THREE ESSAYS ON ENERGY ECONOMICS AND FORECASTING

A Dissertation

by

YOON SUNG SHIN

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

December 2011

Major Subject: Agricultural Economics

Three Essays on Energy Economics and Forecasting

THREE ESSAYS ON ENERGY ECONOMICS AND FORECASTING

A Dissertation

by

YOON SUNG SHIN

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Approved by:

Chair of Committee,	Piya Abeygunawardena
Committee Members,	Ximing Wu
	Henry L. Bryant
	Bill Payne
Head of Department,	John Nichols

December 2011

Major Subject: Agricultural Economics

ABSTRACT

Three Essays on Energy Economics and Forecasting. (December 2011)

Yoon Sung Shin, B.A., Pusan National University;

M.A., The State University of New York at Buffalo

Chair of Advisory Committee: Dr. Piya Abeygunawardena

This dissertation contains three independent essays relating energy economics. The first essay investigates price asymmetry of diesel in South Korea by using the error correction model. Analyzing weekly market prices in the pass-through of crude oil, this model shows asymmetric price response does not exist at the upstream market but at the downstream market. Since time-variant residuals are found by the specified models for both weekly and daily retail prices at the downstream level, these models are implemented by a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) process. The estimated results reveal that retail prices increase fast in the rise of crude oil prices but decrease slowly in the fall of those. Surprisingly, retail prices rarely respond to changes of crude oil prices for the first five days. Based on collusive behaviors of retailers, this price asymmetry in Korea diesel market is explained.

The second essay aims to evaluate the new incentive system for biodiesel in South Korea, which keeps the blend mandate but abolishes tax credits for government revenues. To estimate changed welfare from the new policy, a multivariate stochastic simulation method is applied into time-series data for the last five years. From the

simulation results, the new biodiesel policy will lead government revenues to increases with the abolishment of tax credit. However, increased prices of blended diesel will cause to decrease demands of both biodiesel and blended diesel, so consumer and producer surplus in the transport fuel market will decrease.

In the third essay, the Regression - Seasonal Autoregressive Integrated Moving Average (REGSARIMA) model is employed to predict the impact of air temperature on daily peak load demand in Houston. Compared with ARIMA and Seasonal Model, a REGARIMA model provides the more accurate prediction for daily peak load demand for the short term. The estimated results reveal air temperature in the Houston areas causes an increase in electricity consumption for cooling but to save that for heating. Since the daily peak electricity consumption is significantly affected by hot air temperature, this study makes a conclusion that it is necessary to establish policies to reduce urban heat island phenomena in Houston.

To my wife, Soo Jun Kim,

my son, Hweejoon Shin,

and my daughter, Hweejin Shin.

ACKNOWLEDGEMENTS

I am grateful for the support of many people in completion of this degree and dissertation. Dr. Piya Abeygunawardena, my advisor, has provided the invaluable guidance and considerate advice on empirical economic approach. Without his support, it is impossible for me to attain my goal to be an economist. I also thank my committee members. Ximing Wu, Henry L. Bryant, and Bill Payne give me useful suggestions in the writing of this dissertation. I appreciate my parents, Jung Sam Shin and Myung Ryeol Cho for financial and spiritual supports. I will always remember devotion of my wife, Soo Jun Kim. She raised me up whenever I would give up.

TABLE OF CONTENTS

Page

LIST OF FIGURES

Page

LIST OF TABLES

1. INTRODUCTION

This dissertation consists of three studies on energy economics, dealing with price asymmetry and cost - benefit analysis for biodiesel in Korea diesel market as well as the effect of air temperatures on daily peak load electricity demand in Houston areas. In the second section, entitled 'The Error Correction Model with a Generalized Autoregressive conditional Heteroskedasticity Process for Price Asymmetry of Diesel Fuel in South Korea,' the asymmetry adjustment speeds of diesel prices were calculated by reformulating the error correction model under heteroskedasticity. The estimated model revealed daily retail prices of diesel respond quickly to the rise of crude oil prices and adjust slowly to the fall of those. This asymmetric response of retail diesel prices was explained based on collusive behaviors of retailers.

In the third section, entitled 'The Impact of a Blend Mandate and Tax Credit on Korean Diesel Market,' the new incentive system for biodiesel was evaluated. To estimate economic effects of the new policy that provides the blend mandate without tax credits, a multivariate stochastic simulation model was applied into time-series data, ranging from August, 2006 to June, 2011. From the estimated results, the new biodiesel policy will increase tax revenues and biodiesel prices so as to decrease consumption in both biodiesel and blended diesel. Therefore, consumer and producer surplus will decrease.

In the fourth section, entitled 'The Economic Impact of Air Temperature on

---

This dissertation follows the style of Energy Policy.

Daily Peak Load Electricity Demand in The Houston Area,' I employed the regression - seasonal autoregressive integrated moving average model to predict air temperature effects on daily peak load demand of electricity in Houston. This study incorporated a seasonal autoregressive integrated moving average model with a piecewise linear regression process. I found air temperature in the Houston areas increases the electricity consumption for cooling in summer whereas decrease that for heating in winter. Additionally, the incorporated model provides the more accurate forecasts for daily peak load electricity demand for the short term.

2. THE ERROR CORRECTON MODEL WITH A GENERALIZED AUTOREGRESSIVE CONDITIONAL HETEROSKEDASTICITY PROCESS FOR PRICE ASYMMETRY OF DIESEL FUEL IN SOUTH KOREA

2.1 Introduction

Crude oil is an essential input to produce transport fuels such as gasoline, diesel, and liquefied petroleum gas (LPG). Since prices of crude oil, gasoline and diesel are easily observable, retail prices of transport fuels tend to move along with the fluctuation of crude oil prices. However, it is argued that gasoline and diesel prices increase quickly when crude oil prices rise but decrease slowly when they fall. In Korea, consumers complain about this price asymmetry of transport fuels. Often, this four major refinery firms are blamed for price collusion, by which they adjust the prices of transport fuels in the rise of crude oil prices faster than in the price fall.

Many previous studies have investigated the presence of price asymmetry in the transport fuel market since Bacon's work was published in 1991. Although some found the evidence of price asymmetries of transport fuels, previous studies made the different conclusions due to characteristics such as frequency and time period of time series data used, and choice of models. The asymmetric adjustment speed of retail gasoline prices responding to crude oil prices is called "rockets and feathers" by Bacon(1991). This means retail gasoline prices are elevated rapidly in increase of crude oil prices whereas those decline slowly in decrease of crude oil prices, although price information of world crude oil is easily visible (Bacon, 1991). After the finding of Bacon, several other studies including Borenstein et al. (1997), Peltzman (2000), and Honarvar (2009) have also supported the asymmetric price response of gasoline and they linked it to oligopolistic market structure, consumers' search cost, and inventory problem.

According to research work of Godby et al. (2000), there was no evidence of price asymmetry in the Canada retail gasoline market by using the threshold error correction model. Bachmeier and Griffin (2003) showed the symmetric pricing response by applying two-step procedure Engle-Granger method to daily data in U.S. They pointed out the problems of previous studies with respect to model choice and length of time lag. Although the conclusions of previous studies are controversial, it is widely believed that the volatility of input prices strongly affects the degree of asymmetry in output prices (Peltzman, 2000). Radchenko (2005) also reported the negative relationship between volatility of crude oil prices and degree of asymmetry in gasoline price by using the vector autoregressive approach (VAR). To make more accurate conclusions of price asymmetries in petroleum products, Gu and Jansen (2006) suggested that traditional ECM models should be applied under homoskedasticity assumption. They recommended removal of possible heteroskedastic disturbances from the error matrix.

Previous studies on the pricing asymmetry relied mostly on the error correction model (hereafter ECM) using the two-stage ordinary least square (hereafter OLS) estimation under the homoskedasticity assumption. However, the standard errors and inferences of their estimations can be misinterpreted because they did not consider time-variant residuals. Therefore, the purpose of the first essay is three-fold. Firstly, I revealed the problems on estimations obtained by the traditional ECM model, which is a modified version of OLS estimation called two-step procedure Engle-Granger method under the homoskedasticity assumption. Secondly, I formulated a trivariate vector error correction model (hereafter VECM) under the heteroskedasticity to obtain more accurate inferences for estimation results. This VECM model as an alternative method to the OLS estimation allows correction of heteroskedasticity problem in the error matrix. This trivariate VECM model with a generalized autoregressive conditional heteroskedasticity (hereafter GARCH) is useful to fix different variances of three random variables in error terms. I derived the system-wide impulse response functions to compare results of positive and negative shocks of crude oil prices in the world market as well as shocks of diesel prices in the South Korea domestic markets. Lastly, I applied the model with a GARCH process into the weekly prices at each of pass-through in the diesel market. I reinvestigated daily retail diesel prices to explain the characteristics of asymmetry because daily data provided more plentiful and specific interpretations.

I focused on Bachmeier and Griffin in 2003 (hereafter BG), which used daily data and traditional two-stage OLS estimation procedure under the homogeneity assumption to estimate the asymmetric response of daily retail gasoline prices. From BG's findings, it was evident that a pass-through asymmetry does not exist in Korean diesel market when weekly data used. Calculating the adjustment speeds of retail prices to crude oil prices, I found out retail prices respond asymmetrically to crude oil prices. Testing for the heteroskedasticity test, I found the error term has an autoregressive conditional heteroskedasticity (hereafter ARCH) process. Therefore, I established the trivariate VECM model to derive BG model with a generalized ARCH process (hereafter GARCH) and apply to daily and weekly retail prices.

This paper is organized as follows. Section 2.1 provided an introduction to this study and Section 2.2 is to give an overview of the previous studies on "rockets and feathers". Section 2.3 describes the procedure of deriving traditional ECM model from the VECM model. This section also includes the econometric methodology to establish the GARCH process. Section 2.4 describes the nature and types of data used, whereas the estimation results of price asymmetry for both daily and weekly data are reported and discussion are presented in Section 2.5. The concluding remarks and a list of further studies are covered in Section 2.6.

2.2 Overview of Previous Studies

Bacon (1991) found the asymmetric response of retail gasoline prices to the variation of crude oil in the U.K. market by using biweekly data. He described this price asymmetry as "rockets and feathers": retail gasoline prices go up rapidly like rockets and fall down slowly like feathers in response to changes of crude oil prices. Since discovery of this relationship between crude oil and gasoline prices was claimed by Bacon (1991), there have been many studies to test the hypothesis of "rockets and feathers" based on the ECM model with two variables – different time segments of crude oil prices and gasoline prices (Geweke, 2005).

Some studies have found the evidence of asymmetric price adjustment speeds. The paper of Borenstein et al. in 1997 (hereafter BCG) showed that retail gasoline prices responded faster to the rise in crude prices than to the fall by comparing change of spot price of crude oil with retail gasoline prices based on fortnightly data. To explain the asymmetric time adjustment of retail gasoline prices, the BCG proposed three possible factors including the oligopolistic coordination of oil refinery companies, adaptation of production and inventory cost, and search cost of consumers (Borenstein et al., 1997). The hypothesis of price asymmetries was supported by analyzing monthly data of 77 consumer and 165 producer goods in U.S. from 1982 to 1996 (Peltzman, 2000). Comparing asymmetries of weekly gasoline prices among five European countries, various adjustment speeds in response to crude oil prices were presented (Galeotti et al., 2003). Recently, the hypothesis of "rockets and feathers" was explained by applying the hidden ECM model of Honarvar (2009) to monthly data of retail gasoline price in U.S.

Several other studies have claimed little evidence of asymmetric response of retail prices. However, market structures and characteristics of data can generate many different results. The analysis of Canadian retail gasoline market with the threshold ECM model found out there was no existence of asymmetric pricing due to a different retail gasoline market (Godby et al., 2000). The research of Bachmeier and Griffin in 2003 revealed that retail gasoline and crude oil prices in U.S. can fluctuate symmetrically and instantaneously if one uses daily data rather than weekly data. This is because the estimation of the BCG is not robust in the sense that a length of time lag can cause a biased estimation (Bachmeier and Griffin, 2003). Gu and Jansen (2006) suggested that a traditional ECM model under homoskedasticity assumption can mislead inferences of estimation results in analysis of U.S. retail gasoline market since estimated residuals are autocorrelated.

Some previous studies found out that volatility of crude oil prices heavily influences the degree of asymmetric price response in gasoline. Investigating price asymmetry on 77 consumer and 165 producer goods in U.S., Peltzman (2000) found asymmetric price response and the negative correlation between input price volatility and the degree of output price asymmetry. Radchenko (2005) supported the conclusion of Peltzman (2000) based on the oligopolistic coordination theory. According to this theory, individual firms at the oligopolistic market have less market power exertion in increase of prices. Since high prices reduce market demands and decrease total revenue, they compete with each other to keep their revenue. Therefore, he explained that the degree of asymmetry in gasoline prices falls with an increase in crude oil prices and rises with decrease in crude oil prices due to the market power exertion of oligopolistic firms.

Previous studies on price asymmetry have the key assumption that the residuals of their model specification are homoskedastic, in spite of making controversial conclusions by characteristics of time series data and choice of a model. The presence of homoskedasticity is a key assumption they made but it is not evident that they tested of non-existence of heteroskedasticity in their error terms. If these studies violated homoskedasticity assumption, then they can mislead their inferences for testing price asymmetry because of applying the OLS regression to random variables with different variances. There is a strong possibility for heteroskedasticity problem to exist due to time-variant shocks of crude oil prices and diesel prices. However, positive and negative innovations of error terms have different impacts on future volatility because of leverage effects which means positive shock has less effect on the conditional variance compared to a negative shock. Three types of asymmetric GARCH models are considered to specify effects of conditional variances for the estimation accuracy. Based on Schwarz Bayesian Criterion (hereafter SBC), the best GARCH model was selected and applied into a VECM model.

2.3 Econometric Approach

This section describes the econometric methodology and procedure used in this study to examine the diesel price asymmetry resulting from the shocks of crude oil and to perform diagnostic tests for estimation results. First, I tested the stationarity of variables with two unit-root tests for time series data on diesel prices. Also Johansen's test was used to examine whether variables can be cointegrated. Second, I established the traditional ECM model with two-step Engle-Granger method. Next, I introduced a trivariate VECM model as an alternate framework to find out the long-run relationship among variables and then tested the presence of exogeneity. This VECM model is modified by correcting heteroskedastic disturbances. Finally, I derived impulse response functions to explain dynamic reaction of diesel prices to shocks over time.

2.3.1 Stationarity and Cointegration Tests For ECM models

As an initial procedure in the econometric approach, I tested whether two time-series variables – crude oil and diesel price are time-invariant. I performed the

Augmented Dickey-Fuller (Dickey and Fuller, 1979) and Phillips-Perron (Phillips and Perron, 1988) tests to examine the presence of unit roots for daily and weekly prices of diesel and crude oil. Since the first differenced values of two unstable prices are stationary, two time series variables seem to be I (1) processes. The cointegration of the relationship between two variables can be formulated by an ECM model, which presents short run adjustment procedure in the long run equilibrium. I employed the unrestricted cointegration rank test to find out the number of cointegrating vectors as a stationary linear combination of variables which explains a long run relationship between crude oil and diesel price (Johansen, 1991).

2.3.2 Asymmetric ECM with Homoskedastic Disturbances

Assuming the production function of diesel is constant over tested periods, the log price of diesel LPD_t at time *t* is defined as an autoregressive process with lagged changes of the previous log price of diesel LPD_{t-1} and the log price of crude oil at time *t* LPC_t given by;

$$LPD_t = \alpha(L) \cdot LPC_t + \beta(L) \cdot LPD_{t-1} + \varepsilon_t \tag{1}$$

where $\alpha(L)$ and $\beta(L)$ are lagged adjustments of each price, and ε_t is the error term at time *t*.

From the Johansen' test for two I(1) variables, both prices can be cointegrated. The relationship between differenced values of diesel and crude oil price is presented with an ECM model, which specifies the partial adjustment speeds to the changes of two variables in the short terms and the equilibrium in the long term. Thus, Equation (1) can be modified with the backward differenced form Δ as follows;

$$\Delta LPD_t = \sum_{i=0}^{k} \alpha_i \cdot \Delta LPC_{t-i} + \sum_{i=1}^{n} \beta_i \cdot \Delta LPD_{t-i} + \gamma T_{t-1} + \varepsilon_t \tag{2}$$

where α_i and β_i are the response speeds of crude oil prices and diesel prices for the short-run equilibrium, respectively, and coefficient γ is the long-run adjustment speeds between diesel prices and crude oil prices. The cointegrating term T_{t-1} for the long run equilibrium can be written as follows;

$$T_{t-1} = LPD_{t-1} - \sigma_0 - \sigma_1 \cdot LPC_{t-1} \tag{3}$$

Defining the super scripts + and – are positive change of prices and negative change of prices in the first backward log difference, the value of diesel prices is given by;

$$\Delta LPD_{t-i}^{+} = \begin{pmatrix} \Delta LPD_{t-i} & \text{if } \Delta LPD_{t-i} > 0 \\ 0 & \text{otherwise} \end{pmatrix} \quad \text{and}$$

$$\Delta LPD_{t-i}^{-} = \begin{pmatrix} 0 & \text{if } \Delta LPD_{t-i} > 0 \\ \Delta LPD_{t-i} & \text{otherwise} \end{pmatrix} \tag{4}$$

The values of crude oil prices ΔLPC_{t-i}^{+} and $\Delta LPC_{t-i}^{-}$are set by the same way. To test the asymmetry response of diesel prices to crude oil prices, equation (2) is formulated into the asymmetric ECM as follows;

$$\Delta LPD_t = \sum_{i=0}^{k} \alpha_i^{+} \cdot \Delta LPC_{t-i}^{+} + \sum_{i=1}^{n} \beta_i^{+} \cdot \Delta LPD_{t-i}^{+} +$$
$$+ \sum_{i=0}^{k} \alpha_i^{-} \cdot \Delta LPC_{t-i}^{-} + \sum_{i=1}^{n} \beta_i^{-} \cdot \Delta LPD_{t-i}^{-} + \gamma \cdot T_{t-1} + \varepsilon_t \tag{5}$$

The coefficient $\alpha_i^{+}$and β_i^{+} are relevant to the positive changes of ΔLPD_{t-i}^{+} and ΔLPC_{t-i}^{+} respectively in the short run, and α_i^{-} and β_i^{-} are similar. Both of the coefficient γ^{+} and γ^{-} imply error correction terms to deviations in the long run.

2.3.3 Asymmetric VECM with Heteroskedastic Disturbances

To investigate the price asymmetry of retail diesel responding to crude oil prices, I set up a trivariate VECM model of the form,

$$\begin{pmatrix} \Delta LPD \\ \Delta LPC^{+} \\ \Delta LPC^{-} \end{pmatrix}_t = \Phi(L) \begin{pmatrix} \Delta LPD \\ \Delta LPC^{+} \\ \Delta LPC^{-} \end{pmatrix}_{t-1} + \Lambda CV_{t-1} + e_t \tag{6}$$

$$\Phi(L) = \begin{pmatrix} \Phi_{11}(L) & \Phi_{12}(L) & \Phi_{13}(L) \\ \Phi_{21}(L) & \Phi_{22}(L) & \Phi_{23}(L) \\ \Phi_{31}(L) & \Phi_{32}(L) & \Phi_{33}(L) \end{pmatrix}$$

where L is a lag operator and $\Lambda = (\lambda_1,\ \lambda_2)'$ is a 3×1 vector representing the cointegrating relationship. The disturbance e_t is a 3×1 vector innovation. I performed Mardia's skewness and kurtios method (Mardia, 1970), for testing the normality of the residuals. To check out whether the error terms are autocorrelated, I also tested for ARCH effects in the residuals by using Portmanteau Q test and Lagrange multiplier (LM) test. From the results, I concluded that there is an ARCH component in the innovations of equation (6).

