, $\left\{\theta^{(j)}\right\}_{j=N_0+1}^{N}$ are considered to be the samples following $p\left(\theta \mid \tilde{\mathbf{y}}_T\right)$.[5]

As for the prior distributions of the unknown parameters, we basically assume the conjugate diffuse priors. However, to obtain reliable estimation results, we make some adjustments. In Step 2, we draw $\{s_t\}_{t=1}^{T}$ conditional on $\theta_2^{(j)}, \theta_3^{(j)}, \theta_4^{(j)}$ and $\tilde{\mathbf{y}}_T$. If the number of observations that are classified in a particular regime is small, it is difficult to conduct the random sampling in Steps 4 and 5. For instance, in Step 5, we need to estimate VAR coefficients for each regime by using the data classified into each regime. This will clearly be difficult if the number of observations in a particular state is too small. In this paper, we assume that each state has at least 52 data points, or one year of observations. This assumption is needed in order to obtain reliable estimation results. If the number of observations in a regime is less than 52 for a generated series of $\{s_t\}_{t=1}^{T}$, then we discard the

[5]In this paper, we set $N = 30{,}000$ and $N_0 = 20{,}000$.

sample and draw another sample. For the priors of the transition probabilities, p_{11} and p_{22}, we assume independent uniform distributions between 0 and 1. For Steps 4 and 5, we simply use the Normal-Wishart diffuse priors for β and Ω.[6] The only difference between our model and the normal VAR model is that in order to generate parameters for state i, we only use the data classified into state i in Step 2.

3. Analysis

3.1 Data

In this paper, we use the same weekly data as those of Henriques and Sadorsky (2008), which are the following: the stock index of clean energy firms (CE), the index of the prices of technology stocks (TECH), the oil price, and the short-term interest rate. All stock data are obtained from Bloomberg.

The stock market performance of clean energy firms is measured by the WilderHill Clean Energy index. It is a modified equal-dollar weighted index that is comprised of publicly traded companies whose businesses stand to substantially benefit from a societal transition toward the use of cleaner forms of energy, such as hydrogen fuel cells, wind, and solar energy (for more details, see www.wilderhill.com). CE is disseminated by the American Stock Exchange (AMEX) and was the first index to track the stock prices of clean, renewable energy companies, which consist of approximately 40 companies.

In the late 1990s, investments in clean energy firms were considered to be similar for investors to investments in other high-technology firms (Henriques and Sadorsky, 2008). During the stock market boom for high-technology firms, a number of fuel cell companies experienced increases similar to those of high-technology firms. As a consequence, we apply two datasets, one set based on clean energy stock prices and one set based on technology firm stock prices, to investigate the relationship. This study applies the Arca Tech 100 index, formerly known as the Pacific Stock Exchange technology index (TECFH), to measure the stock market performance of high-technology firms.

TECH includes firms listed on leading stock exchanges and over-the-counter shares. TECH is a price-weighted, broad-based index composed of 100 listed and over-the-counter stocks from 15 industries, including computer hardware, software, semiconductors, telecommunications, data storage and processing, electronics, and biotechnology (for more details, see www.nyse.com/marketinfo/indexes/pse.shtml).

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[6] See Kadiyala and Karlsson (1997) for the Normal-Wishart diffuse priors for the VAR model.

We use the price of oil (OIL), conventional fossil fuel energy. This is the most widely-traded physical commodity in the world. Though oil will not be replaced by clean energy anytime soon, more of our energy needs might be met by clean energy in the future. Therefore, rising oil prices are expected to encourage investment in clean energy firms. We evaluate oil prices by using the average of the closing prices of the nearest contract on the West Texas Intermediate (WTI) and BRENT crude oil future contract (see http://tonto.eia.doe.gov/dnav/pet/xls/PET_PRI_SPT_S1_D.xls).

It has been noted that there is a significant relationship between stock price movements and interest rates (see Sadorsky, 2001). Thus, we apply a three-month yield on a US Treasury bill interest rate (RATE) in order to investigate the relationship between the stock prices of clean energy firms and interest rates. Interest rate data are obtained from the Federal Reserve Economic Data (FRED) of Federal Reserve Board of St. Louis (see http://research.stlouisfed.org/fred2/).

The sample period is from January 3, 2001 to February 24, 2010, containing a total of 478 available weekly observations. For the stock market prices and the price of oil, we use data from the Wednesday closing of the stock market. Wednesday closing prices are used because in general, there are fewer holidays on Wednesdays relative to Fridays. Any missing data on the Wednesday closings are replaced with closing prices from the most recent trading session.