2.3.3.1 Asymmetric VECM with a GARCH Process

Multivariate VECM system (6) is modified into the traditional ECM model to calculate the price asymmetry of retail diesel under heteroskedasticity by specifying innovation terms with a GARCH process. First, disturbance e_t is a 3×3 variance covariance matrix represented as follows;

$$var(e_t) = var\begin{pmatrix} \varepsilon_{D,t} \\ \varepsilon_{C^{+},t} \\ \varepsilon_{C^{-},t} \end{pmatrix} = \begin{pmatrix} \sigma_{DD,t} & \sigma_{DC^{+},t} & \sigma_{DC^{-},t} \\ \sigma_{C^{+}D,t} & \sigma_{C^{+}C^{+},t} & \sigma_{C^{+}C^{-},t} \\ \sigma_{C^{-}D,t} & \sigma_{C^{-}C^{+},t} & \sigma_{C^{-}C^{-},t} \end{pmatrix} \tag{7}$$

Assuming that crude oil price residual ε_C affects the retail diesel price residual ε_D contemporaneously, whereas ε_D is uncorrelated with ε_C because the domestic diesel market in Korea has little influence on the world crude oil. Applying Cholesky decomposition into equation (7), innovations at t period is represented with the lower triangular matrix L as follows;

$$L = \begin{pmatrix} \sigma_{DD} & \sigma_{DC^+} & \sigma_{DC^-} \\ 0 & \sigma_{C^+C^+} & \sigma_{C^+C^-} \\ 0 & 0 & \sigma_{C^-C^-} \end{pmatrix} \tag{8}$$

$$LL' = \begin{pmatrix} \sigma_{DD}^2 + \sigma_{DC^+}^2 + \sigma_{DC^-}^2 & \sigma_{DC^+}\sigma_{C^+C^+} + \sigma_{DC^-}\sigma_{C^+C^-} & \sigma_{DC^-}\sigma_{C^-C^-} \\ \sigma_{C^+C^+}\sigma_{DC^+} + \sigma_{C^+C^-}\sigma_{DC^-} & \sigma_{DC^+}^2 + \sigma_{DC^-}^2 & \sigma_{C^+C^-}\sigma_{C^-C^-} \\ \sigma_{C^-C^-}\sigma_{DC^-} & \sigma_{C^+C^-}\sigma_{C^-C^-} & \sigma_{C^-C^-}^2 \end{pmatrix} \tag{9}$$

The ARCH component in ε_D can be specified as;

$$\varepsilon_{D,t} = \theta_1 \varepsilon_{C^+,t} + \theta_2 \varepsilon_{C^-,t} + \eta_{D,t} \tag{10}$$

where θ_1 and θ_2 are constant, $\eta_{D,t}$ is the innovation in the diesel price equation, which is determined by the domestic market. Substituting the disturbance e_t with equation (10), the trivariate VECM model is represented as follows;

$$\begin{pmatrix} \Delta LPD \\ \Delta LPC^+ \\ \Delta LPC^- \end{pmatrix}_t = \Phi(L) \begin{pmatrix} \Delta LPD \\ \Delta LPC^+ \\ \Delta LPC^- \end{pmatrix}_{t-1} + \Lambda CV_{t-1} + \begin{pmatrix} \theta_1 \varepsilon_{C^+} + \theta_2 \varepsilon_{C^-} + \eta_D \\ \varepsilon_{C^+} \\ \varepsilon_{C^-} \end{pmatrix}_t \tag{11}$$

From this VECM system, the equations of in crude oil prices are derived given by;

$$\Delta LPC_t^+ = \Phi_{21}(L)\Delta LPD_{t-1} + \Phi_{22}(L)\Delta LPC_{t-1}^+ + \Phi_{23}(L)\Delta LPC_{t-1}^- + \lambda_2 CV_{t-1} + \varepsilon_{C^+,t} \tag{12}$$

$$\Delta LPC_t^- = \Phi_{31}(L)\Delta LPD_{t-1} + \Phi_{32}(L)\Delta LPC_{t-1}^+ + \Phi_{33}(L)\Delta LPC_{t-1}^- + \lambda_3 CV_{t-1} + \varepsilon_{C^-,t} \tag{12'}$$

Since crude oil prices and diesel prices are weakly exogenous, two equations of crude oil prices do not include error correction term CV_{t-1}, so λ_2 and λ_3 are zero.

Substituting $\varepsilon_{C^+,t}$ and $\varepsilon_{C^-,t}$ with equation (12) and (12'). The diesel price equation can be rewritten including concurrent crude oil prices as follows;

$$\Delta LPD_t = \left(\Phi_{11}(L) - \theta_1\Phi_{21}(L) - \theta_2\Phi_{31}(L)\right)\Delta LPD_{t-1} + \theta_1\Delta LPC_t^+ + \theta_2\Delta LPC_t^-$$
$$+\left(\Phi_{12}(L) - \theta_1\Phi_{22}(L) - \theta_2\Phi_{32}(L)\right)\Delta LPC_{t-1}^+$$
$$+\left(\Phi_{13}(L) - \theta_1\Phi_{23}(L) - \theta_2\Phi_{33}(L)\right)\Delta LPC_{t-1}^- + \Gamma_1 CV_{t-1} + \eta_{D,t} \quad (13)$$

The diesel price equation (13) is modified into BG model shown as equation (14).

$$\Delta LPD_t = \sum_{i=0}^{k}\alpha_i^+\Delta LPC_{t-i}^+ + \sum_{i=1}^{n}\beta_i^+\Delta LPD_{t-i}^+ + \delta^+\cdot T_{t-1}^+$$
$$+\sum_{i=0}^{k}\alpha_i^-\Delta LPC_{t-i}^- + \sum_{i=1}^{n}\beta_i^-\Delta LPD_{t-i}^- + \delta^-\cdot T_{t-1}^- + \eta_{D,t} \quad (14)$$

Using error term $\eta_{D,t}$ of each equation, I performed the LM test and Portmanteau Q test to check out the presence of autoregressive conditional heteroskedasticity (ARCH). Based on this test result, two traditional asymmetric ECM models are used as conditional mean and a GARCH process is applied to measure conditional variances.

2.3.3.2 Asymmetric VECM with a GARCH Process

Positive innovations of error terms have less effect on the conditional variance compared to negative ones. To specify different impacts of positive and negative innovations on conditional variance h_t of $\eta_{D,t}$, I considered three asymmetric GARCH models - quadratic GARCH model (Engle and Ng, 1993), threshold GARCH model (Glosten et al., 1993; Zakoian, 1994), and power GARCH model (Ding et al., 1993).

In the quadratic GARCH model (hereafter QGARCH), the centers of lagged errors are shifted from zero to a constant values according to shocks by the following specification;

$$h_t = \omega + \sum_{i=1}^{q} \varphi_i (\varepsilon_{t-i} - \Psi_i)^2 + \sum_{j=1}^{p} \rho_j \, h_{t-j} \quad (15)$$

The threshold GARCH model (hereafter TGARCH), putting an extra slope coefficient for each lagged squared error, specify asymmetric of volatility response as follows;

$$h_t = \omega + \sum_{i=1}^{q} (\varphi_i + \mathrm{I}_{\varepsilon_{t-i}<0} \Psi_i) {\varepsilon_{t-i}}^2 + \sum_{j=1}^{p} \rho_j \, h_{t-j} \quad (16)$$

where the indicator function $\mathrm{I}_{\varepsilon_{t-i}<0}$ is one if $\varepsilon_t < 0$: otherwise, zero.

The PGARCH model provides the asymmetric effect as well as the long memory property in the volatility by a given equation;

$$h_t = \omega + \sum_{i=1}^{q} \varphi_i (|\varepsilon_{t-i}| - \Psi_i \varepsilon_{t-i})^{2\mu} + \sum_{j=1}^{p} \rho_j \, h_{t-j}^{\mu} \quad (17)$$

where $\mu > 0$ and $|\Psi_i| \leq 1 \; i = 1, \cdots, q$.

From results of three asymmetric GARCH model, the best process with optimal lag length is adopted based on SBC. To illustrate price asymmetry of diesel, system impulse response functions are derived with respect to each of shocks from diesel prices and crude oil prices.

2.4 Data

Time series data of retail, rack (refinery) prices of diesel, and crude oil prices are obtained from the Korea National Oil Corporation website. Crude oil at the world market level and retail diesel prices at the gas station level are provided at a week and a day whereas rack prices of diesel at the refinery level are informed at only a week. Therefore, I analyzed the price asymmetry at each step to pass-through of crude oil prices by using weekly data of pre-tax prices with total 444 observations ranging from April 15, 2008 to February 28, 2011. After finding the asymmetry and the heteroskedastic error terms related with retail prices, I reinvestigated the pre-tax prices of daily retail diesel and Dubai crude oil prices with total 742 observations for the same periods.

Korea depends entirely on crude oil out of the country and imports over 85% total from the Middle East, the exchange rate is one of most important factors to affect input costs of diesel. Therefore, crude oil prices are converted from U.S. dollar (US$) per barrel to Korea won (₩) per litter by a daily and weekly average exchange rate and unit price. Table 2.1 summarizes some statistical characteristics of the data on daily and weekly prices of retail, rack diesel, and crude oil.

Figure 2.1 illustrates the movements of weekly crude oil prices, rack prices and retail prices of diesel over sample periods. Prices of crude oil and diesel rapidly increased and peaked at July, 2008. Both prices plunged at the end of 2008 because of the global economic recession, triggered by the credit crunch in the U.S. After that, they have followed the upward trend with the world business recovery. Additionally, the standard deviation shows the volatility of crude oil prices is greater than those of retail and rack diesel prices. Figure 2.2 presents the first log differences of crude oil prices and two kinds of diesel prices reveal that crude oil prices have higher volatility than retail diesel prices.

2.5 Estimation Results and Discussions

As mentioned in Section 2.3.1, I performed some tests for three variables to establish a traditional ECM models - BG model. As two unit root tests - ADF and PP test - are exercised, the results show that three time series variables are unstable I (1). Johansen's procedure is used to find long run relationship among log value of crude oil prices, rack, and retail diesel prices. From results of Johansen's test, I rejected the null hypothesis that no cointegration exists and found the number of cointegrating is at most one. Therefore, the long run relationship is represented by a stationary linear combination mentioned as equation (1). Based on both of unit root and cointegration test, I established a traditional ECM model - BG model by employing two-step procedure Engle-Granger method. However, I reexamined daily prices of retail diesel and crude oil with a multivariate VECM model with a GARCH model because retail diesel price equation has heteroskedastic disturbances. Of three types of asymmetric GARCH models, the best GARCH process was chosen by SBC and added into the error term, considering the heteroskedasticity of time-varying disturbances. Finally, I specified the VECM model with the asymmetric GARCH process to examine the presence and characteristic of price asymmetry of retail diesel related with crude oil prices. To explain asymmetric response of retail diesel prices, the oligopolistic coordination theory was discussed.

2.5.1 Price Asymmetry in Pass-Through of Crude Oil Prices to Diesel Prices

Based on a traditional ECM model under the homoskedasticity assumption, I calculated the price adjustment speeds of diesel at two main steps in the pass-through of crude oil. One step is the upstream level at which I examined the asymmetric response of rack prices to changes of crude oil prices. For the other step as the downstream, I looked into the asymmetries of retail diesel prices responding to changes in crude oil prices and rack prices.

Table 2.2 shows the long run relationship among crude oil prices, rack prices, and retail prices. The estimated coefficients are not equal to one statistically. This means a change in the crude oil price or rack prices does not fully pass through to rack prices or retail prices, respectively. Thus, the rack prices and retail prices of diesel in the long run are not only affected by a change in the crude oil price or rack price but also by other factors such as the market power of refineries, the government regulation, the exchange rate, and the mark up of retailers.

Table 2.3 reports the estimation results of ECM model for three prices in the pass-through. From the error correction terms, the estimated coefficients are negative at the rack price equation and the retail price equation. This is because the deviation of positive or negative margins has to converge to the long-run equilibrium. To check out the presence of heteroskedasticity on OLS residuals in each specification, I performed ARCH tests and identified that the error terms in both of the rack price and retail price equation satisfy the homoskedasticity assumption.

Table 2.3 shows rack prices at the upstream level responds to changes of crude oil prices at the contemporary period – LCP. However, rack prices are not affected by positive and negative changes in LCP(-1), LCP(-2), and LRP(-1) because the coefficients on three explanatory variables are not statistically significant. In the short run, rack prices tends to increase by 0.34 ~ 0.53% in the 1% rise of crude oil prices and decrease by 0.36 ~ 0.55% in the 1% fall of crude oil prices for the same week.

With the Wald tests used by previous studies, I test the price asymmetry for the hypothesis that the coefficients of positive and negative changes of prices are equal. Results for the price asymmetry test are reported in Table 2.4. From column headed 'Rack', the coefficient on the positive change of crude oil prices – PLCP is statistically equal to that on the negative price change – NLCP. Additionally, the coefficient on positive change of rack prices - PLRP(-1) is statistically equal to that on negative change of rack prices - NLRP(-1). Therefore, there exists no price asymmetry in weekly rack prices of diesel at the upstream level.

In the downstream level, the estimation results of the retail price equation from Table 2.3 are somewhat different. The coefficients on positive and negative DLRP are statistically insignificant, which means retail prices are not affected by changes of rack prices at the same week. For two positive changes of rack prices at lag one and two, I failed to reject the null hypothesis of zero coefficient on PLRP(-1) at the 1% significance level and PLRP(-2) at the 10% significance level. Therefore, the 1 % rise of rack prices at lag one and at lag two increases retail prices by 0.08 ~ 0.18% and by 0.04 ~ 0.13%, respectively. For the negative change of rack prices, the coefficient on NLRP(-1) is statistically insignificant while that on NLRP(-2) is significant at the 1 % level. The 1% negative change of rack prices decreases retail prices by 0.25 ~ 0.35% after two weeks.

From column headed 'Downstream (Retail Price)' in Table 2.4, the asymmetry tests are performed only for changes of retail prices and those of rack prices. The hypothesis test for the symmetry of changes in LDP(-1) is rejected at the 5% significance level. It infers retail prices increase by PLDP(-1) more than decrease by NLDP(-1). Testing for the asymmetry to changes of rack prices at lag one and two – LRP(-1), LRP(-2), I failed to reject the null hypothesis at the 1% significance level. At lag one, PLRP(-1) increases retail prices more than NLRP(-1) decreases. At lag two, NLRP(-2) has greater influences on changes of retail prices than PLRP(-2) does.

I calculated the cumulative impulse response functions from two estimations for making better interpretation on the price asymmetry test because the adjustment speeds of retail prices differ in a lag. The impulse response functions were obtained from the first period shock with the absolute value to be compared easily. The confidence intervals for the impulse response functions were generated by Monte Carlo simulation with 1,000 iterations.

Figure 2.3 illustrates the response of rack prices to a shock from crude oil prices. Consistent with results of Wald test, the traces of rack prices seem to be symmetry for a positive and negative shock of crude oil prices. On the other hand, Figure 2.4 shows the response of retail prices to a shock from rack prices is symmetry although the impacts of a shock from rack prices have the different strength and duration.

2.5.2 Price Asymmetry of Retail Prices to Crude Oil Prices

I examined the price asymmetry of retail prices to crude oil prices based on two-step OLS procedure used by many previous studies. Table 2.5 presents estimates for the application of ECM model into weekly data. Even if all coefficients are statistically significant, I obtained irregular estimations in the sense that the coefficient on PDLCP is negative. It infers the positive changes of crude oil prices even decreases retail prices. Therefore, I conducted some diagnostic tests such as normality test and heteroskedasticity test to check out a possible misspecification of ECM model under homoskedasticity.

From the normality test results shown at Table 2.6, I failed to reject the hypothesis that the residuals of the estimated ECM model are distributed normally. From column headed 'ARCH test' in Table 2.6, I also failed to reject the white noise null hypothesis of disturbances because both of the Q statics and LM statics from residuals of ECM model indicated heteroskedasticity for all lags. Therefore, it is likely that the ECM model under the homoskedasticity assumption has ARCH error terms although all coefficients on explanatory variables are statistically significant. Fixing the error term with a GARCH process, I recalculated adjustment speed of retail prices and tested for the asymmetry.

Table 2.7 reports results of the specification and asymmetry test about the retail diesel price equation, allowing heteroskedasticity. Of asymmetric GARCH models, PGARCH(1, 1) process was chosen by SBC. Unlike the estimation under the homoskedasticity assumption, the coefficient on PLCP is statistically significant and positive. It means the 1% positive change of crude oil prices increases retail prices by 0.01 ~ 0.06%. Testing for the asymmetry with Wald tests, I found out retail prices have different adjustment speeds for all weeks except the second week. It means retail prices of diesel respond asymmetrically to changes of crude oil prices.

Prior researchers pointed out the problems of time aggregation, so I utilized daily data to analyze the asymmetry of retail prices to crude oil prices. Table 2.8 presents the estimation results for both ECM model and the ECM model with QGARCH to daily retail prices. Based on the value of SBC, I determined ten lags for crude oil prices and two lags for retail diesel prices as the optimal lag length. From column headed 'ECM' in Table 2.8, PLCP and PLCP(-1) affect retail prices. In the negative changes, I found out retail prices are not influenced for the first five days, when failing to reject the null hypothesis. It implies that retail prices of diesel respond faster to positive price changes of crude oil than to negative ones.

Table 2.9 reports results of the normality and ARCH test. It is found out that the estimated residuals are distributed normally but kurtosis of residuals is very high. Figure 2.5 exhibit much of the variance results from infrequent extreme deviation. To check out a potential misspecification of ECM model, I investigated serial correlation by calculating Q statistics test and LM test statistics from residuals of ECM model. From column of ARCH test in Table 2.9, both statistics provide the strong evidence that the white-noise null hypothesis is rejected based on the chi-square distribution. Based on the results of ARCH tests, I established the ECM model with a GARCH process for fixing the misspecification of the traditional ECM model under the homoskedasticity assumption.

The column headed 'ECM with QGARCH' in Table 2.8 reports the coefficient estimates for the ECM model with QGARCH (1, 2). Of three asymmetric GARCH types, the QGARCH model with the lowest SBC is chosen. The test for the significance of coefficients reveals that retail prices are not affected by price changes of crude oil for the first two days. Further, the estimates under heteroskedasticity are different from those of the traditional ECM model. On the contrary to the estimations under homoskedasticity, negative price changes of crude oil even slightly decrease retail prices after the first two days whereas positive ones increase retail prices after the first three days. It means that retail prices adjust faster to the fall of crude oil prices than to the rise of ones.

Table 2.10 presents the results of Wald tests for price asymmetry on two types of ECM models. From column headed on 'ECM', retail prices – LDP have the price asymmetry for LCP and LDP(-1), so retail prices rise faster than they fall. From column head on 'ECM with PGARCH', LDP responds differently only to LCP(-6) and LDP(-1). However, .the coefficients of LCP for the first 5 lags are so small as to be close to zero, so the asymmetry tests for these coefficients have small F-Statistics, indicating the presence of price symmetry. However, the coefficients on PLCP after five lags are greater than that on NLCP. It refers that there is the obvious evidence for the asymmetric response of diesel prices to price changes of crude oil after the first five days.

I presented the impulse response function to check out the price asymmetry and compare estimates for two types of ECM model. I obtained the confidence intervals for the impulse response functions with Monte Carlo simulation with 1,000 iterations. Figure 2.6 and 2.7 illustrate cumulative impulse response functions of the traditional BG model and ECM model with QGARCH(1, 2) for weekly data, respectively. Both Graphs show overall retail prices tend to increase in the positive shock from crude oil faster than in the negative one from crude oil. Comparing the estimation results for both ECM models, the estimation results of ECM model with QGARCH(1, 2) is greater than those of the traditional ECM model.

The cumulative impulse response function in Figure 2.6 illustrates the price asymmetry for the traditional ECM models applied into daily data. The graph shows retail prices increase to positive shocks from crude oil prices faster than to negative one. For the one period positive shock, retail prices increase by 0.74% for 30 days. However, retail prices even increase to the negative shock for the first four days and then decrease by 0.26 % for 23 days. Applying BG model into daily data, it infers the positive shock of crude oil prices lasts longer and stronger than the negative shock.

Figure 2.7 presents the impulse response function for The ECM model with QGARCH. I find out there is a strong evidence for price asymmetry. This is because the rise of retail prices to a positive shock is 0.64% for about 30 days whereas the fall to a negative shock is 0.23% for 15 days. It means that the cumulative adjustment speeds for a positive shock are significantly different from those for a negative shock. However, the cumulative adjustment speeds in Figure 2.7 are very diminutive for the first five lags but get substantial after five days. Especially, the interpretation for the shocks at the first day is somewhat different in the sense that the coefficients on LCP under homoskedasticity are changed to be statistically insignificant by using the ECM with QGARCH. It seems that the shocks from crude oil do not affect retail prices directly but transfer them through rack prices. Therefore, the inventory of retailers is the one of factors to determine prices. In Korea, retail prices adjust slowly to price changes of crude oil with a week time lag due to the inventory problem. After one week, retail prices increase faster in the rise of rack prices than in the fall of ones.

Figure 2.8 illustrates the comparison of impulse response functions between the traditional model and ECM model with QGARCH. Based on the difference of cumulative adjustment speeds for the traditional model and ECM model with QGARCH, the estimates for ECM model with QGARCH are smaller than those for the traditional model. It means coefficients specified by the OLS method are misspecified. In other words, the calculation for price asymmetry based on the traditional model can be improved by fixing the heteroskedastic disturbance.

2.5.3 Discussion

The estimated results of ECM model with asymmetric GARCH revealed that the daily retail prices in Korea adjust slowly to crude oil prices for the first week and then respond to the increase of crude oil prices more quickly than to the decrease of ones. Although the public complain price collusion of four major refinery firms, the results implies that the price asymmetry in the diesel market does not results from oligopolistic market powers but from price collusion of retailers.

In Korea, four major firms at the upstream level have a very strong oligopoly power with the vertical integration management and the exclusive sales right, which hinder the entry of a new firm to the transport fuel market. In spite of potential oligopolistic market powers, weekly rack prices of diesel respond symmetrically to price changes of crude oil. This is because Korea government has conducted tight price monitoring and heavy antitrust fine system to prevent collusive behaviors of four refineries.

Generally, it seems that the number of retailers is so large as to compete with each other effectively. In addition, it is thought that individual gas stations respond quickly by posting and changing diesel prices at low cost easily. On the contrary to the public thoughts, retail prices of diesel at the downstream market adjust slowly to decrease in crude oil prices but rapidly to increase in crude oil prices.

Estimated results infer that asymmetry price response at the downstream level results from collusive behaviors of local retailers. Since the government has difficulty in price monitoring at every local market, local retailer and only four-brand diesel can be traded, local retailers can sell diesel at a cooperative price. Therefore, they seldom respond to changes of crude oil prices and rack diesel prices for the first week. Especially, retail prices are so observable that defection can be punished without difficulty. Even if defection occurs, possible gains are too small for local retailers to sustain price collusion easily.

2.6 Conclusions and Further Studies

It is disputable in the public that prices of transport fuels rise fast but fall slowly responding to price changes of crude oil. To examine the presence of price asymmetry of diesel, this study analyzed two markets in the pass-through of crude oil and calculated the adjustment speed of retail diesel prices to crude oil prices. It was found out that it takes at least five days for retail diesel prices to adjust to price changes of crude oil prices. The estimation results made two important conclusions are one is that the price asymmetry in the diesel market is attributed to behaviors of retailers rather than to those of four major refineries, another is that retail diesel prices do not reflect crude oil prices simultaneously due to collusive behaviors of retailers.

I investigated two markets in the pass-through of crude oil by applying the standard ECM model into weekly data. Contrary to the public suspicion of refineries' price collusion, this study revealed that diesel prices adjust symmetrically to price changes of crude oil at the upstream level but respond asymmetrically to those of crude oil at the downstream level. Additionally, I calculated the response speed of retail diesel prices to price changes of crude oil for daily and weekly data. Even if the same estimation procedure is applied, this study found out both specifications for retail prices generate non-constant disturbances because the volatility of price shocks from the international market or the domestic market differs in any period of time.

Since the estimates under the homoskedasticity assumption are unbiased but inefficient, I applied three asymmetric GARCH models to improve the inference for estimated results. The ECM model with a GARCH process revealed that retail prices seldom response to price changes of crude oil for the first three days. Based on these specifications for weekly and daily data, the impulse response functions illustrate that the daily retail prices respond very slowly to crude oil prices for the first week and then reflect the increase of crude oil prices more quickly than the decrease of ones.

For price asymmetry of petroleum products, further studies are required with respect to heteroskedasticity. Most of previous studies are based on the ECM model under the homoskedasticity assumption. However, this study pointed out the volatility of price shocks is different in time so it is necessary to research the relationship between price asymmetry and heteroskedasticity.

3. THE IMPACT OF A BLEND MANDATE AND TAX CREDIT ON KOREAN DIESEL MARKET

3.1 Introduction

Most countries in the world have sought to develop alternative energy resources in order to overcome the volatility of crude oil prices, the depletion of world oil reserve in the future, and climate change. Of a variety of new energy resources, biofuels are the fastest developing energy resources although the energy resources for transportation depend mainly on petroleum. According to the report of IEA in 2007, they will provide 7% of world total road transport fuels by 2030.

Biofuels are mostly used as two types of transport fuels. Bioethanol is extracted from starch crops such as sugar cane or corn, whereas biodiesel is produced from vegetables oils, animal fats, or wasted greases. Brazil and the U.S. have been two leaders for production and consumption of bioethanol (Shapouri and Salassi, 2006). Biodiesel has been mostly developed and used as transport fuel in Europe (EBB, 2011). In Korea, biodiesel was introduced as an alternative fuel in 2002 to reduce dependency of imported petroleum and greenhouse gas (hereafter GHG) emissions. The production and consumption of biodiesel have increased very rapidly for the last decade since it was used to be mixed with diesel for transportation in 2007.

Recently, many governments provide various types of biofuel policies to encourage the use of biofuels (Kojima et al., 2007). Of these policies, two incentives are widely implemented to increase the production and consumption of biofuel. One is a blend mandate to require a certain percentage of biofuels to be mixed in gasoline or diesel. Another is a tax credit to reduce taxes or tariffs imposed on biofuels. The Korea government also provides both incentives for the biodiesel industry in youth.

Previous studies on the economic effects of biofuel policies have focused mainly on two incentives. The report of the World Bank (Kojima et al., 2007) explained economic effects of biofuels policies and forecasted increase of international trade for biofuels due to a blend mandate. The studies of Gorter and Just (2008) pointed out import tariffs on bioethanol produced in Brazil distorted gasoline prices in the U.S. market. Ando et al. (2010) showed that the Renewable Fuel Standard (hereafter RFS) in U.S. has played an important role in production and consumption for bioethanol, evaluating economic and environmental effects of two policies.

Most previous papers in Korea have been concerned with costs and benefits of crops cultivation for biofuel production. However, research on effects of biodiesel incentives has been rarely performed because production and consumption of biofuel markets in youth is very limited. Park (2006) compared the production costs of biofuels and found out biofuel resources for production of transport fuels are too expensive to compete with petroleum. The study of Steenblik in 2007 also claimed that both Japan and Korea have the limited capacity to produce biofuels with respect to high opportunity costs of farmlands and agricultural products. The paper of Lee and Han (2008) analyzed costs and benefits of various scenarios for two incentives and concluded that the use of blended diesel as a transportation fuel would have positive effects on the domestic biodiesel industries if crude oil prices increase by over 120$ per barrel.

The feature of prior studies on Korea biodiesel is to give little consideration of the correlation between biodiesel and diesel prices and to have the limited analysis for the only transport diesel market. However, blended diesel price is not determined independently by its own market. Since both biodiesel and diesel are mixed at a required ratio under blend mandate, prices of blended diesel are correlated with two input prices. Two incentives for biodiesel affect not only the blended diesel market for transportation but also other diesel and biodiesel markets.

The objective of the second essay is to evaluate the new biodiesel policy in Korea that keeps the blend mandate but abolishes tax credits for the required content of biodiesel mixed with transport diesel. Unlike previous research, I estimated the costs and benefits of the new policy with consideration of the correlation among diesel and biodiesel markets. Based on the multivariate framework, a stochastic simulation method was applied into time-series data. From the results, I found out the new biodiesel policy in Korea will decrease consumer and producer surplus although the government revenue increases owing to the abolishment of tax credit.

This article is organized as follows. Section 3.1 was the introduction on this study. Section 3.2 provides an overview of the previous analysis based on the partial equilibrium and background information on transportation fuel markets in Korea. Section 3.3 describes the econometric methodology and data used in this study. Section 3.4 presents the results of a simulation model to a new blend mandate for biodiesel, concluding remarks and discussion on further research needs are presented in Section 3.5.

3.2 Korea Biodiesel Market and Previous Studies on Biofuels

3.2.1 The Outline of Korea Diesel Market

In Korea, the energy consumption has rapidly increased accompanying with economic development and improvement of living standard. For the production of transport fuels such as gasoline, diesel, and liquefied petroleum gas (hereafter LPG), Korea depends entirely on imported crude oil. Figure 3.1 shows annual petroleum imports and imported countries. The Korea economy has increased imported oil by over 5% from 2000 and enlarged the dependency on crude oil imported from the Middle East.

In terms of the demand, the consumption of transport fuels has largely increased by an average of 5.3% per year for the last decade. Figure 3.2 presents the annual consumption for three types of transport fuels from 1994 to 2010. The consumption of gasoline, diesel, and LPG has increased 1.5%, 6.3%, and 58% per year, respectively. Especially, the use of diesel and LPG has increased very steeply. Diesel is the most used transport fuel in Korea because the government exempts diesel-powered vehicles from some taxation.

The production of transport fuels has been largely expanded by four major refineries for the last decade. The import of petroleum fuels has been almost zero whereas the excess production of gasoline and diesel has been exported for the same periods. However, the entire production relies on only four major refineries with the exclusive sales right. In the transport diesel market, four firms purchase biodiesel to be mixed with diesel as oligopsonists at the upstream level and directly provide most retailers with blended diesel as oligopolists at the downstream level. Even, they started to produce their own biodiesel to be mixed for internalizing transaction costs in 2009.

The Korea government altered the target of energy policies to comply with Kyoto Protocol in 1997. In the policy for transport fuels, the government established the planning for the development of renewable energy resources and the reduction of GHG emission. Biodiesel was introduced as one of alternatives to fossil fuels in 2002 and then has been used for mixing with diesel from 2008. According to the annual report of the Ministry of Knowledge and Economy (MKE) in 2010, the production for biodiesel has expanded from 1,500 kiloliters in 2002 to 237,000 kiloliters in 2010 and the consumption has doubled for the same periods[1].

To encourage the use of biodiesel, two incentives have been provided by the Korean administrative guidance. The blend mandate is to require the content of biodiesel to increase from 0.5% in 2007 to 2% in 2010. Additionally, the tax credit is to exempt biodiesel manufactures from 77% of oil taxes. The tax credit enables these manufactures to compete with crude oil because the production costs of biodiesel are over twice as high as those of diesel. The government announced that the new blend mandate would increase a required content of biodiesel by 5% in 2015 whereas the tax credit would be abolished in 2012 because of a drop in tax revenue.

3.2.2 Literature Review for Previous Studies

The study of Kojima et al. (2007) claimed biofuels have positive effects on the

[1] Biodiesel is only used to be mixed with diesel for the domestic transport fuel market, so the quantities of biodiesel produced in Korea are almost as same as required contents of blended diesel.

economies and environments in the world based on the partial equilibrium model. It forecasted the increase of international trade for biofuels due to high petroleum prices and incentives for biofuels. The research of Farinelli et al. (2009) pointed out that both of blend mandate and tax credit caused the demand schedule to be less price elastic by comparing the relation among demands for ethanol imported from Brazil and energy policies of six countries – U.S., Europe, Mexico, Caribbean region, Japan, and Nigeria.

Gorter and Just (2009) claimed both of tax credits and blend mandates distort domestic market prices with deadweight loss. Ando et al. (2010) showed the partial equilibrium model to investigate the economic and environmental effects of the RFS including blend mandates, tax credits, and subsidies. Their model emphasized the energy-efficiency of transport fuels to obtain more accurate estimation of consumers' costs for gasoline mixed with bioethanol.

On the other hand, most of Korean research about biofuels has focused on the economic and environmental effects of technology development to extract biodiesel from various crops and biomass. The report of Korea Institute of Energy Technology (KIET) in 2005 argued that the Korea government had to invest in biofuel technology to deal with economic and environmental problems resulting from fossil fuels. The study of Lee and Han (2008) revealed that the production of biodiesel from domestic rapeseed oil was too expensive to substitute petroleum although cultivating rapeseed is one of the most productive crops.

The studies on effects of a blend mandate and tax credit in Korea have been rarely performed because it is very difficult to obtain data on the biodiesel market in youth. The studies of Park in 2006 and Steenblik in 2007 came to the same conclusion that the biodiesel production was very limited in Korea because of high opportunity costs to convert idle lands into rapeseed plantations and to give subsidies to farmers. The report of Korea Energy Economics Institute (Bae, 2008) showed two incentives were essential to increase the use of biodiesel and concluded the introduction of carbon taxes would lead biodiesel prices to be competitive.

The analysis of previous studies was performed under the assumption that each of demands and supplies in the diesel market is independent from one another. However, this study find out they are correlated and interwoven with each other based on tests for correlation. Therefore, it is necessary to employ a multivariate framework for obtaining more accurate estimation results of the biodiesel policies. For this analysis, a multivariate framework was utilized to cope with the interaction among diesel markets. A stochastic simulation method was applied to estimate the impacts of the new biodiesel policy, which would require the blend mandate without any tax credit.

3.3 Methodology for Simulation and Data

This section describes the framework to analyze the economic effects of a new biodiesel policy for maintaining the blend mandate without any tax credit for biodiesel. Since data on biodiesel prices are inaccessible and the policy is not performed, I used a stochastic simulation analysis as the most reasonable method to forecast and evaluate a hypothesized situation to occur to the real world based on economic theories. To simulate the scenario on the implement of new biodiesel incentive, a baseline model should be established by utilizing estimated results from multiple regressions.

3.3.1 Conceptual Framework for the Analysis

To begin with, the hypothesized model for Korea diesel market is built up under both of blend mandate and tax credit provided simultaneously. In the diesel market, the total domestic demand of diesel DD at period t is the sum of domestic consumption of diesel CD_t and ending reserved stocks ST_t as follows;

$$DD_t = CD_t + ST_t \tag{1}$$

The domestic consumption of diesel is divided by four sectors – transportation CD_t^T, industry CD_t^I, residential heating CD_t^R, and public use CD_t^P. It has the following functional form;

$$CD_t = CD_t^T + CD_t^I + CD_t^R + CD_t^P \tag{2}$$

Each of diesel quantities consumed by four sectors is represented as follows;

$$CD_t^T = f_T(DP_t, CD_{t-1}^T, T) \tag{2-1}$$

$$CD_t^I = f_I(DP_t, CD_{t-1}^I, T) \tag{2-2}$$

$$CD_t^R = f_R(DP_t, CD_{t-1}^R, T) \tag{2-3}$$

$$CD_t^P = f_I(DP_t, CD_{t-1}^P, T) \tag{2-4}$$

where DP_t is the price of diesel at period t and T is the time trend.

Ending reserved stocks ST_t are given by;

$$ST_t = f_S(DP_t,\ ST_{t-1}) \tag{3}$$

On the other hand, the total domestic supply for diesel SD at period t consists of diesel production, imported diesel, exported diesel, and the beginning stocks at period t. The supply function is written by;

$$SD_t = PD_t + ID_t + ST_{t-1} - ED_t \tag{4}$$

where PD_t is the domestic production of diesel at period t, ID_t is the imported diesel at period t, ED_t is diesel exported abroad and ST_{t-1} is the reserved stocks at period $t-1$ as the beginning stock.

The production, import, and export function of diesel are described with respect to the price of diesel as follows;

$$PD_t = g_P(DP_t,\ PD_{t-1}) \tag{5}$$

$$ID_t = g_I(DP_t,\ ID_{t-1}) \tag{6}$$

$$ED_t = g_I(DP_t,\ ED_{t-1}) \tag{7}$$

In the domestic market, diesel price is attained at the market equilibrium where total demand should be equal to total supply.

In the transport diesel market, all diesel sold has to contain a certain amount of biodiesel due to the blend mandate. The total supply of blended diesel BDS_t is the sum of the quantity of diesel consumed and biodiesel supplied in the transport fuel market. Since blended diesel price BDP_t is determined by the total supply and demand of blended diesel at period$t$, BDS_t and BDD_t are represented with the following equations;

$$BDS_t = \phi_S(BDP_t) \tag{8}$$

$$BDD_t = \phi_D(BDP_t) \tag{9}$$

Blended diesel price BDP_t is determined when total supply is the same to total demand in the blended diesel market.

Here, the simulation model is established based on hypothesized blended diesel prices. Under the blend mandate, blended diesel price BDP_t is defined as a linear combination with biodiesel price BP_t and the price of diesel DP_t given by;

$$BDP_t = \alpha BP_t + (1 - \alpha) DP_t \tag{10}$$

where α is a minimum share of biodiesel for $\alpha \in (0, 1)$ and determined by a blend mandate. However, data on biodiesel price in Korea are inaccessible because biodiesel produced is directly provided to be mixed with diesel for transportation. Since Korea depends entirely on two inputs imported abroad for production of diesel and biodiesel, both of diesel and biodiesel prices are heavily affected by prices of crude oil and soybean oil in the world market[2]. To analyze blended diesel prices, soybean oil SP_t is used as the instrument variables for biodiesel price. Equation (10) can be written by;

$$BDP_t = (1 - \alpha) \cdot \psi_D(DP_t) + \alpha \cdot \psi_B(SP_t) \tag{11}$$

Assuming that each of diesel and soybean prices at period t is correlated with crude oil prices, two equations can be represented with CP_t as the independent variable as follows:

$$DP_t = \psi_D(CP_t) \tag{11-1}$$

$$SP_t = \psi_S(CP_t) \tag{11-2}$$

From two equations, diesel and soybean oil prices are determined by hypothesized crude

[2] According to the annual report of MKE in 2010, soybean oil and wasted oil are used as two main inputs for biodiesel production. 80% of biodiesel produced in Korea is extracted from soybean oil imported from U.S., Argentina, and Brazil.

oil prices. Applying these prices into equation (11), blended diesel prices are simulated with consideration of blend mandate. Costs and benefits of the new biodiesel policy are calculated by using these simulated prices of blended diesel.