Figure 1 shows a time series plot of the CE, TECH, and oil prices. All of the variables are expressed in natural logarithms to reduce heteroskedasticity in the data. In addition, for the sake of comparison, each series is set equal to 100 on January 3, 2001. We observe relatively similar dynamics between the stock prices of clean energy firms and high-technology firms. The prices for clean energy firms rose at a higher rate and were more volatile in comparison not only to general stocks but also to the stocks of high-technology firms. During the financial crisis of 2007, the fall in prices for clean energy stocks was relatively greater than the fall in prices of both general stocks and the stocks of high-technology firms.

Lastly, we calculate the average continuously compounded returns on investments for clean energy firms, high-technology firms, and oil prices. The average annual returns are obtained by multiplying the weekly returns by a factor of 52. The average annualized compounded returns on investment in clean energy and high-technology firms were 2.69% and 0.18%, respectively, whereas the average annualized returns on investments in oil were 11.43%, and the return on three-month US Treasury bills was 2.29%. We believe that this difference comes from the degree of rising in the sample period, shown in Figure 1. The price of oil rose more than clean energy. Therefore, oil investments perform best, and clean energy investments are second.

3.2 Results of unit root and cointegration tests

The main purpose of this paper is to examine the relationships among oil prices, clean energy stock prices, and high-technology stock prices by applying VAR models with/without the Markov-switching framework to the aforementioned four variables: the WilderHill Clean Energy index (CE), the Arca Technology index (TECH), U.S. West Texas intermediate crude oil future prices (OIL), and the interest rate (RATE). Before applying the VAR models, we must determine the appropriate model specification by identifying the order of integration of each data series and the existence of cointegration among the four variables. If the variables have a unit root, it is best to take the first difference in order to make the series stationary. In addition, if there is a cointegrating relationship in the system, we use the vector error correction model rather than the VAR model in the first differences. We, therefore, conduct the unit root and cointegration tests and summarize the results.

For the unit root tests, we use the Augmented Dickey-Fuller (ADF) tests, the Phillips and Perron (PP) tests, and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root tests in accordance with Henriques and Sadorsky (2008). The null hypothesis for the ADF and PP tests is that the data series has a unit root, whereas the null hypothesis for the KPSS test is that the data series is stationary. The results of three unit root tests for each data series are reported in Table 1. As can be seen, all unit root tests indicate that each series has a unit root in levels and is stationary in the first differences, suggesting that all variables are integrated at order 1 or $I(1)$ processes.

We further examine whether there is a cointegrating relationship in the four-variable systems. Here, two conventional cointegration tests are performed: the Johansen's trace test of no cointegration against one cointegrating vector and the maximum eigenvalue test of no cointegration against four cointegrating vectors. We allow for a linear trend in the data and use the lag length of nine, which is selected via the Akaike information criterion (AIC) for both tests. The P-values of the two tests are 0.398 and 0.649, respectively, indicating that there is no cointegration in the system at the 5% significance level.

In sum, our results suggest that all four variables are $I(1)$ without any cointegrating relationship. Therefore, we will use VAR models in the first differences in the following analysis.

3.3 Results of the VAR model without Markov switching

In this subsection, we estimate the recursive structural VAR model without Markov switching for comparison with Henriques and Sadorksy (2008). For the recursive structural VAR model, the ordering of variables is determined by the degree of exogeneity of the variables. In our VAR model, the variables are stacked in the order of OIL-RATE-TECH-CE.[7] We treat the oil prices as the most exogenous because the oil prices heavily depend on OPEC's decisions regarding petroleum supply, which are arguably independent of other variables.[8] We also assume that the interest rate is the second most exogenous because the three-month US Treasury bill rate is closely related to the federal fund rate, which only includes the output gap and the inflation gap according to the standard Taylor rule for the federal fund target.[9] Though this assumption can be skeptical (Rudebusch, 2009), the interest rate is at least exogenous to high-tech and clean energy stock prices. Finally, we apply the technology stock price index before the clean energy stock price index, assuming that the technology stock price is predetermined for the clean energy stock price.

Regarding the lag length for the VAR models, we set the lag length to be fixed at four for all cases. Although the AIC selected a lag length of one for the VAR models in the first-differenced data, we allow three more lags in order to capture possible long-term effects.[10]

As a benchmark, we first estimate a simple VAR model without Markov-switching. Figure 2 depicts the impulse response functions of each variable in the system to a one-standard-deviation shock. The 90% confidence intervals are also shown in the figure (dotted line). Because the main purpose of the paper is to investigate the relationships among oil prices, clean energy stock prices, and high-technology stock prices, we focus on the responses of technology and clean energy stock prices to the oil price shock and the technology stock price shock. A one-standard-deviation shock to oil prices has no significant

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[7] We try other orders to examine the robustness of our results and confirm that our main findings are robust with respect to the order of variables.