3.3.2 Econometric Framework for the Stochastic Simulation

To establish the stochastic simulation model, I specify conceptual equations mentioned in Section 3.3.1 by applying multiple regressions into time series data. For the total demand of diesel, the components of domestic consumption are estimated by the following multiple regressions;

- Transportation: $CD_t^T = \alpha_0^T + \alpha_1^T DP_t + \alpha_2^T CD_{t-1}^T + \alpha_3^T T + \varepsilon_t^T$ (2′-1)
- Industry : $CD_t^I = \alpha_0^I + \alpha_1^I DP_t + \alpha_2^I CD_{t-1}^I + \alpha_3^I T + \varepsilon_t^I$ (2′-2)
- Resident : $CD_t^R = \alpha_0^R + \alpha_1^R DP_t + \alpha_2^R CD_{t-1}^R + \alpha_3^R T + \varepsilon_t^R$ (2′-3)
- Public : $CD_t^P = \alpha_0^P + \alpha_1^P DP_t + \alpha_2^P CD_{t-1}^P + \alpha_3^P T + \varepsilon_t^P$ (2′-4)

Letting $\alpha_0^T + \alpha_0^I + \alpha_0^R + \alpha_0^P = \alpha_0$, $\alpha_1^T + \alpha_1^I + \alpha_1^R + \alpha_1^P = \alpha_1$, $\alpha_3^T + \alpha_3^I + \alpha_3^R + \alpha_3^P = \alpha_3$, and $\varepsilon_t^T + \varepsilon_t^I + \varepsilon_t^R + \varepsilon_t^P = \varepsilon_t^C$, the domestic consumption of diesel CD_t is represented as follows;

$$CD_t = \alpha_0 + \alpha_1 PD_t + \alpha_2^T CD_{t-1}^T + \alpha_2^I CD_{t-1}^I + \alpha_2^R CD_{t-1}^R + \alpha_2^P CD_{t-1}^P + \alpha_3 T + \varepsilon_t^C \qquad (2')$$

The ending stocks of diesel are given by

- Ending Stock: $ST_t = \beta_0 + \beta\gamma_1 DP_t + \beta_2 ST_{t-1} + \varepsilon_t^S$ (3′)

Since total demand of diesel DD_t is the sum of domestic consumption and ending stocks, equation (1) is represented as follows;

$$DD_t = (\alpha_0 + \beta_0) + (\alpha_1 + \beta_1)DP_t + \alpha_2^T\ CD_{t-1}^T + \alpha_2^I\ CD_{t-1}^I + \alpha_2^R\ CD_{t-1}^R$$

$$+\alpha_2^P\ CD_{t-1}^P + \alpha_3\ T + \beta_2\ ST_{t-1} + (\varepsilon_t^C + \varepsilon_t^S) \qquad (1')$$

Let $A_D = \alpha_0 + \beta_0$

$B_D = \alpha_1 + \beta_1$

$C_D = \alpha_2^T\ CD_{t-1}^T + \alpha_2^I\ CD_{t-1}^I + \alpha_2^R\ CD_{t-1}^R + \alpha_2^P\ CD_{t-1}^P + \alpha_3\ T + \beta_2\ ST_{t-1}$

$\bar{\varepsilon}_{D,t} = \varepsilon_t^C + \varepsilon_t^S$

Total demand equation $(1')$ can be written by;

$$DD_t = A_D + B_D \cdot PD_t + C_D + \bar{\varepsilon}_{D,t} \qquad (1'')$$

To define the total domestic supply of diesel, each of the production, import, and export is estimated by the following equations;

- Production : $PD_t = \gamma_0 + \gamma_1 DP_t + \gamma_2\ PD_{t-1} + \gamma_3 T + \varepsilon_t^{PD}$ (5′)
- Import : $ID_t = \delta_0 + \delta_1 DP_t + \delta_2\ ID_{t-1} + \varepsilon_t^I$ (6′)
- Exports : $ED_t = \eta_0 + \eta_1 DP_t + \eta_2\ ED_t + \varepsilon_t^E$ (7′)

Combining the equation (5′), (6′) and (7′), the total domestic supply of diesel is written by;

$$SD_t = (\gamma_0 + \delta_0 - \eta_0) + (\gamma_1 + \delta_1 - \eta_1)DP_t + \gamma_2\ PD_{t-1} + \delta_2\ ID_{t-1} + \gamma_3\ T$$

$$+ ST_{t-1} - \eta_2 ED_t + \varepsilon_t^{PD} + \varepsilon_t^I - \varepsilon_t^E \qquad (4')$$

Let $A_S = \gamma_0 + \delta_0 - \eta_0$

$B_S = \gamma_1 + \delta_1 - \eta_1$

$C_S = \gamma_2\ PD_{t-1} + \delta_2\ ID_{t-1} + \gamma_3\ T + ST_{t-1} - \eta_2 ED_t$

$\bar{\varepsilon}_{S,t} = \varepsilon_t^{PD} + \varepsilon_t^I - \varepsilon_t^E$

Total domestic supply equation (4′) can be rewritten by;

$$SD_t = A_S + B_S DP_t + C_S + \bar{\varepsilon}_{S,t} \tag{4''}$$

Total supply of blended diesel for transportation is the sum of diesel and biodiesel under blend mandate. Total supply and demand of blended diesel is estimated by the following regression on blended diesel price BDP_t;

$$BDS_t = \phi_{S,0} + \phi_{S,1} BDP_t + \phi_{S,2} BDS_{t-1} + \varepsilon_t^{BDS} \tag{8'}$$

$$BDD_t = \phi_{D,0} + \phi_{D,1} BDP_t + \phi_{D,2} BDD_{t-1} + \phi_{D,3} T + \varepsilon_t^{BDD} \tag{9'}$$

The equilibrium price of blended diesel is obtained by solving each simultaneous equation with the restriction, which is total supply should be equals to total demand.

To estimate prices of diesel and soybean oil, equation (11-1) and (11-2) are specified by following regression procedures;

$$DP_t = \pi_0^D + \pi_1^D CP_t + \varepsilon_t^D \tag{11'-1}$$

$$SP_t = \pi_0^S + \pi_1^S CP_t + \varepsilon_t^S \tag{11'-2}$$

Applying two equations estimated by the regression into equation (12), blended diesel prices are obtained to make a simulation corresponding to shocks from crude by the following equation;

$$BDP_t = (1 - \alpha) \cdot DP_t + \alpha \cdot SP_t \tag{11'}$$

Suppose that crude oil prices fluctuate from US$ 80 to US$ 110 per barrel, diesel prices cover from ₩ 1450 to ₩ 1919 per liter and soybean oil prices range from US$ 1,000 to US$ 1,300 per Metric Ton. Based on this assumption, the blended diesel prices are obtained by using the equation (11′).

To specify the total demand and supply, quantities of production, consumption, exports and stocks are used as the deterministic variable. Each of regression estimates for these variables is correlated with one another. In this case, applying univariate probability distributions into individual variables will cause to misestimate key output variables related with total supply and demand. In other words, simulated results will be understated if the positive correlation among variables is not considered whereas they will be overstated for the negative correlation. Therefore, the simulation model is constructed based on the multivariate framework.

From each of the regressions, residuals and their standard deviations generate multivariate normal distributions of variables, which are used for simulating each of components for total supply and demand under the blend mandate without any tax credit with Monte Carlo approach.

3.4 Data

This study investigates the welfare changes under the new biodiesel policy by employing the multivariate simulation model. The time-series data used are from Korea Energy Statistics Information System (KESIS), covering August, 2006 to June, 2011. They consist of monthly prices of three oils, and quantities of diesel supplied and consumed. In Korea, tax credits for biodiesel have been constant for the last 5 years whereas the blend mandate has gradually increased the required content of biodiesel from 0.5 percent in 2007 to 2 percent in 2010. Table 3.1 summarizes some statistical characteristics of monthly data on diesel prices, quantities of diesel produced, and consumed at each sectors in Korea diesel market.

Figure 3.3 illustrates the movements of monthly prices of two inputs imported from oversea - crude oil, and soybean oil. From August, 2007 to June, 2011, prices of crude oil are higher than those of soybean oil. Two prices elevated and reached the peak in July, 2008. They fell down with the global economic recession at the end of 2008 and then have increased.

3.5 Results of Estimation and Simulation for the Diesel Market

The estimates from each regressions mentioned at Section 3.3.2 are used to establish the baseline model in order to define the equilibria for three markets such diesel, biodiesel, and blended diesel. In consideration of the correlation among each of estimation results, the baseline model is the framework for simulating the scenario that the government keeps providing the blend mandate with biodiesel industry firms but abolishes tax credits.

3.5.1 Estimation Results for the Baseline Model

Korea diesel market is defined by applying the multiple regressions into monthly data on production, domestic consumption, export, import, and stock. These estimators are used to obtain the total supply and demand of diesel. Table 3.2 presents results of the multiple regressions for a separate sector in total supply and demand of diesel. For total domestic demand and supply of diesel, estimates of each separate regression are specified as a reduced form, which is a function of diesel price. Total domestic supply is an increasing function in diesel price whereas total domestic demand is a decreasing function in diesel price.

Table 3.3 presents the results from three regression of diesel price DP_t, soybean oil price SP_t, and blended diesel price BDP_t on crude oil CP_t. BDP_t has the positive relationship with both prices and the coefficient of CP_t is greater than that of SP_t by adjusting the required mixture ratio under blend mandate. Each of estimates from multiple regressions is used as a deterministic component, which becomes a component of mean equations to explain the relationship with diesel price and blended diesel price. Deterministic components consist of the predicted values from multiple regressions for production, export, four domestic use, and stocks in the diesel market, and for total supply and demand in the blended diesel market.

To investigate the correlation of each variable in the diesel markets, residuals from regressions are used to obtain correlation matrix. Table 3.4 presents the correlation matrix and test result for correlation coefficients at the 95% significance level. Since the correlation coefficients are statistically different from zero, all individual residuals of regressions are correlated with each other. Therefore, standard deviations of residuals from regressions are represented as stochastic components to measure the dispersion about deterministic components. Multiplying the correlation matrix of residuals by independent standard normal distribution, a vector of correlated standard normal deviates (hereafter CSND) is calculated. By multiplying the CSND by the diagonal matrix of standard deviations, the stochastic components are generated as the multivariate normal distribution for the simulation of diesel and blended diesel markets. The stochastic results of each variable are estimated by adding deterministic components to stochastic ones.

3.5.2 Simulation Results

The baseline model is established under the assumption that both blend mandate and tax credit are provided. The costs and benefits of two incentives are calculated on the basis of total supply and demand specified by each of regressions in diesel and blended diesel market. Under blend mandate, the use of diesel in transportation decrease in the increase of the required mixture ratio of biodiesel. However, tax credits affect prices of blended diesel by decreasing biodiesel prices to be mixed with diesel. Assuming that crude oil prices are determined within US$ 80 to US$ 110 per barrel, diesel prices fluctuate from ₩1450 to ₩ 1919 per liter and soybean oil prices range from US$ 1,000 to US$ 1,300 per Metric Ton. Based on this assumption, the scenario for blend mandate without any tax credit is simulated for estimating costs and benefits.

Based on the simulation results for the diesel and blended market, diesel and blended diesel price is ₩ 1,747.68 and ₩ 1,747.64 per liter, respectively. The domestic use of blended diesel is about 1.33 billion liter composed of 1.31 billion liter of diesel and 0.01 billion liter of biodiesel. The tax credits for biodiesel range from ₩ 14 billion to ₩ 16 billion each month.

Under the scenario that the blend mandate is provided without any tax credit, blended diesel price increases by about 3 percent owing to taxes imposed on biodiesel. Therefore, the quantity of blended diesel consumed decreases by 1.9 to 2.6 percent. Further, the domestic use of diesel decreases by 0.6 to 1.3 percent due to the decrease in blended diesel for transportation. However, total demand and price of diesel are unchanged because ending stocks just increases by 0.6 to 1.3 percent. On the other hand, biodiesel prices increase owing to oil-related taxes, ₩ 529 per liter. Total demand of biodiesel decreased by 1.9 to 2.6 percent, which is equal to the quantity decreased in the blended diesel market. Therefore, the new biodiesel policy of blend mandates without tax credit causes to transfer increase of biodiesel prices to blended diesel prices at the same rates. Removal of tax credits decreases both producer and consumer surplus by 2 percent and 0.19 percent, respectively. The government revenues increase by about ₩ 15 billion. For biodiesel market, producer surplus decreases by 0.09 percent. However, consumer surplus is not changed or almost zero. Since the consumption of biodiesel is not determined by biodiesel price but by the required content of blended diesel, the price elasticity of biodiesel demand is perfectly inelastic so the demand curve of biodiesel is assumed to be a vertical line[3].

The simulation results reveal the blend mandate without any tax credit do not affect only the blended diesel market but also other markets. Although the new biodiesel policy increases government revenues, the economic benefits for consumers and producers in blended diesel market decrease as well as producer surplus in the biodiesel market declines. Tax credits are provided for biodiesel industry firms. However, they play a role as the subsidy for consumers by lowering prices in the blended diesel market. By imposing oil-related taxes on biodiesel products, the implement of this policy in 2012 will place biodiesel industry firms under disadvantages. This is because the production

[3] According to the annual report of MKE in 2010, prices of biodiesel are double to those of diesel due to high production costs. If the government abolishes tax credits for biodiesel, the demand of biodiesel depends entirely on blended diesel produced for transportation.

cost of biodiesel is too high for biodiesel to compete and substitute diesel in other markets without any tax credit.

Figure 3.4 illustrates the effects of blend mandates and tax credits on the blended diesel market. Suppose that the supply and demand of blended diesel under both incentives is S_{BD} and D_{BD}, respectively. The market equilibrium is attained at point a where the supply and demand curve of blended diesel are intersected. At the market equilibrium, the quantity of blended diesel is Q_e and the price of blended diesel comes to be P_e. If the government maintains blend mandates but imposes oil-related taxes on biodiesel industry firms, the supply curve shifts upward from S_{BD} to S_t by paying tax $\boldsymbol{\alpha \cdot t}$. When the market equilibrium moves from point *a* to *b,* the price of blended diesel rises from P_e to P_t at point b whereas the quantity of blended diesel decreases from Q_e to Q_t. In this case, both of consumer and producer surplus decrease by area abP_tP_e and adP_dP_e, respectively. The government revenue is rectangle area bdP_dP_t and the deadweight loss is triangle area *abd*. Consequently, the new biodiesel policy is inefficient because the sum of deadweight loss and economic surplus decreased is greater than the government tax revenue.

3.6 Summary and Conclusion

The blend mandate and tax credit for biodiesel play an important role in increasing the production and consumption of biodiesel in Korea. However, the government announced the abolishment of tax credits for biodiesel by 2012 in order to increase the fiscal revenue. This study analyzed economic effects of two incentives on three markets related with biodiesel. I evaluated the new biodiesel policy to implement the blend mandate without any tax credit from 2012 by comparing outcomes from blend mandate without tax credit with those from the situation under two incentives provided simultaneously. To estimate the welfare effects of the new policy, I utilized the simulation model for three markets correlated with each other.

From simulation results, I found out three kinds of welfare effects of the tax credit abolishment under blend mandate. First, the new biodiesel policy decreases consumer and producer surplus in the blended diesel and biodiesel market but does not affect the diesel market. Second, it causes the economic loss because the sum of economic surplus decreased at two markets is greater than the increase of government revenue. In this situation, some deadweight loss even occurs in the blended diesel market. Lastly, tax credits binding the blend mandate do not only support the biodiesel industry in youth but also subsidize consumers in the blended diesel market.

The biodiesel policy combined with a blend mandate and a tax credit has greatly increased the production and consumption of biodiesel in Korea for the last decades. However, removal of tax credits will reduce both of blended diesel and biodiesel market under a blend mandate. Even if a blend mandate gives an advantage to biodiesel producers by guaranteeing certain amount of consumption, the elimination of tax credits causes the market reduction for biodiesel. In this case, it is difficult to apply economy of scale into the biodiesel industry for lowering production costs in the long run. Consequently, Korea government cannot attain the policy target to increase the use of biodiesel and develop biodiesel production technologies unless other incentives for biodiesel are provided.

The blend mandate without any tax credit is the most desirable policy instrument in the sense that the government revenue increases. However, elimination of a tax credit causes to decrease biodiesel consumption. Since the small market demand of biodiesel is one of the biggest obstacles to development of the biodiesel industry, the priority for further studies should be on the optimal blend mandate. Although the production costs for biodiesel are absolutely high, research on the incentive to develop biodiesel technologies is also required for lowering high dependency on imported crude oil and GHG emission.

4. THE ECONOMIC IMPACT OF AIR TEMPERATURE ON DAILY PEAK LOAD ELECTRICITY DEMAND IN THE HOUSTON AREA: IMPLICATIONS OF URBAN HEAT ISLAND

4.1 Introduction

As many people have migrated from rural to urban areas with population growth and industrialization, the United Nation (2010) projected that half of the world's population would reside in urban areas at the end of 2011. This physical growth of urban area has a huge amount of influence on human socio-economic lives as well as environments in the world. With respect to climate, urbanization causes the air or surface temperature of a metropolitan area to be higher than that of its rural surroundings (Oke, 1995). The temperature difference between urban and rural areas is commonly defined as 'Urban Heat Island' (hereafter UHI). This phenomenon apparently appears at night during both summer and winter. The main cause of UHI is that the surfaces of buildings and pavements in a city block solar heat from radiating into the atmosphere and become so hot as to increase the surrounding air temperature (Oke, 1982).

The higher temperatures in urban areas affect energy consumption because people inside the buildings use energy to remove thermal discomfort. In other words, air temperature can increase energy demand for cooling in summer but decrease energy demand for heating in winter. With high interests in climate changes, several studies were performed to investigate the impact of weather variables on energy consumptions. The research of Linder et al. (1987) showed the climatic variables can potentially affect eletricity utility planning and operation for the long term by analyzing utility systems in the Southeastern U.S. and New York State. Sailor and Muñoz (1997) assessed sensitivity of energy consumption to climatic factors in eights states in U.S. and concluded the relationship between energy demand and temperature is positive in summer, but negative in winter. Santamouris, et al. in 2001 found higher temperatures at the city centers of Athens, Greece, affect the electricity consumptions in summer more than in winter. Therefore, the impacts of air temperature resulting from UHI can seriously mislead the forecast and estimation to electricity demand for cooling and heating (Hor et al., 2006; Kolokotroni et al., 2010).

The typical UHI phenomenon apparently appears in Houston, the fourth-largest city in U.S. Similar to previous studied megalopolitan cities, Houston downtown is hotter although the climatic variables are same as boundary areas (Orville, et al., 2001; Burian and Shephard, 2005; Chen et al., 2011). According to research of Shepherd, et al. (2010), the UHI intesity over the metropolitan area of Houston is proportional to the city size and most evident at night. They concluded both land use and air pollution result in UHI effects in the central Houston areas, which increase the average air temperature in the urban area by 1.5º F to 4º F. However, the study on the relationship between air temperature and electricity consumption in Houston are rarely performed.

The objective of this study is to predict daily peak load demand in Houston more acccurately. Since the misestimation of daily peak load demand can produce costly consequences in terms of energy security and supply reliability, the exact forecast for electricity demand is very important to calcuate the optimal day to day generation of eletricity (Ismail et al., 2009; Sigauke and Chikobvu, 2011). In previous studies, the short-run electricity demand was estimated based on an autoregressive integrated moving average (hereafter ARIMA) model. However, this study utilized a seasonal ARIMA (hereafter SARIMA) model for short-run forecasting with consideration of the intraweek seasonality. Moreover, a regression – SARIMA (hereafter REGSARIMA) model is established by incorporating a SARIMA model with a piecewise linear regression model to estimate impacts of air temperature, which is affected by UHI phenomena in Houston areas.

Since it is very difficult to calculate the UHI effects on daily peak load demand of eletricity directly, air temperature was used as a proxy variable. Compared with estimation results of three models, the REGSARIMA model revealed that air temperature in Houston areas has more influences on the electricity consumption for cooling than on that for heating. Additionally, the REGSARIMA model provided the more accurate forecasts for daily peak load demand for the short term.

This paper is organized as follows. Section 4.1 provided an introduction to this study and Section 4.2 presents background information on air temperature and UHI phenomena in Houston and previous studies on the weather effects on eletricity demand. Section 4.3 describes the econmetric methodology and data used in this study. A deatiled discussion of the estimation results is covered in Section 4.4. The summary and conclusion is presented in Section 4.5.

4.2 The UHI Phenomenon in Houston and Literature Review

4.2.1 The Outlines of UHI in Houston

The air or surface temperature at the Houston metropolitan area becomes higher compared to its surrounding rural areas with the physical growth of a city size (Shepherd et al., 2010). According to previous research on UHI in Houston, the air temperature over the Houston downtown areas is higher by by 1°- 3°C than that of rural boundaries (Orville, et al., 2001; Burian and Shephard, 2005; Shepherd, et al., 2010; Chen, et al., 2011).

Figure 4.1 presents the thermal image of central Houston in September 1999 by NASA's Marshall Space Flight Center. The colors indicate the surface temperatures detected by airborne sensor. The temperatures range from about 90º F at the dark blue areas to over 160º F at the red ones. The dark blue colors represent low temperature areas such as bayous, large parks and trees. Light blue colors show major roadways with cement concrete, which has moderate reflection levels. Yellow colors present the hotter surfaces, which are composed of parking lots and heat absorbing rooftops. Orange and red represent dark rooftops as the hottest areas. Geographic reference indicates that each CBD and U of H is the Central Business District and University of Houston, respectively.

From Figure 4.1, the CBD area is the hottest spot in Houston of which temperature is higher by 30º to 70º F than its boundaries. It appears that the surface temperature at the areas out of the center gradually decreases. The UHI phenomenon in

Houston, a typical characteristics studied by previous research, attributed to land covers and air pollution, which absorb solar energy as to increase air temperature (Oke, 1982).

4.2.2 Previous Studies about Impacts of Weather Factors on Energy Demand

Since people consume energy to obtain thermal comfort, climatic factors are highly correlated with energy demand for heating or cooling. As climate changes proceed worldwide, several studies have been performed to investigate the relationship among energy consumption and weather variables such as air temperature, humidity, precipitation, and wind. Linder et al., (1987) concluded that the long-run eletricity supply schedule should be established based on climate change with analysis for utility systems in the Southeastern US and New York State.

Additionally, Santamouris, et al. (2001) found out the UHI in urban areas of Athens, Greece, strongly affected the electricity consumptions in summer more than in winter by using a multiple regression model. The study of Hor et al., (2006) pointed out the UHI effect at a metropolitan city could produce a serious problem in the electricy market. Applying an ARIMA model into daily load demand of eletricity, they showed this abnormal temperature effect at urban areas would misestimate the daily peak load demand for electricity. Ismail et al., (2009) suggested that the accurate estimation for daily peak load demand should be very important because the establishment of a new electricity plant is very costly in the overestimation whereas a lack of electricity supply can cause huge amount of economic and social losses in underestimation.

On the other hand, there are a few studies about weather effects on energy demand. The research of Sailor and Muňoz in 1997 revealed the relationship between air temperature and energy demand is positive in summer but negative in winter at eights states in U.S. Akbari and Konopacki (2005) analyzed the features of UHI phenomena at five metropolitan cities in U.S. such as Baton Rouge in Louisiana, Chicago in Illinois, Houston in Texas, Sacramento in California, and Salt Lake City in Utah. They concluded electricity consumption for cooling would be much greater than that for heating and suggested eletricity consumption of residents could be saved by four strategies for UHI reduction such as replacedment of solar -reflective roofing material on building, plantation of shade trees near south and west walls of building, and urban reforestation.

The analysis of previous studies are mainly based on two models. One is a multiple regression, which is useful for calculating comparative statics, which just explains how much energy consumption is changed by a unit change of weather variables. The other is a ARIMA model, which is widely used to forecasting daily peak load demand of electricity for the short run. However, this paper developed a REGSARIMA approach by combining a pairwise linear regression with a SARIMA model. This REGSARIMA model was used to obatin more accurate forecasts for daily peak load demand of eletricity as well as to estimate the impact of air temperature.

4.3 Econometric Methodology and Data

4.3.1 Seasonal ARIMA model with a Regression Process

To begin with, an ARIMA model generally used to forecast a time series, which is decomposed into three terms cosisting of as an Autoregressive (hereafter AR), Integrated, and Moving Average (hereafter MA) process. The AR(p) process displays a memory of past events in the sense that the present daily peak load demand of electricity is related with those at the previous days. The Integrated(d) part makes the data stationary or ergodic for forecasting, and the MA(q) process indicates the forecast errors, which lead to more accurate forecasts over time. These three terms are represented as follows;

- AR(p) process: $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$ (1)
- Integrated(d) part: $I(d) = \nabla^d$ (2)
- MA(q) process: $\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_p B^p$ (3)

where B is the backward shift operator. ϕ_p and θ_q are polynomials of order p and q, respectively. The daily peak load electricity demand (y_t) is represented by ARIMA (p, d, q) model as follows;

$$\phi_p(B)\nabla^d y_t = c + \theta_q(B)\epsilon_t$$

$$\epsilon_t \sim N(0, \sigma^2) \quad (4)$$

where c is a constant. For backward shift operator B, $By_t = y_{t-1}$, and for backward difference ∇^d, $\nabla^d y_t = (1 - B)^d y_t$.

Since the daily peak load demand of electricity is affected by intraweek seasonality, the ARIMA model is reformulated as a seasonal ARIMA(SARIMA) model with the similar structure. Three terms of the seasonal part are defined as follows;

- AR(P) process: $\Phi_P(B_s) = 1 - \Phi_1 B_s - \Phi_2 B_s^2 - \cdots - \Phi_P B_s^P$ (5)
- Integrated(D) part: $I(D) = \nabla_s^D$ (6)
- MA(Q) process: $\Theta_Q(B_s) = 1 - \Theta_1 B_s - \Theta_2 B_s^2 - \cdots - \Theta_Q B_s^Q$ (7)

where s is the seasonal length B_s is the backward shift operator. Φ_P and Θ_Q are polynomials of order P and Q, respectively. The SARIMA $(p, d, q) \times (P, D, Q)$ model can be written as:

$$\phi_p(B)\Phi_P(B_s)\nabla^d \nabla_s^D y_t = c + \theta_q(B)\Theta_Q(B_s)\epsilon_t$$

$$\epsilon_t \sim N(0, \sigma^2) \tag{8}$$

The daily peak load demand is affected by weather variables such as UHI, climate change, and air temperature[4]. Therefore, the SARIMA model is incorporated with a regression procedure to estimate I on electricity load demand. A time series y_t can be represented as linear regression model as follows;

$$y_t = x_t'\beta + u_t \qquad for\ t = 1, 2, 3, \cdots, T \tag{9}$$

where x_t' is a $k \times 1$ vector of regressor variables, and β is a $k \times 1$ vector of regression coefficients. The error term u_t follows a SARIMA process given by;

$$\phi_p(B)\Phi_P(B_s)\nabla^d \nabla_s^D u_t = c + \theta_q(B)\Theta_Q(B_s)\epsilon_t$$

$$\epsilon_t \sim N(0, \sigma^2) \tag{10}$$

[4] To estimate the impact of UHI on the eletricity consumption for thermal conforts, air temperature is used as a proxy variable because UHI effects are mainly related with air temperature in summer and winter.

Equation (9) and (10) are combined to define the REGSARIMA model as a single equation as;

$$\phi_p(B)\Phi_P(B_s)\nabla^d\nabla_s^D(\, y_t - x_t'\beta) \; = c + \; \theta_q(B)\Theta_Q(B_s)\epsilon_t \tag{11}$$

From equation (9), a series u_t with a zero mean is obtained by first subtracting the regression effects ($x_t'\beta$) from y_t. Since u_t is differenced to get a stationary series, a stationary REGSARIMA model is represented as follows;

$$\phi_p(B)\Phi_P(B_s)\psi_t \; = c + \; \theta_q(B)\Theta_Q(B_s)\epsilon_t \tag{12}$$

where $\psi_t = \; \nabla^d\nabla_s^D y_t - \; \nabla^d\nabla_s^D x_t'\beta$. The stationary REGSARIMA model can also be written as;

$$\nabla^d\nabla_s^D y_t = \; \nabla^d\nabla_s^D x_t'\beta + \psi_t \tag{13}$$

Daily peak air temperature T_p on the Fahrenheit scale is used to define air temperature for cooling, and for heating. Suppose daily peak air temperature ranges from 80 to 60 degrees Fatheheit, it is defined as non-weather senstive daily temperature at which neither cooling nor heating system is necessary. Therefore, it is assumed that daily peak electricity demand is not affected by daily air temperature. Daily air temperature for cooling (T_C) and heating (T_H) is classified by the following way;

$$T_C = \begin{cases} T_p & if \;\; T_p > 80 \\ 0, & otherwise \end{cases} \tag{14}$$

$$T_H = \begin{cases} T_L & if \;\; T_p < 60 \\ 0, & otherwise \end{cases} \tag{15}$$

where T_L is daily lowest temperature. Two variables T_C and T_H are inserted in the regression term of equation (13). In this study, the estimation results from each equation (4), (8), and (13) were compared and evaluated by using Root Mean Square Error (hereafter RMSE) and Mean Absolute Percentage Error(hereafter MAPE), which present forecasting error.

4.3.2 Data Description

Time series data on daily peak load profile of electricity, and daily average air temperature observed at Hobby Airport in Houston are obtained from the Electric Reliability Council of Texas (ERCORT) and the National Oceanic and Atmospheric Administration *(*NOAA*)* website, respectively. These data consist of total 5,636 observations ranging from April 16, 2003 to December 31, 2011. Table 4.1 summarizes some statistical characteristics of the data. To test for the presence of a unit root in daily peak load electricity consumption, augmented Dickey-Fuller (ADF) test was performed. Table 4.2 shows results of ADF tests. This time series sample is non-stationary because the hypothesis for the presence of unit root is rejected at the 5% significance level.

Figure 4.2 (a) illustrates the movements of daily peak load consumption of electricity over sample periods. Every highest and lowest point of daily peak consumption appears at summer and spring, respectively. Although daily electricity consumptions fluctuate annually, electricity consumption dropped rapidly at the end of 2008 because of the global economic recession caused by the financial crisis in the U.S. With respect to seasonality, the annual electricity consumption is highest in summer but lowest in spring or autumn at which it is unnecessary for any cooling or heating system to remove thermal discomforts.

Figure 4.2 (b) depicts daily average temperature in Houston over sample periods. The typical seasonality appears in the movement of air temperature, which swings between the highest point in summer and the lowest in winter. Since the effect of UHI strongly appears in Houston, it seems that the air temperature at the central Houston areas is higher by 10º to 20º F than its corresponding rural areas and affects the use of cooling or heating systems. Therefore, air temperature is one of the most potential factors to make accurate forecast for daily peak load electricity consumption.

4.4 Estimation Results and Discussions

This section presents the estimation results of simple ARIMA, SARIMA, and REGSARIMA represented by equation (4), (8), and (13), respectively. Each optimal lag length of AR, Integration, and MA process is determined on the basis of Schwarz Bayesian Information Criterion. These models tranformed by log are estimated using the maximum likelihood method. Based on RMSE and MAPE, their prediction errors are compared and evaluated. To calculate the impact of air temperature on daily peak electrcity demand, REGSARIMA model is employed as the best model for forecasting.

4.4.1 Estimation Results of ARIMA Models

The ARIMA(1,1,1) model is selected to apply the most recent events since the long distant events from the present lead to be less confident (Hor, Watson, & Majithia, 2006). This model can be specified as follows;

$$(1-\phi_1 B)(1-B)\,ln\,y_t = (1-\theta_1 B)\epsilon_t \tag{16}$$

From column headed ‘ARIMA’ in Table 4.3, all coefficients of ARIMA(1,1,1) are significant at 5% significance level. For this model, both the autocorrelation and partial autocorrelation of prediction errors indicate that there exists intraweek seasonality. As shown by ‘Prediction Error Autocorrelation Plots of ARIMA (1, 1, 1)’ headed on Figure 4.3, every seven lag is highly correlated with. Therefore, a SARIMA model is needed to attain more accurate forecasting for daily peak load electricity demand.

To apply intraweek seasonality, a SARIMA is established. With Schwarz Bayesian Information Criterion, the best model is chosen as SARIMA (1,0,1)(1,0,1) which is specified by the following form;

$$(1-\phi_1 B)(1-\Phi_1 B^7)\omega_t = (1-\theta_1 B)(1-\Theta_1 B^7)\epsilon_t + c \tag{17}$$

where $\omega_t = (1-\phi_1 B)^d (1-\Phi_1 B^7)^D \ln y_t$ for $d = 0, D = 0$. From column headed ‘SARIMA’ at Table 4.3, all coefficients of this model are positive and significant at 1% significance level. $\Phi_1$and Θ_1 are seasonal parameters at lag 7, indicating strong intraweek seasonality. Figure 4.4 illustrates autocorrelation and partial autocorrelation of prediction error for SARIMA(1,0,1)(1,0,1). It shows there is no significant autocorrelation among each lag.

A REGSARIMA model is utilized for analyzing the effects ofair temperature on daily peak demand. Several models are considered and REGSARIMA(1,0,1)(0,0,2) is selected. The model can be specified as follows;

$$(1-\phi_1 B)\psi_t = (1-\theta_1 B)(1-\Theta_1 B^7 - \Theta_2 B^{14})\epsilon_t \tag{18}$$

where $\psi_t = (1-\phi_1 B)^d (1-\Phi_1 B^7)^D (ln\, y_t - \beta_1 T_H - \beta_2 T_C)$ for $d = 0, D = 0$. The column headed ‘REGSARIMA’ at Table 4.3 presents the estimated coefficients for this model with p-value. All parameters are significant at 1% level and two lags of MA term show the presence of intraweek seasonality. From Figure 4.5, both of autocorrelation and partial autocorrelation shows each lag of prediction errors is not correlated over time.

Table 4.4 presents goodness-of-fit statistics for three types of ARIMA model used to forecast daily peak load electricity demand. Applying four accuracy measurements to the period from 1 to 12 January, 2011, REGSARIMA is selected as the best fitting model. This is because REGSARIMA model has the least RMSE and MAPE, which are generally used to evaluate these models because two accuracy measurements are appropriate for short term forecasting (Munoz et al., 2010).

Figure 4.6 shows prediction errors for SARIMA and REGARIMA model. Prediction errors of REGSARIMA model are much smaller than those of SARIMA model. Therefore, REGSARIMA model provides more reliable short-run prediction for daily peak load electricity demand.

4.4.2 Air Temperature Impact on Daily Load Peak Electricity Demand

Air temperature tends to increase in the core of metropolitan city because green areas have been reduced by the intensive land use for building and pavement. In Houston, it is known that UHI increases air temperature by 1^{o}- 3^{o}C because of obstructing solar heat radiation into the atmosphere boundaries (Shepherd, et al., 2010; Chen, et al., 2011). Since air temperature has an influence on electricity consumption for cooling or heating, it is employed for REGARIMA model to make more accurate predictions for daily peak load electricity demand.

Applying air temperature for heating or cooling into REGARIMA model, air temperature increases the daily peak load electricity demand for cooling but decrease that for heating. From column headed ‘REGSARIMA’ at Table 4.3, coefficients of air temperature for cooling (T_C) and for heating (T_H) are significant at 1% significance level. The coefficient of T_C is positive whereas that of T_H is negative. It implies the rise of air temperature caused by UHI can consume more electricity in summer but less electricity in winter. Compared with the absolute values for two coefficients of T_C and T_H, they are statistically same at 1% significant level. It infers the impact of UHI is symmetry for daily peak load electricity demand.

As UHI phenomena increase air temperature, impacts of air temperature on electricity consumption are neutralized by increasing the electricity consumption for cooling in summer and decreasing that for heating in winter. However, air temperature resulting from UHI eventually cause to increase total electricity consumption because the number of cooling days is almost three times more than that of heating days in Houston. Therefore, reduction of UHI phenomenon can be helpful for saving electricity generation and consumption for cooling days.

4.4.3 Discussion

In the recent years more and more people have migrated from rural to urban areas for obtaining more job opportunities and social services. A lot of cities continue to expand so largely as to be metropolitian or megalopolitian cities and to utilize lands for building and pavement intensively. UHI phenomena occur more frequently and affect air temperature and total energy consumption. Especially, these phenomena in Houston incur additional costs for both supply and demand of electricity owing to the long periods necessary for the use of cooling electric appliances.

For electricity supply, air temperature, which is increased by UHI, causes power plants to generate and reserve more electricity for providing the peak consumption because insufficient supply of electricity almost shuts down economic and social activities of residents and restoration expenditure is very massive. Therefore, electricity firms are required to establish a long term plan and to construct a plant for preparing additional electricity consumption for population growth and weather. In the central Houston area, it seems that high air temperature is likely to make additional production costs of electricity to catch up with increased daily peak load electricity profile.

Electricity demand for thermal comforts depends on changes of air temperature in the sense that electrcity consumption increases for cooling in the summer but decreases for heating in the winter due to UHI phenomena. In the core of Houston, residents have to pay more costs for the long cooling periods accompanied with high air temperature.

To reduce the UHI effects on air temperature in a metropolitan city, scientists and engineers have focused on a method to prevent absorption of solar radiation, the main cause of UHI. They suggest the technical strategies composed of material replacedment of solar -reflective roofing, plantation of shade trees, and urban reforestation. Since these solutions are very helpful for curtailing extra costs resulting from UHI with respect to demand and supply of electricity.

4.5 Conclusions and Further Studies

This study was conducted to investigate the air temperature impacts on daily peak load electricity demand in Houston by applying REGSARIMA model into daily weather and electricity data. The estimation results revealed that REGSARIMA model improved forecasting for short-run daily peak electricity demand. Compared with prediction errors resulting from ARIMA and SARIMA, this model generated relatively robust based two kinds of goodness-of- fit statistics such as RMSE and MAPE. Additionally, REGSARIMA model provided information about effects of air temperature, which is used as an explanatory variable. Since air temperature affects electricity consumption to remove thermal comforts, high air temperature from UHI causes the electricity to be consumed for cooling but to be saved for heating. In Houston, air temperature increases the daily peak load electricity demand in summer but decrease that for winter with respect to the use of electric appliance for thermal comforts.