[8] However, recent high prices have depended on short-run production capacity constraints (for example, from fewer discoveries of new fields) and on high demand from worldwide economic growth, especially because of China's rapid growth. These other movers of oil prices would be important to model because they could cause omitted variables bias, but we reserve this analysis for future research.

[9] See Taylor (1993) for the Taylor rule.

[10] We also estimate the VAR models with one lag and obtain essentially the same results, except that the impulse responses become almost flat after three weeks.

effect on technology stock prices, but a positive and significant impact on clean energy stock prices. From the figures, we see that there are permanent effects. A one-standard-deviation shock to technology stock prices has a significant positive effect on both technology and clean energy stock prices. Although the latter is consistent with the findings of Henriques and Sadorsky (2008), the former is in contrast to their findings of a negative significant impact on technology stock prices from oil prices and an insignificant effect on clean energy stock prices from oil prices. Because our analysis uses the same variables as those of Henriques and Sadorsky (2008) but includes approximately three more years of data, the results of the VAR model without Markov switching suggest that there might be significant changes in the relationships among oil prices, technology stock prices, and clean energy stock prices in the last three years. Therefore, it is important to examine the possible structural change in the last three years, as well as possible asymmetric effects by using a MSVAR model.

3.4 Results of the VAR model with Markov switching

In this subsection, we estimate the possible structural changes and asymmetry by using the two-state MSVAR model. As discussed in the introduction, previous studies have indicated the possibility of both structural changes and asymmetry in the relationships among oil prices, technology stock prices, and clean energy stock prices. It is therefore instructive to consider the MSVAR model's potential to accommodate both possibilities.

Figure 3 shows the smoothed probability of Regime 2 as estimated from the MSVAR model. As can be seen from the figure, the regime is usually identified as Regime 1 prior to the middle of 2007, but changes in the regimes occurred often between the end of 2007 and the middle of 2008. After the end of 2008, the regime had moved almost completely into Regime 2, suggesting that the regime change may not be a temporary event. Thus, the result of the smoothed probability strongly indicates that there is a permanent structural change between the end of 2007 and the middle of 2008. It also demonstrates that it is more important to consider the possible structural changes than the asymmetric effects in the relationships among oil prices, technology stock prices, and clean energy stock prices. Therefore, to more precisely identify the timing of the structural change, we estimate the MSVAR model with transition probability matrix (3), hereafter referred to as the MSVAR2 model, explicitly modeling a permanent structural change.

The smoothed probability of Regime 2 that is generated by the MSVAR2 model is shown in Figure 4. As can be seen from the figure, the smoothed probability of Regime 2 suddenly increased in January 2008, indicating that the timing of the structural change was estimated with great accuracy. This is completely consistent with the results of the MSVAR model above. These results strongly suggest the appropriateness of MSVAR2 Model 2. The value of AIC also demonstrates a considerable improvement from the VAR model, with a large decrease from -11.1 to -13.7, meaning that the MSVAR2 model fits much better than the VAR model.

Our identified timing for the structural change coincides with the timing of economic turmoil, which is potentially due to an oil price increase. The oil price doubled from June 2007 to June 2008. This was the largest price increase in oil since the 1970s. Commodity price speculation, strong world demand, geological limitations on increasing production, OPEC's monopoly pricing, and the increasing contribution of the scarcity rent are the reasons for the high oil price in summer of 2008 (Hamilton, 2009a). During this most recent increase, the U.S. economy entered into a recession in the fourth quarter of 2007. Though a number of factors were responsible for the recession, one of the reasons for the recession could be the oil price shock. Supporting this premise, Hamilton (2009b) argues that "In my mind, there is no question that this latest surge in oil prices was an important factor that contributed to the economic recession that began in the U.S. in 2007:Q4." The smoothed probability shown in Figure 4 suggests that the increase in oil prices also affected the relationships among oil prices, technology stock prices, and clean energy stock prices. Consequently, the oil price plummeted. This might have been because world demand and other factors that could have increased the oil price were diminished by the economic downturn.