Scientists and engineers introduced three UHI reduction strategies consisting of replacedment of solar -reflective roofing material on building, plantation of shade trees near south and west walls of building, and urban reforestation. However, the cost benefit analysis for each strategy is seldom performed because of lack of geographic information system (GIS) data. Economic approach to UHI reduction strategies is strongly required to select the best way for UHI reduction based on more specific data.

Another interest in further study is to develop more accurate models for forecasting weather effects on daily peak load demand of electricity. For research on UHI effects, multiple regression models were mainly used in natural scientific areas whereas previous economic studies focused on implementation of ARIMA type model to minimize prediction errors. This study incorporated two models into REGSARIMA model to estimate the impact of air temperature on daily peak load electricity demand. This model led to improve forecasting for daily peak load electricity demand. If data on air temperature can be observed at the central business district of Houston, at which UHI phenomena occur more frequently and seriously, it is possible to attain more accuracy of forecasts for daily peak load electricity demand and compare the core of Houston with its surrounding rural areas with respect to UHI effects on energy consumption.

5. OVERALL CONCLUSION

This dissertation develops three kinds of econometric models to analyze and forecast energy markets. The first essay implements a traditional ECM model to test for the presence of price asymmetry at the diesel market in Korea. By conducting ARCH test, residuals of the ECM model have time-variant variances, which can generate misinterpretation of estimation. Therefore, three kinds of asymmetric GARCH process are utilized to fix conditional variances. The ECM model with a GARCH process reveals that asymmetric price response exists at the downstream market. Both weekly and daily retail prices at the downstream level increase fast in the rise of crude oil prices but decrease slowly in the fall. The price asymmetric adjustment is caused by collusive behaviors of retailers in Korea diesel market.

The second essay deals with the new incentive system for biodiesel, which will hold the blend mandate without any tax credit from 2012. A multivariate stochastic simulation model is established and applied to evaluate this new biodiesel policy. Simulation results show the policy will increase government revenues but decrease social welfare. Since high biodiesel prices increase prices of blended diesel, demands of both biodiesel and blended diesel decline and consumer and producer surplus in the transport fuel market will shrink. Therefore, tax credits under the blend mandate play an important role in subsidizing biodiesel industry in youth as well as consumers in the blended diesel market.

The third essay analyzes the impact of air temperature on daily peak load demand in Houston by incoporating a SARIMA model with a pairwise multiple regression model. Compared with ARIMA and SARIMA model, REGSARIMA leads more accurate prediction for daily peak load demand for the short term. Further, estimation results of REGARIMA model provide more information on air temperature effects on energy consumption in Houston areas. It infers high air temperature, attributted to UHI phenomena, causes to increase electricity consumption for cooling but to save that for heating. Therefore, it is very useful to perform further studies on three UHI reduction strategies such as replacedment of solar -reflective roofing material on building, plantation of shade trees near south and west walls of building, and urban reforestation.

REFERENCES

Akbari, H., Konopacki, S., 2005. Calculating energy-saving potentials of heat-island reduction strategies. Energy Policy 33, 721–756.

Ando, A.W., Khanna, M., Taheripour, F., 2010. Market and Social Welfare Effects of the Renewable Fuels Standard. Natural Resource Management and Policy 33(4), 233-250.

Bachmeier, L.J., Griffin, J.M., 2003. New Evidence on Asymmetric Gasoline Responses. The Review of Economics and Statistics 85(3), 772-776.

Bacon, R.W., 1991. Rockets and Feathers: the Asymmetric speed of adjuxtment of UK retail gasoline prices to cost changes. Energy Economics 13(3), 211-218.

Bae, J.H., 2008. Forecasting the Competitiveness of Biodiesel in Korea. Korean Energy Economic Review 7(1), 1-207.

Borenstein, S., Cameron, A., Gilbert, R., 1997. Do Gasoline Prices Respond Asymmetrically to Crude Oil Price Changes?. Quarterly Journal of Economics 112(1), 305-339.

Burian, S., Shephard, J., 2005. Effect of urbanization on the diurnal rainfall pattern in Houston. Hydrological Processes 19(5), 1089-1103.

Chen, F., Miao, S., Tewari, M., Bao, J.W., Kusaka, H., 2011. A numerical study of interactions between surface forcing and sea breeze circulations and their effects on stagnation in the greater Houston area. Journal of Geophysical Research 116 (D12105), doi:10.1029/2010JD015533.

de Gorter, H., Just, D., 2008. The Economics of the U.S. Ethanol Import Tariff with a Blend Mandate and Tax Credit, Journal of Agricultural & Food Industrial Organization 6 (2), doi:10.2202/1542-0485.1239.

Dickey, D.A., Fuller, W. A., 1979. Distrubution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Society 74(366), 427-431.

Ding, Z., Granger, C.W.J., Engle, R., 1993. A Long Memory Property of Stock Market Returns and a New Model. Journal of Empirical Finance 1, 83–106.

EBB (European Biodiesel Board), 2011. The EU biodiesel industry. Retrieved November

7, 2011, from http://www.ebb-eu.org/stats.php.

Engle, R.F., Ng, V.K., 1993. Measuring and testing the impact of news on volatility. Journal of Finance 48(5), 1749-78.

Farinelli, B., Carter, C.A., Lin, C.Y., Sumner, D.A., 2009. Import Demand for Brazilian Ethanol: A Cross-Country Analysis. Journal of Cleaner Production 17(1), S9-S17.

Galeotti, M., Lansa, A., Manera, M., 2003. Rockets and featers revisited: An international comparison on European gasoline markets. Energy Economics 25(2), 175-190.

Geweke, J., 2005. Issue in the "Rockets and Feathers" Gasoline Price Literature. Report to the Federal Trade Commission.

Glosten, L., Jaganathan, R., Runkle, D., 1993. Relationship between the Expected Value and Volatility of the Nominal Excess Returns on Stocks. Journal of Finance 48, 1779–1802.

Godby, R., Lintner, A.M., Stengos, T., Wandschneider, B., 2000. Testing for asymmetric pricing in the Canadian retail gasoline market. Energy Economics 22(3), 251-276.

Gu, J., Jansen, D.W., 2006. Evidence on Asymmetric Gasoline Price Responses from Error Correction Models with GARCH Errors. Texas A&M University.

Honarvar A., 2009. Asymmetry in retail gasoline and crude oil price movements in the United States: An application of hidden cointegration technique. Energy Economics 31(3), 395-402.

Hor, C.L., Watson, S.J., Majithia, S., 2006. Daily Load forecasting and Maximum Damand Estimation Using ARIMA and GARCH. 9th International Conference on Probabilistic Methods Applied to Power System. Stockholm, KTH.

IEA, 2007. Renewables in Global Energy Supply. Retrieved March 29, 2010, from http://www.iea.org: http://www.iea.org/papers/2006/renewable_factsheet.pdf

Ismail, Z., Yahya, A., Mahpol, K., 2009. Forecasting peak load electricity demand using statistics and rule based approach. American Journal of Applied Sciences 6 (8), 1618-1625.

Johansen, S., 1991. Cointegration and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. Econometrica 59 (6), 1551-1580.

KIET, 2005. The technical and economic analysis of import of bioethanol. Seoul: Korea Institute for Industrial Economics & Trade.

Kojima, M, Mitchell D., Ward W., 2007. Considering Trade Policies for Liquid Biofuels. Washington DC:ESMAP World Bank.

Kolokotroni, M., Davies, M., Croxford, B., Bhuiyan, S., 2010. A validated methodology for the prediction of heating and cooling energy demand for buildings within the Urban Heat Island: Case-study of London. Solar Energy 84(12), 2246–2255.

Lee, S., Han, H., 2008, Benefit-Cost Analysis of Biodiesel Production in Korea. Journal of Rural Development/Nongchon-Gyeongje 31(5), 49-65.

Linder, K., Gibbs, M., Inglis, M., 1987. Potential impacts of climate change on electric utilities: Final report. Washington, DC: ICF Incorporated.

Mardia, K.V., 1970. Measures of multivariate skewness and kurtosis with applications. Biometrika 57(3), 519-530.

Munoz, A., Sanches-Ubeda, E., Cruz, A., Marin, J., 2010. Short-term forecasting in power systems: a guided tour. Energy systems 2, 129-160, DOI: 10.1007/978-3-642-12686-4_5.

Oke, T. R., 1995. The heat island of the urban boundary layer: characteristics, causes and effects. In T. Oke, J. Cermak, A. Davenport, E. Plate, & D. Viegas (Eds.), Wind Climate in Cities, NAASI Series, 81–107. Dordrecht: Kluwer Academic Publishers.

Oke, T.R., 1982. The energetic basis of the urban heat island. Quarterly Journal of the Royal Meteorological Society 108 (455), 1-24.

Orville, R., Huffines, G., Gammon, J., Zhang, R., Ely, B., Steiger, S., et al., 2001. Enhancement of cloud-to ground lightning over Houston Texas. Geophysical Research Letters 28(13), 2597-2600.

Park, H.I., 2006. The cost-benefit analysis of bio-energy. Seoul: Korea Rural Economy Institute.

Peltzman, S., 2000. Prices rise faster than they fall. . The Journal of Political Economy 108(3), 466-502.

Phillips, P., Perron, P., 1988. Testing for a unit root in time series regression. Biometrica 75(2), 335-346.

Radchenko, S., 2005. Oil price volatility and the asymmetric response of gasoline prices to oil price increases and decreases. Energy Economics 27(5), 708-730.

Sailor, D.J., Munoz, R.J., 1997. Sensitivity Of Electricity And Natural Gas Consumption To Climate In The U.S.A.--Methodology And Results For Eight States. Energy 22 (10), 987-998.

Santamouris, M., Papanikolaou, N., Livada, I., Koronakis, I., Georgakis, C., Argiriou, A., et al., 2001. On the impact of urban climate on the energy consumption of buildings. Solar Energy 70(3), 201-216.

Shapouri, H., Salassi, M., 2006. The Economic Feasibility of Ethanol Production from Sugar in the United States. Washington DC, U.S. Department of Agriculture.

Shepherd, J.M., Manyin, M., Messen, D., Burian, S., 2010. The impact of urbanization on current and future coastal precipitation: a case study for Houston. Planning and Design 37, 284-304.

Sigauke, C., Chikobvu, D., 2011. Prediction of daily peak electricity demand in South Africa using volatility forecasting models. Energy Economics 33(5), 882-888.

Steenblik, R., 2007. Biofuels-at what cost? Government support for ethanol and biodiesel in selected OECD countries. Geneva, Switzerland: The Global Subsidies Initiative of the International Institute for Sustainable Development.

United Nations Department of Economic and Social Affairs, 2011. The 2010 Revision of the World Population Prospects, New York: United Nations publication.

Zakoian, J.M., 1994. Threshold Heteroscedastic Models. Journal of Economic Dynamics and Control 18, 931–955.

APPENDIX A

NOMENCLATURE

CP	Crude oil Price
DP	Retail Price of Diesel
LCP	Log Price of Crude Oil
LDP	Log Retail Price of Diesel
LRP	Log Rack Price of Diesel
RP	Rack Price of Diesel
PLCP	Positive Change of Log Price of Crude Oil
PLRP	Positive Change of Log Rack Price of Diesel
PLDP	Positive Change of Log Retail Price of Diesel
NLCP	Negative Change of Log Price of Crude Oil
NLRP	Negative Change of Log Rack Price of Diesel
NLDP	Negative Change of Log Retail Price of Diesel
PECT	Positive Change of Cointegrating Term
NECT	Negative Change of Cointegrating Term

APPENDIX B

FIGURES

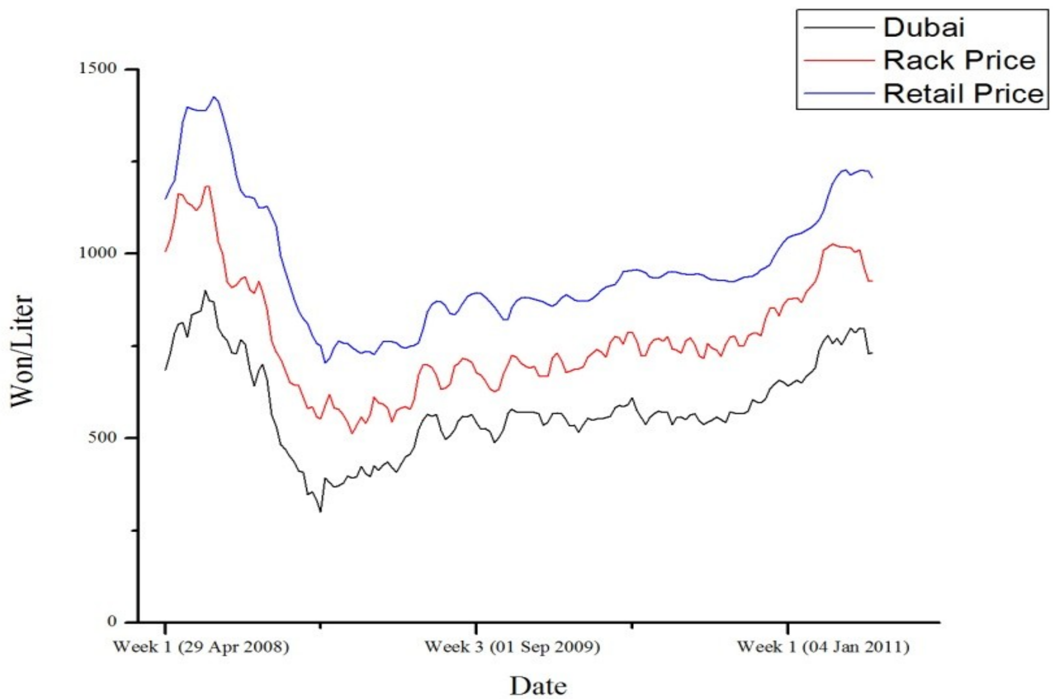


Figure 2.1 Trends of Dubai Price of Crude Oil, Rack Price of Diesel, and Retail Price of Diesel (4/15/2008 – 2/28/2011)

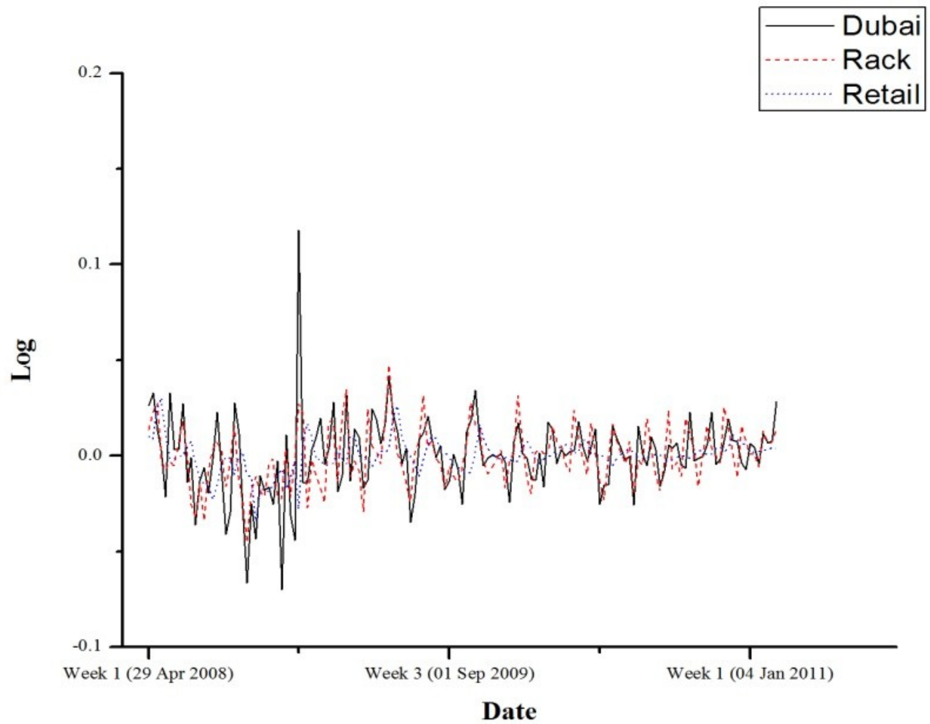


Figure 2.2 Log Difference of Dubai Price of Crude Oil, Rack Price of Diesel, and Retail Price of Diesel (4/15/2008 – 2/28/2011)

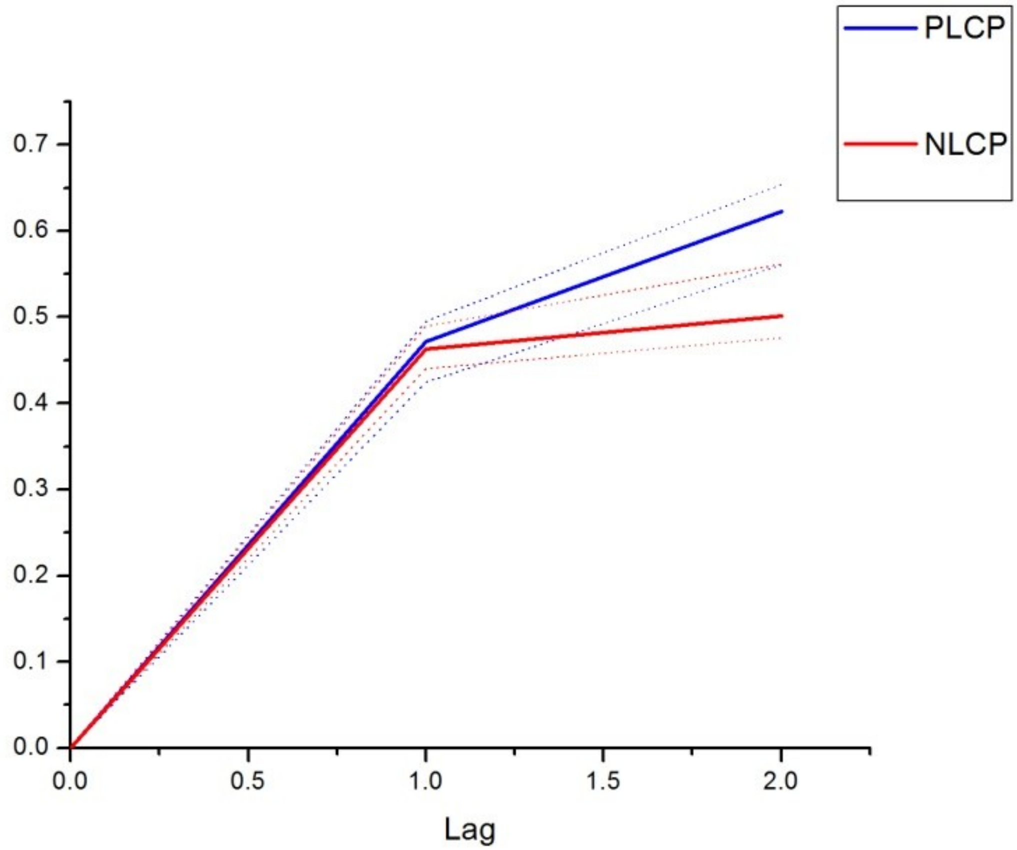


Figure 2.3 Cumulative IRF of Weekly Rack Prices to Weekly Crude Oil Prices (The y-axis is the response speed)