To examine this effect in detail, we compare the impulse response functions for each regime shown in Figures 5 and 6. In Regime 1, a one-standard-deviation shock to oil prices has a marginally significant negative effect on technology stock prices, but it has no significant impact on clean energy stock prices. A one-standard-deviation shock to technology stock prices has a significant positive effect on both technology and clean energy stock prices. These results are perfectly consistent with the results of Henriques and Sadorsky (2008). This is not surprising, because the period of Regime 1 (January, 2001, to December, 2007) is almost the same as the sample period analyzed by Henriques and Sadorsky (2008) (January, 2001, to May, 2007). In contrast, the impulse response functions for Regime 2 illustrate that a one-standard-deviation shock to oil prices has significant positive effects on both technology and clean energy stock prices, although it is only marginal for technology stocks. It is also worth noting that the significant positive response of the clean energy stocks is more relevant to the alternative energy story and is hence more important. While Henriques and Sadorsky (2008) fail to provide evidence of a positive effect from rising oil prices on clean energy stock prices, by extending data up to 2008 and applying the VAR in line with Henriques and Sadorsky (2008), Kumar et al. (2012) show a positive relationship. This suggests the necessity of alternative analytical techniques and that structural changes affect the relationships among oil prices, technology stock prices, and clean energy stock prices. This might be because alternative energy becomes relatively inexpensive via technological improvement and because the oil price becomes relatively expensive, and therefore, substitution occurs in some areas.

Note also that the technology stock price shock has the same impact on clean energy stock prices as in Regime 1. Thus, both oil prices and technology stock prices have been found to positively and significantly affect clean energy stock prices in recent years. This result demonstrates that investors consider the stocks of technology firms to be similar to clean energy stocks.

4. Concluding Remarks

This study analyzed the relationships among oil prices, clean energy stock prices, and high-technology stock prices. We contributed to the literature by considering structural changes in the market and analyzing the importance of clean energy stocks. Specifically, we applied the MSVAR to detect the possibility of a structural change by analyzing smoothed probabilities.

We identified structural changes in the market during November and December of 2007, coinciding with a surge in the price of oil. This was also the period in which the U.S. economy entered a recession. No policy could have avoided the considerable increase in the price of oil between 2005 and the first part of 2008 (Hamilton, 2009a).

Endogenously controlling for structural changes in the market, this study also analyzed the relationships among oil prices, clean energy stock prices, and high-technology stock prices. We found a positive relationship between oil prices and clean energy prices after structural breaks, suggesting a movement from conventional energy to clean energy. That is, structural changes affect the relationship between oil prices and clean energy markets. A similarity between clean energy stock prices and high-tech stock prices is also suggested because technologies related to storage, fuel cells, and other forms of clean energy clearly benefited from a number of government policies.

Although our result suggested that the structural change around the end of 2007 is better characterized as a permanent event rather than a transitory phenomenon, once the economy recovers from the recession, the economic regime may shift again and result in a non-relationship between clean energy stocks and oil prices. Alternatively, oil prices may be the major cause of this shift, which is in line with the literature on oil and the macro-economy (see Hamilton, 2009a; Kapetanios and Tzavalis, 2010). Suppose the oil price returns to the price it was a decade ago, \$20-30 per barrel, from the current stable, much higher price, the economic structure could change again. What is clear is that a surge in oil prices has short-term consequences and clear implications for the stock market. Also, there is a possibility that the absence of government/authority's actions to avoid the surge in oil prices triggered the regime switch. Future studies need to identify more detailed transmission mechanisms, as well as the outcomes of production for clean energy and technology.

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Table 1: Results of unit root tests

	Levels			First differences		
	ADF(lags)	PP(NWBW)	KPSS(NWBW)	ADF(lags)	PP(NWBW)	KPSS(NWBW)
OIL	-2.236(0)	-2.457(8)	0.230(17)***	-11.347(2)***	-21.960(7)***	0.053(7)
RATE	-1.684(4)	-1.911(9)	0.445(17)***	-10.741(3)***	-33.170(8)***	0.161(21)
TECH	-2.585(0)	-2.702(8)	0.229(17)***	-22.195(0)***	-22.194(7)***	0.121(7)
CE	-2.060(3)	-1.803(10)	0.270(17)***	-9.595(2)***	-21.779(9)***	0.122(10)

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). The unit root tests regressions include an intercept and a linear trend for the levels and an intercept for the first differences. 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.

Figure 1: Stock Prices (clean energy and technology) and Oil price: Base year as value of 100

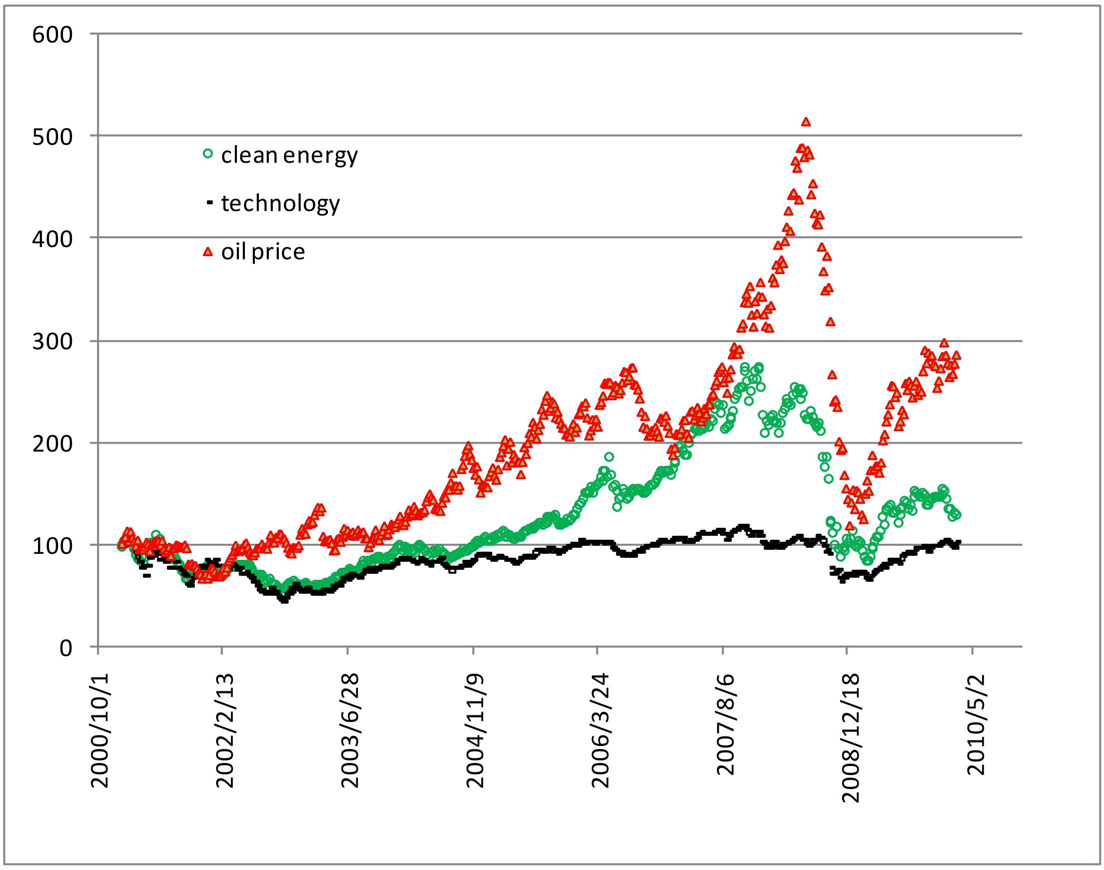