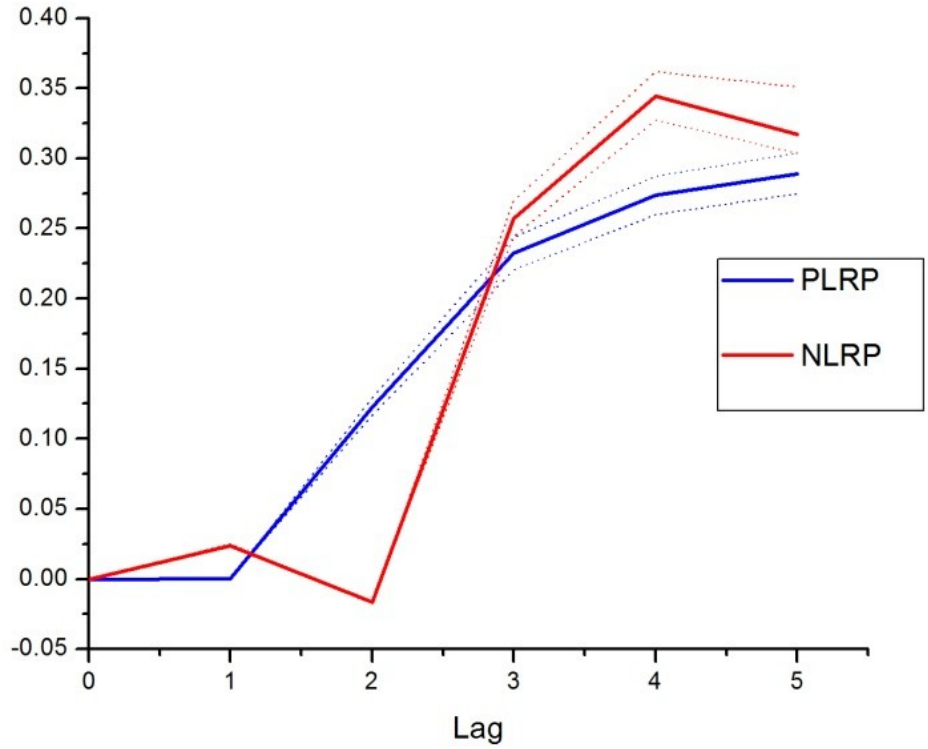


Figure 2.4 Cumulative IRF of Weekly Retail Prices to Weekly Rack Prices (The y-axis is the response speed)

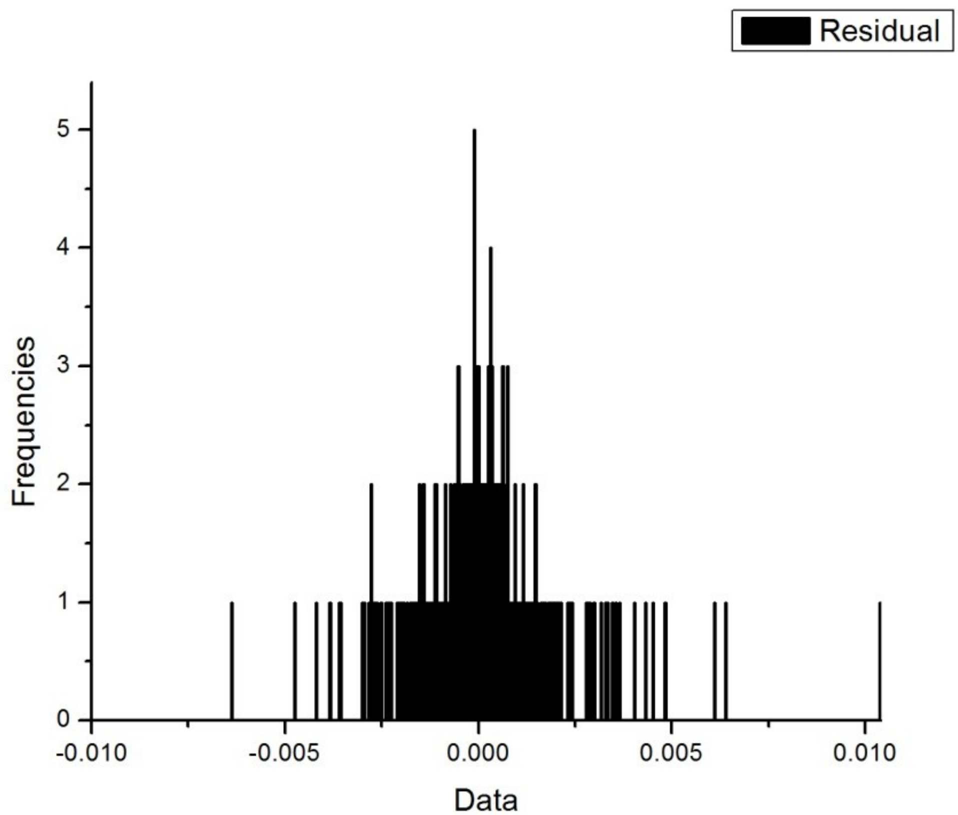


Figure 2.5 Residuals from the Traditional ECM under Homoskedasticity

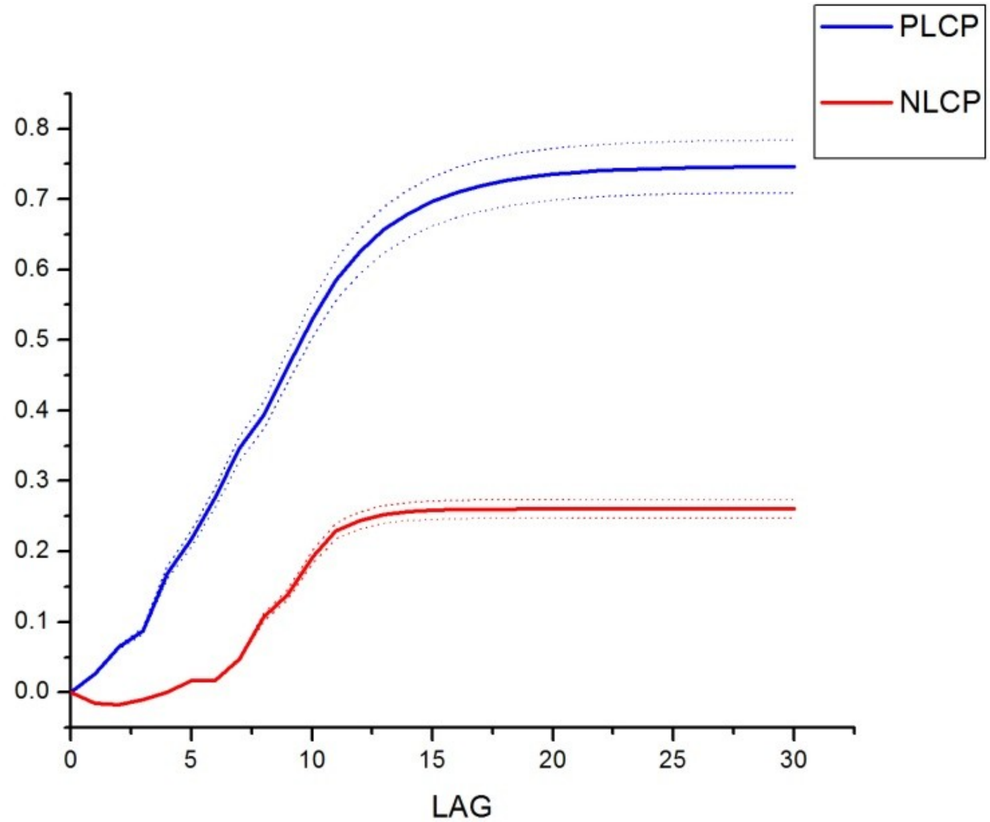


Figure 2.6 Cumulative IRF of ECM Model on Daily Data (The y-axis is the response speed of retail diesel price)

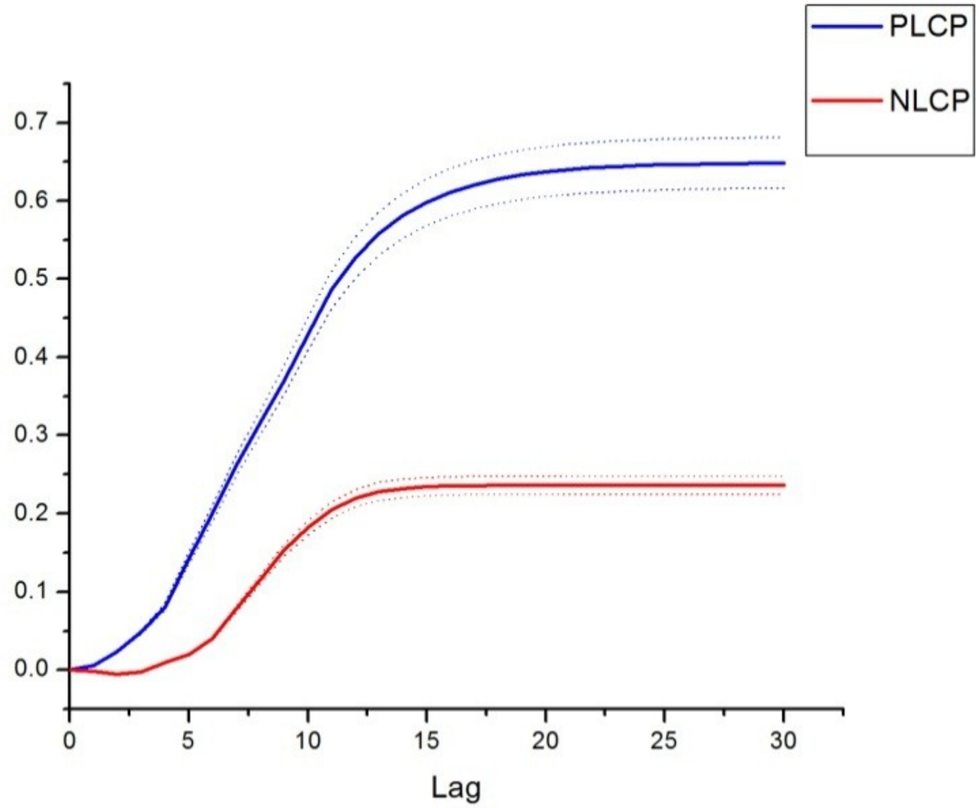


Figure 2.7 Cumulative IRF of ECM Model with QGARCH on Daily Data (The y-axis is the response speed of retail diesel price)