Figure 2: Impulse Response Functions for the VAR model

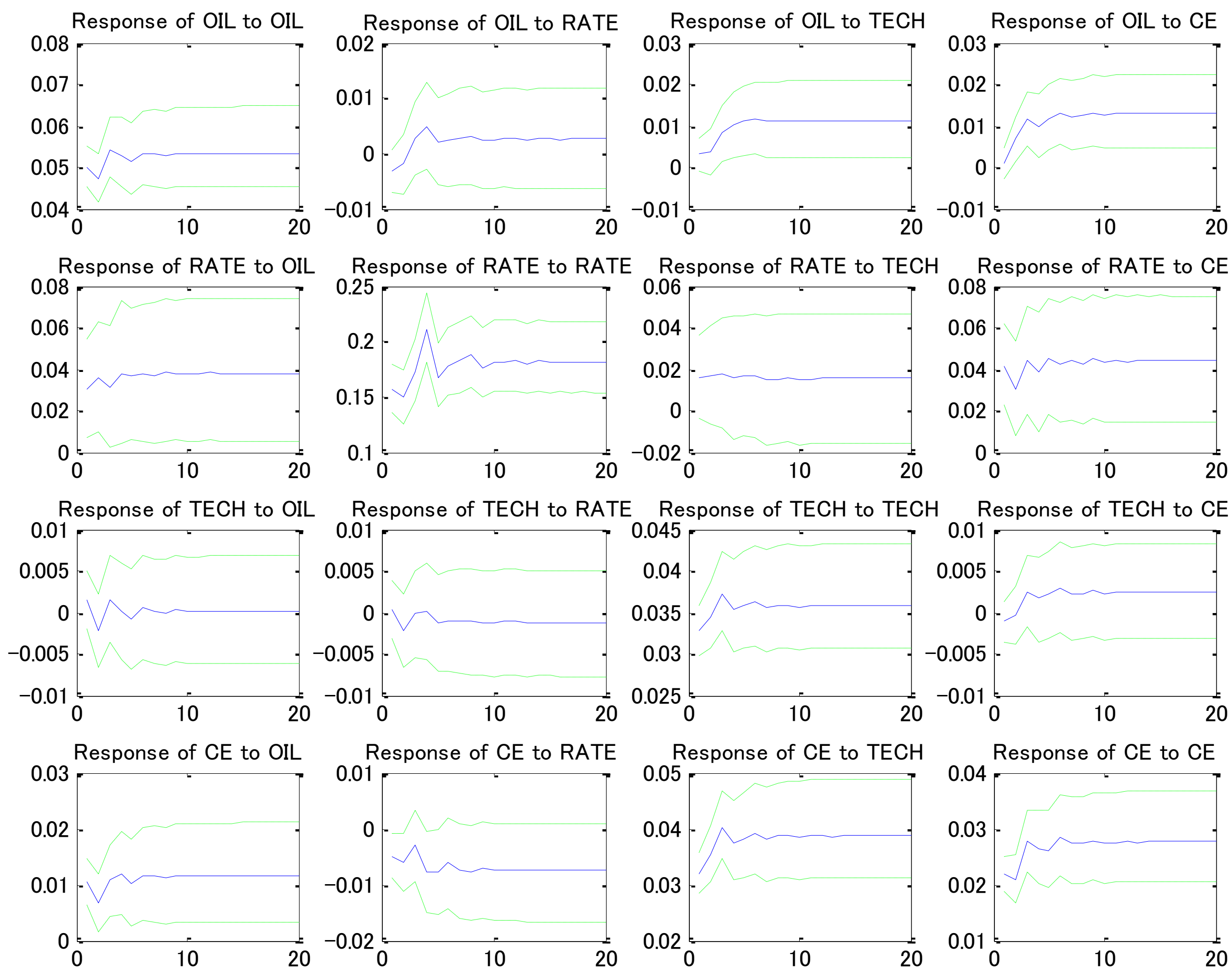

Figure 3: Smoothed Probability of Regime 2 for the MSVAR model

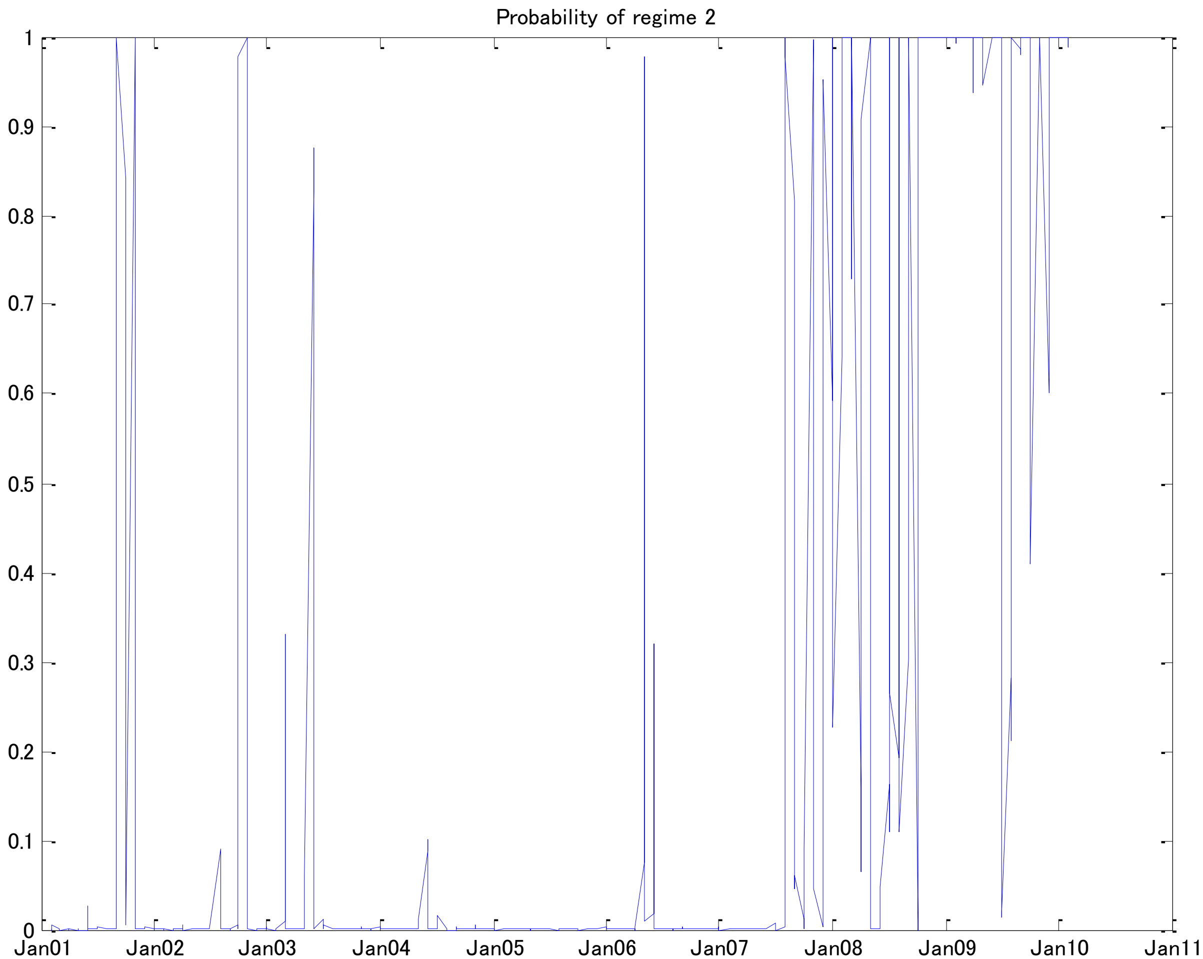

Figure 4: Smoothed Probability of Regime 2 for the MSVAR2 model

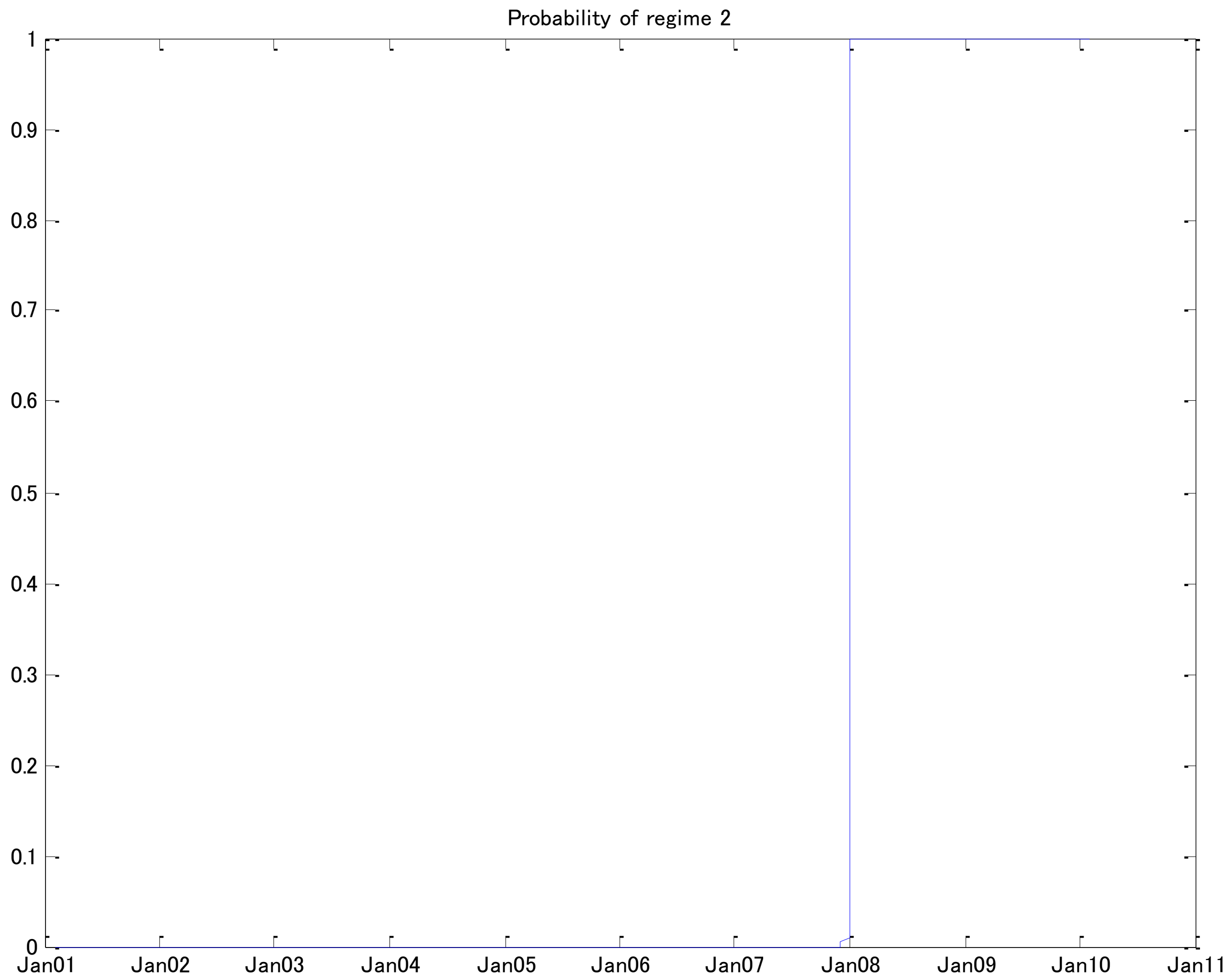

Figure 5: Impulse Response Functions for Regime 1 for the MSVAR2 model

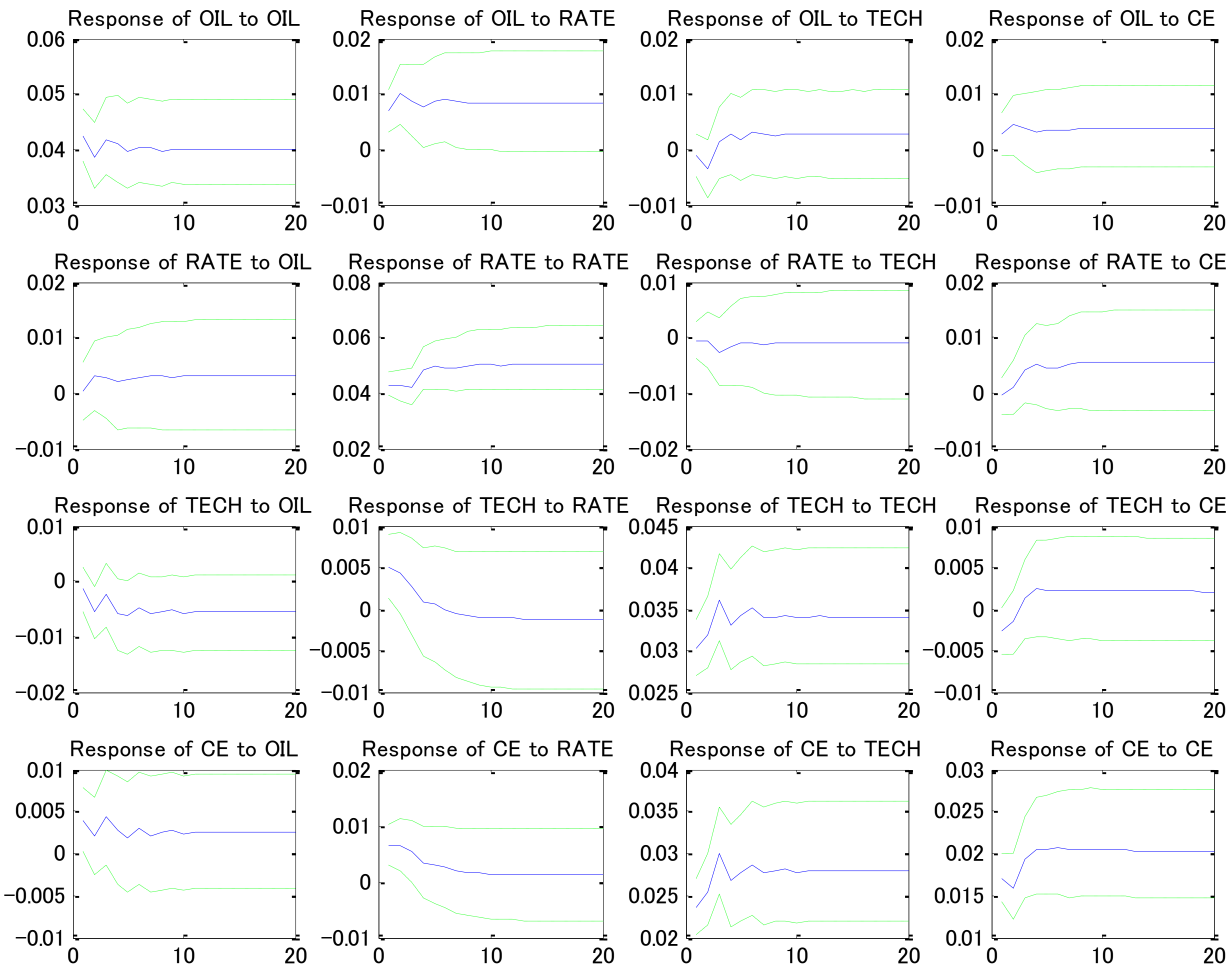

Figure 6: Impulse Response Functions for Regime 2 for the MSVAR2 model