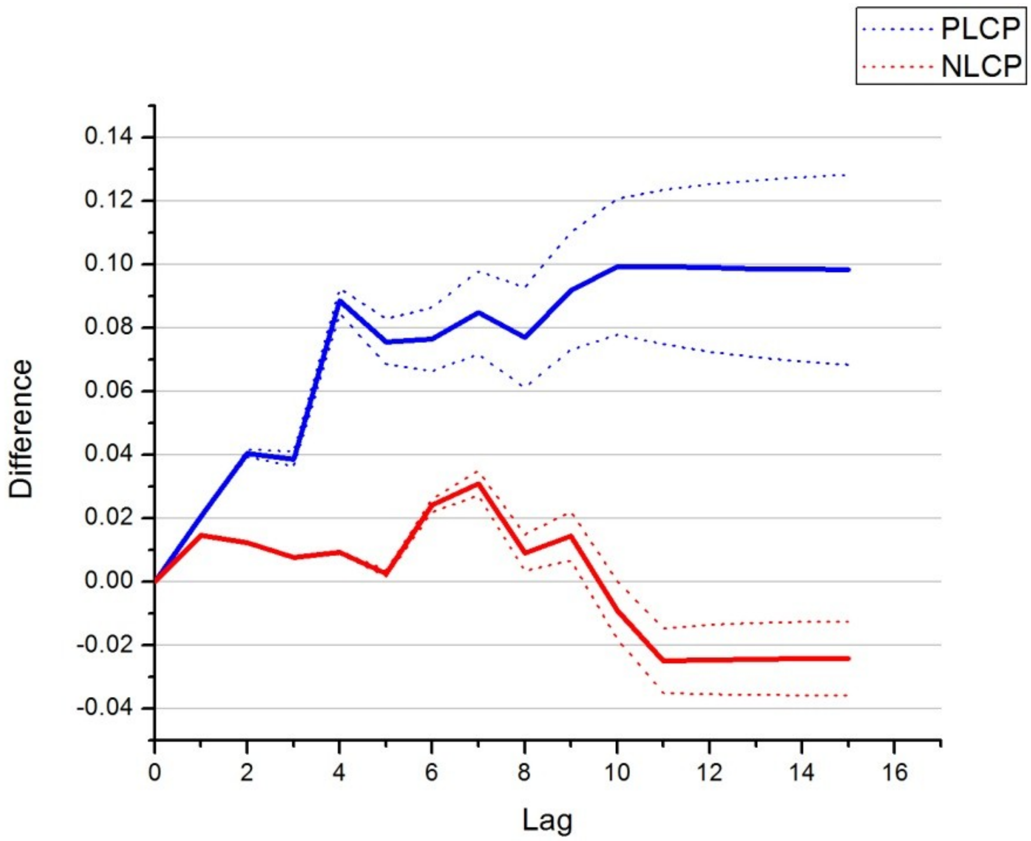


Figure 2.8 Differences of Cumulative IRFs on Daily Price Data

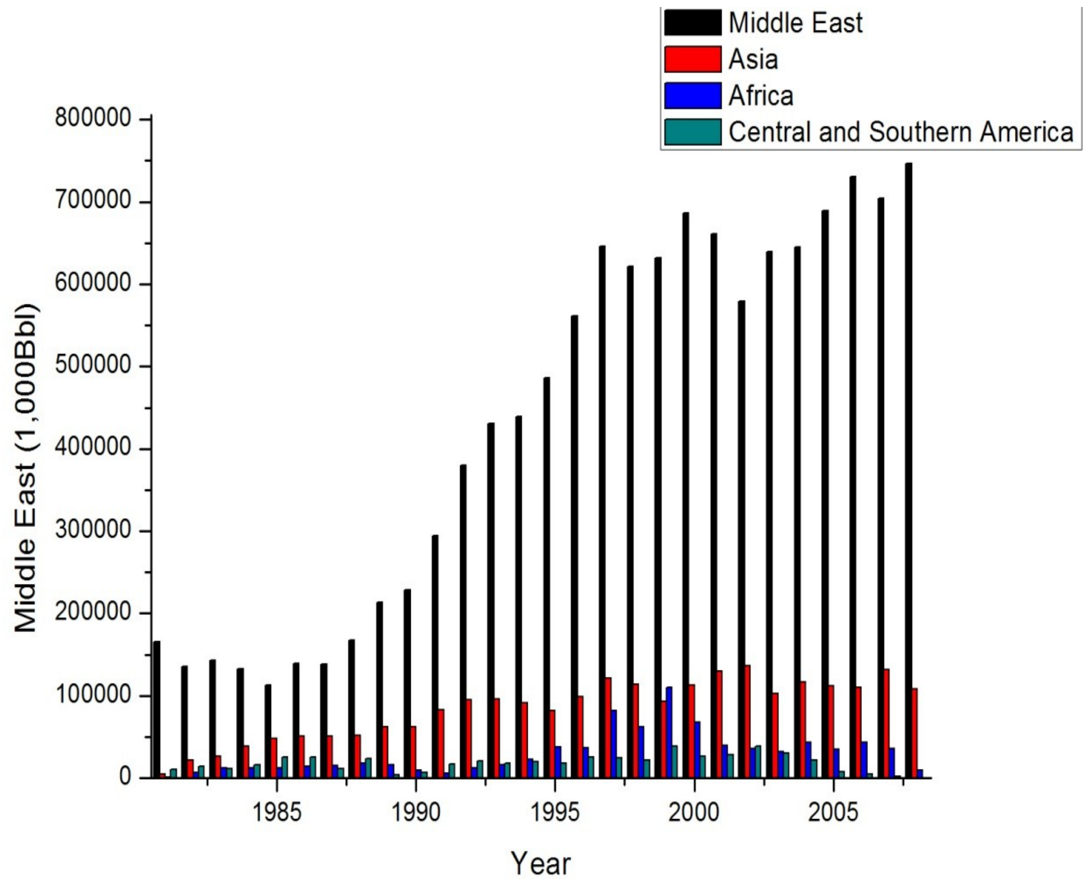


Figure 3.1 Annual Petroleum Imports and Imported Areas

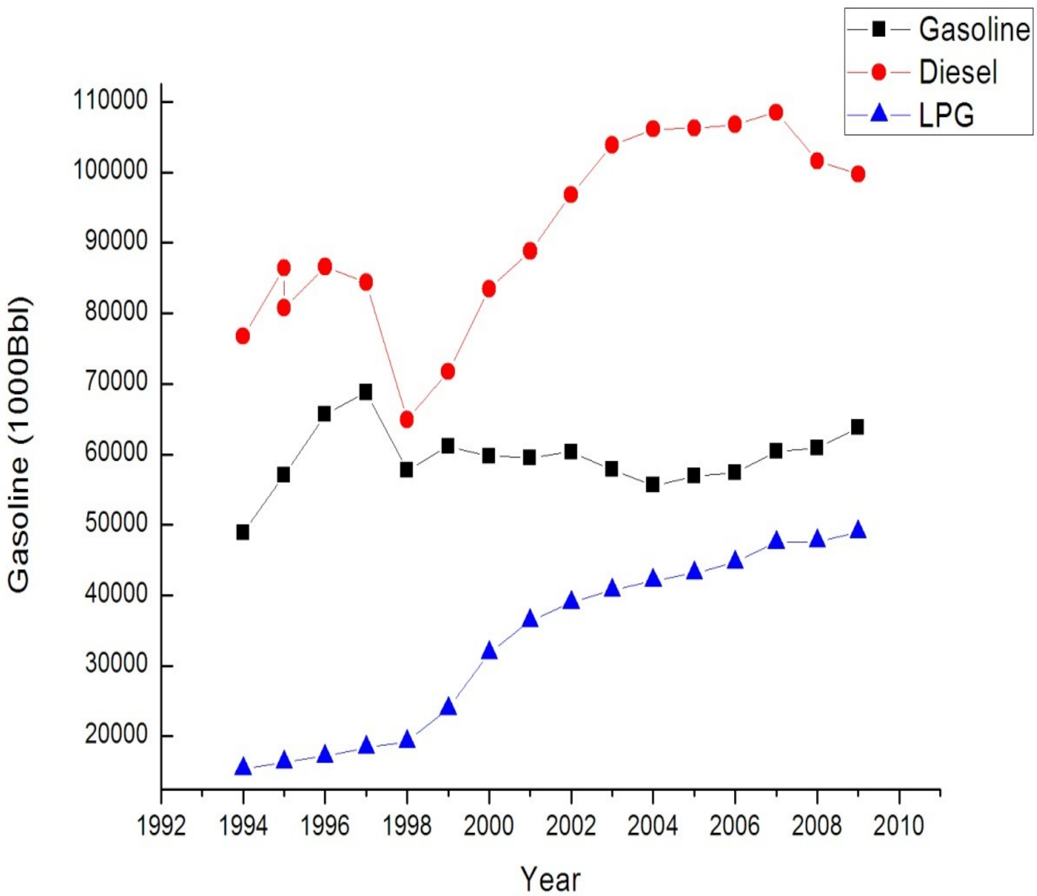


Figure 3.2 Demands for Transport Fuels

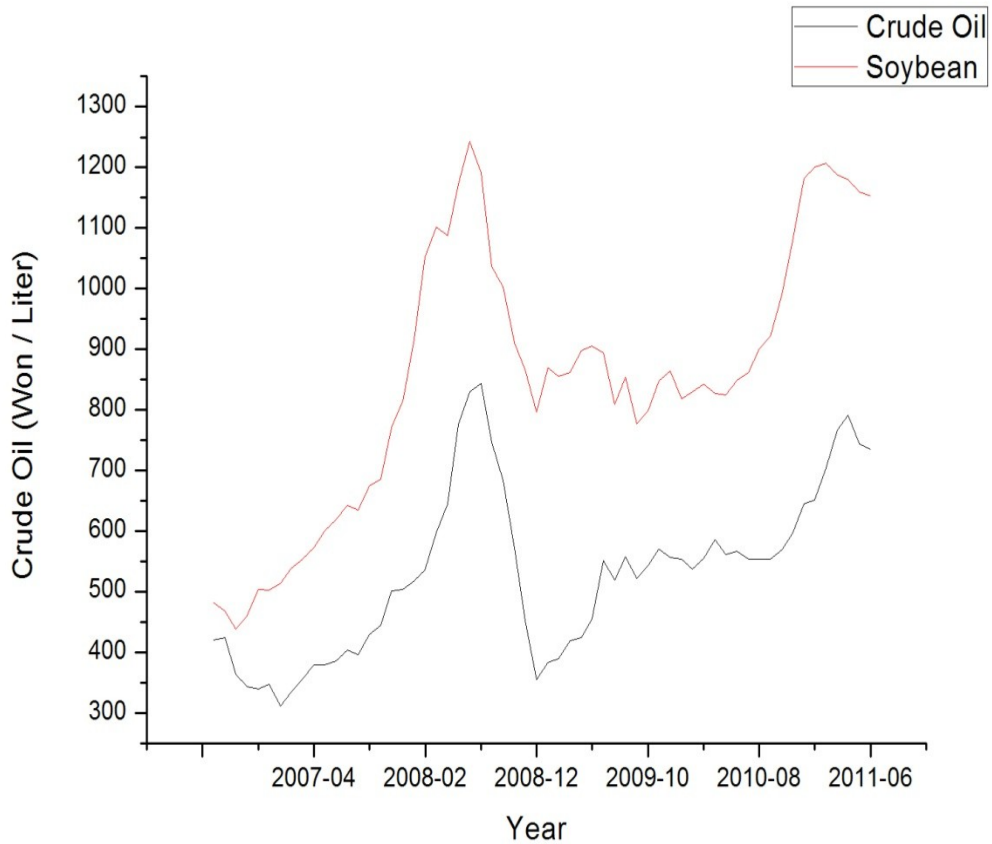


Figure 3.3 Monthly Prices of Crude Oil and Soybean Oil

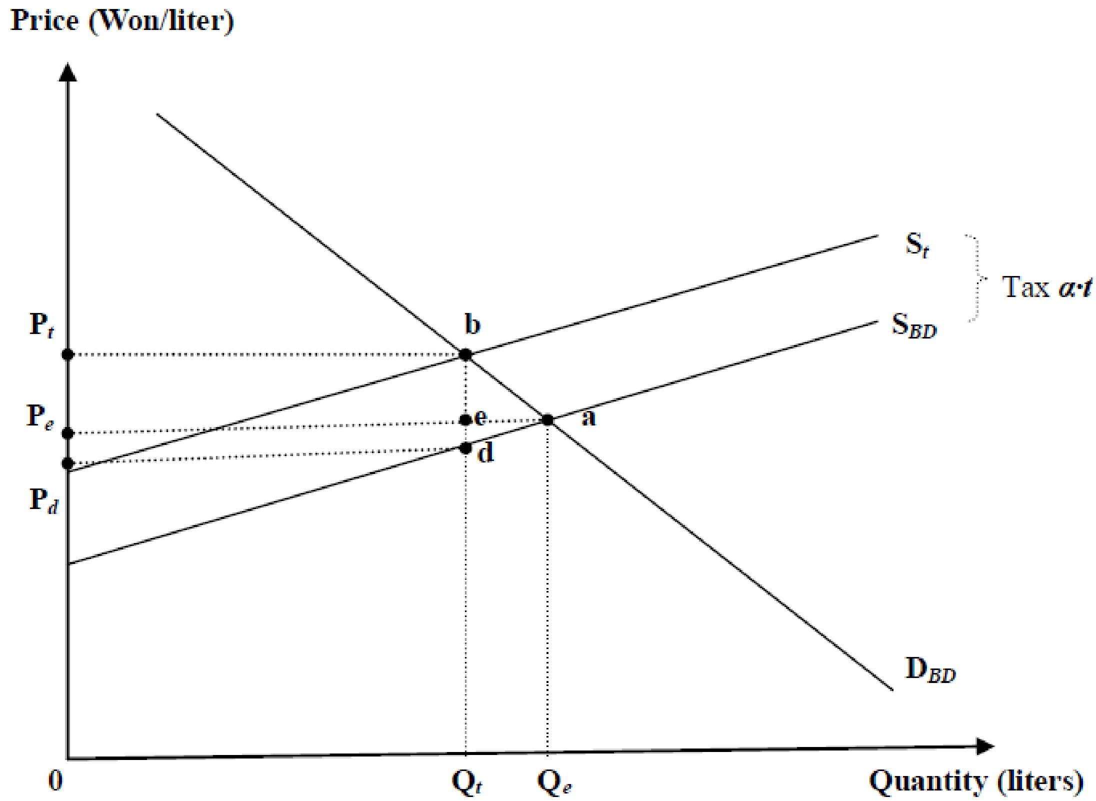


Figure 3.4 The Effects of Blend Mandate and Tax Credit on Blended Diesel Market (S_t is the supply curve of blended diesel without tax credit, S_{BD} is the supply curve of blended diesel with tax credit, D_{BD} is the demand curve of blended diesel, t is tax rates, and α is the required content ratio of biodiesel)

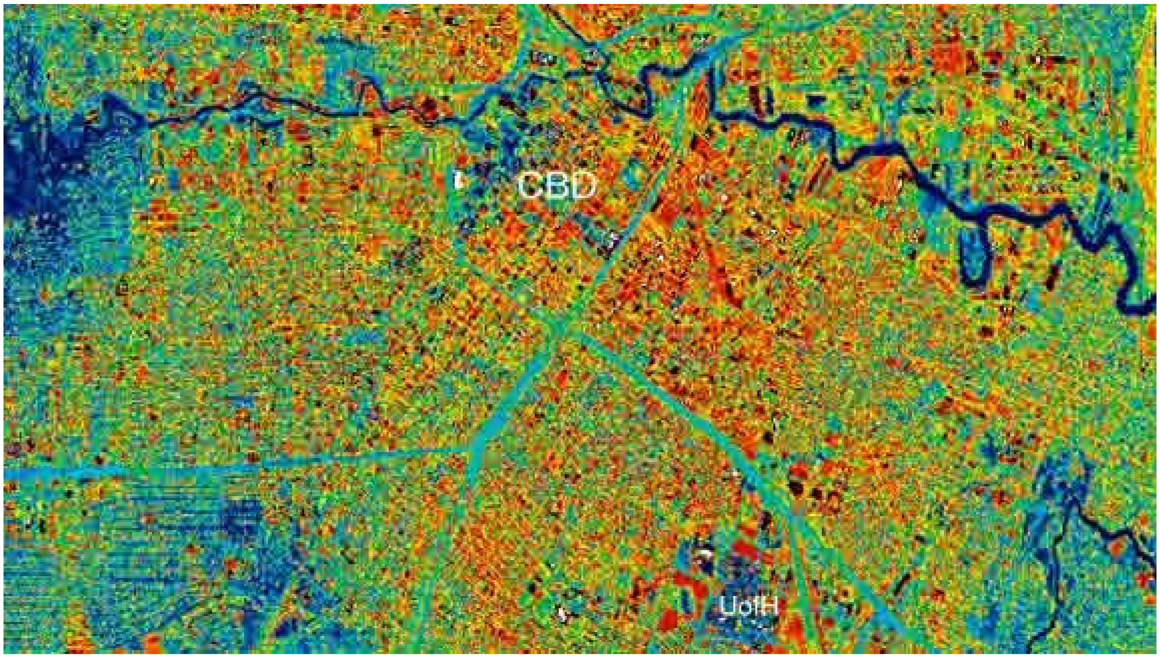
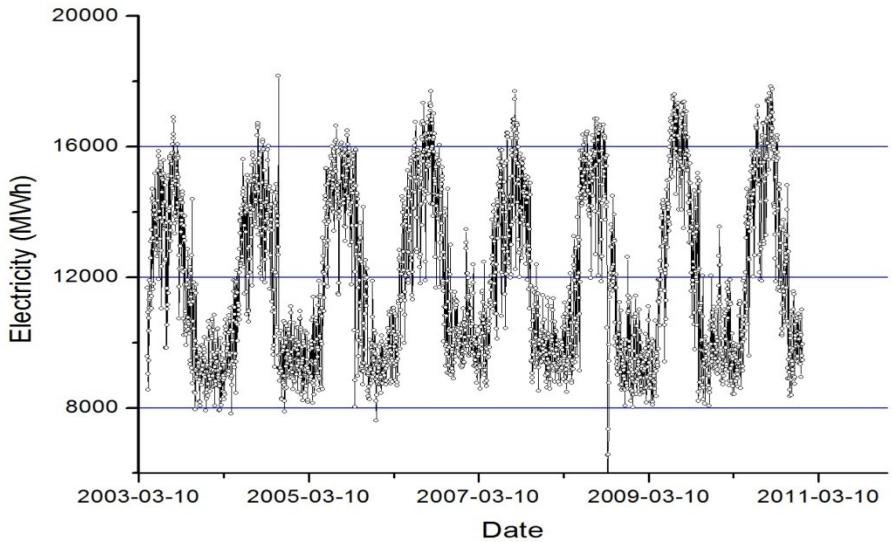


Figure 4.1 Thermal Image of Central Houston in September 2010
Source: NASA's Marshall Space Flight Center

(a) Daily Peak Load Electricity Demand



(b) Daily Average Temperature

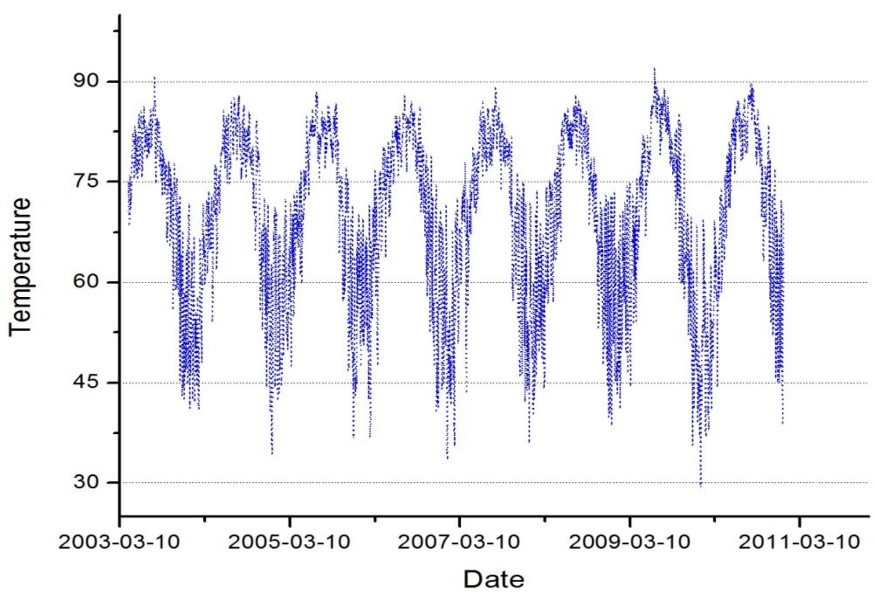
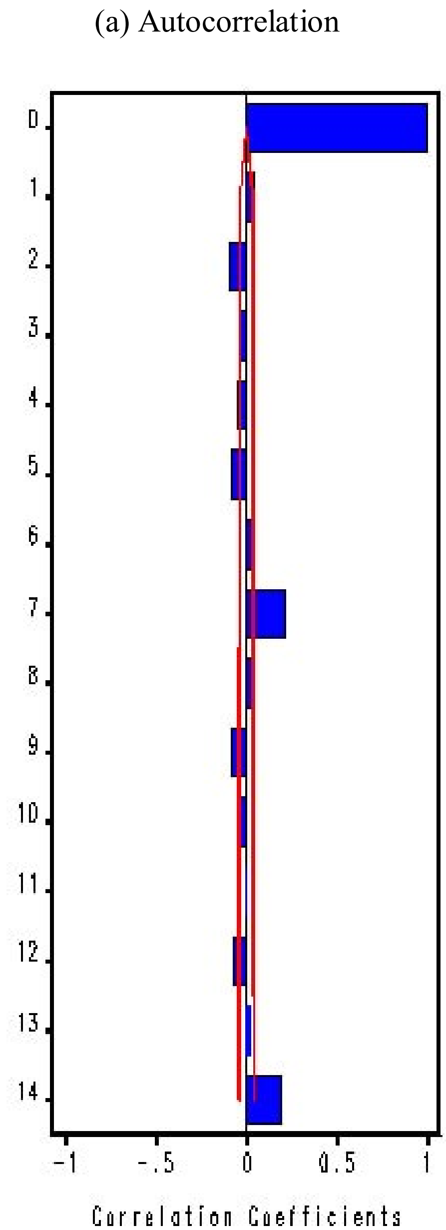


Figure 4.2 Daily Peak Load Electricity Demand and Daily Average Temperature



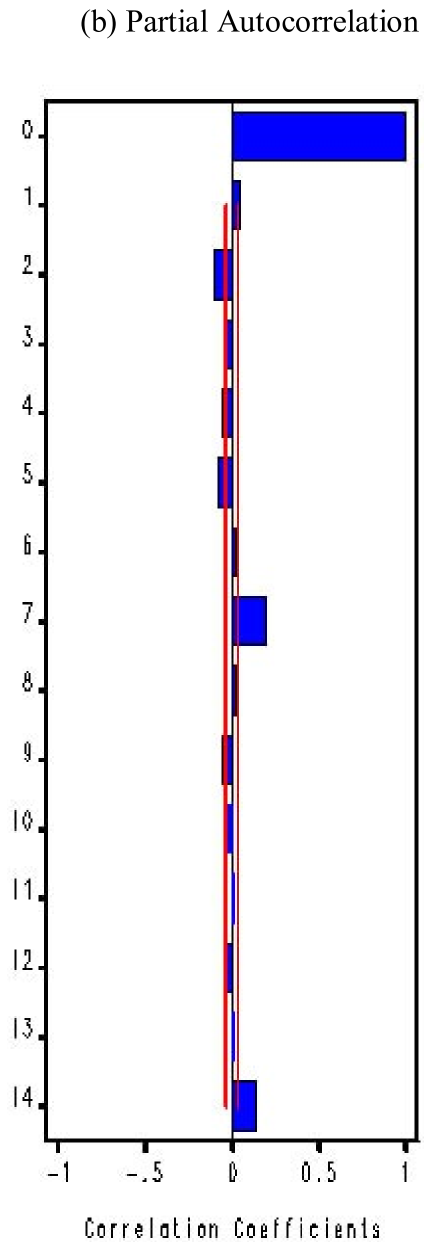


Figure 4.3 Prediction Error Autocorrelation Plots of ARIMA Model

(a) Autocorrelation (b) Partial Autocorrelation

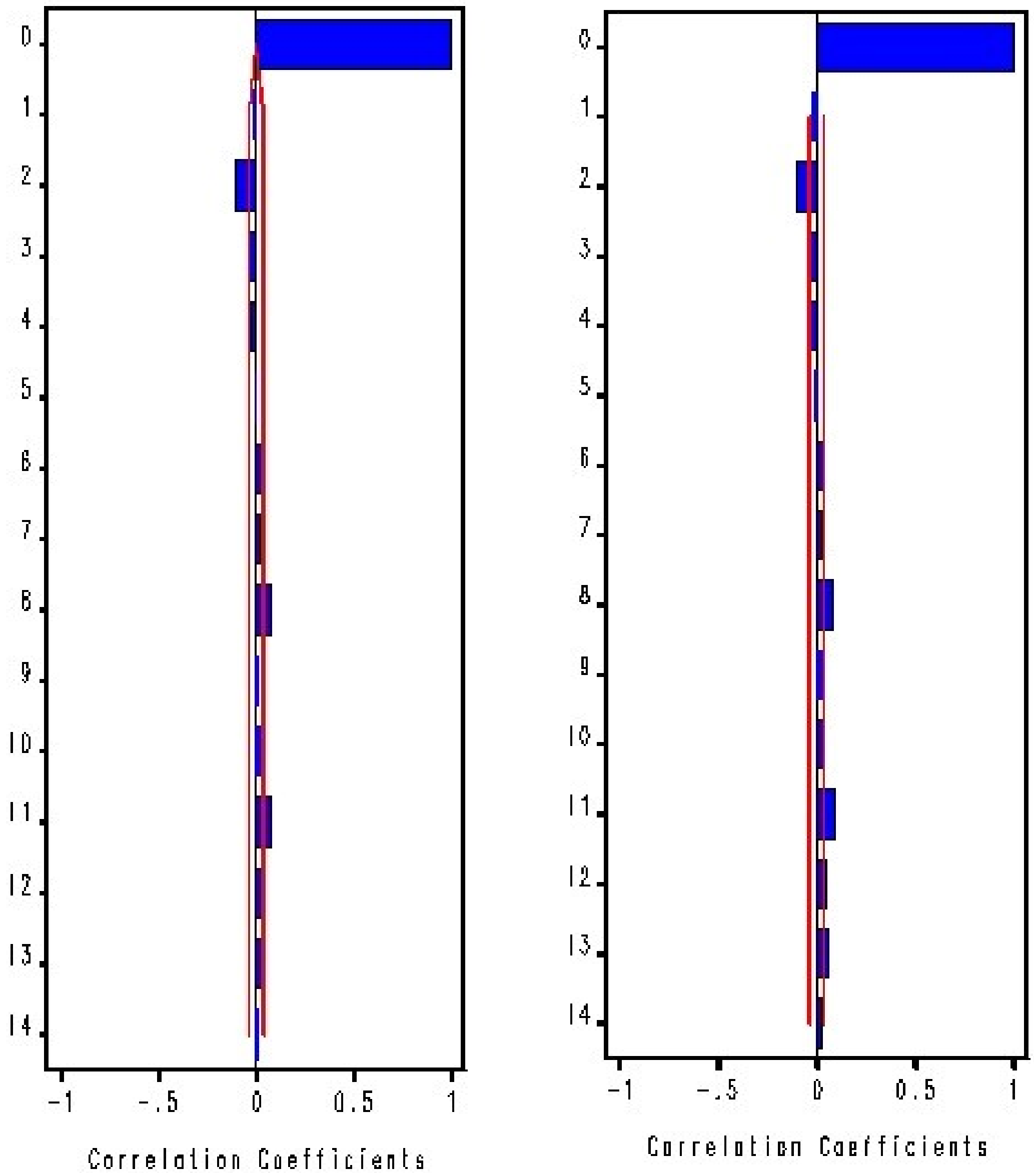


Figure 4.4 Prediction Error Autocorrelation Plots of SARIMA Model

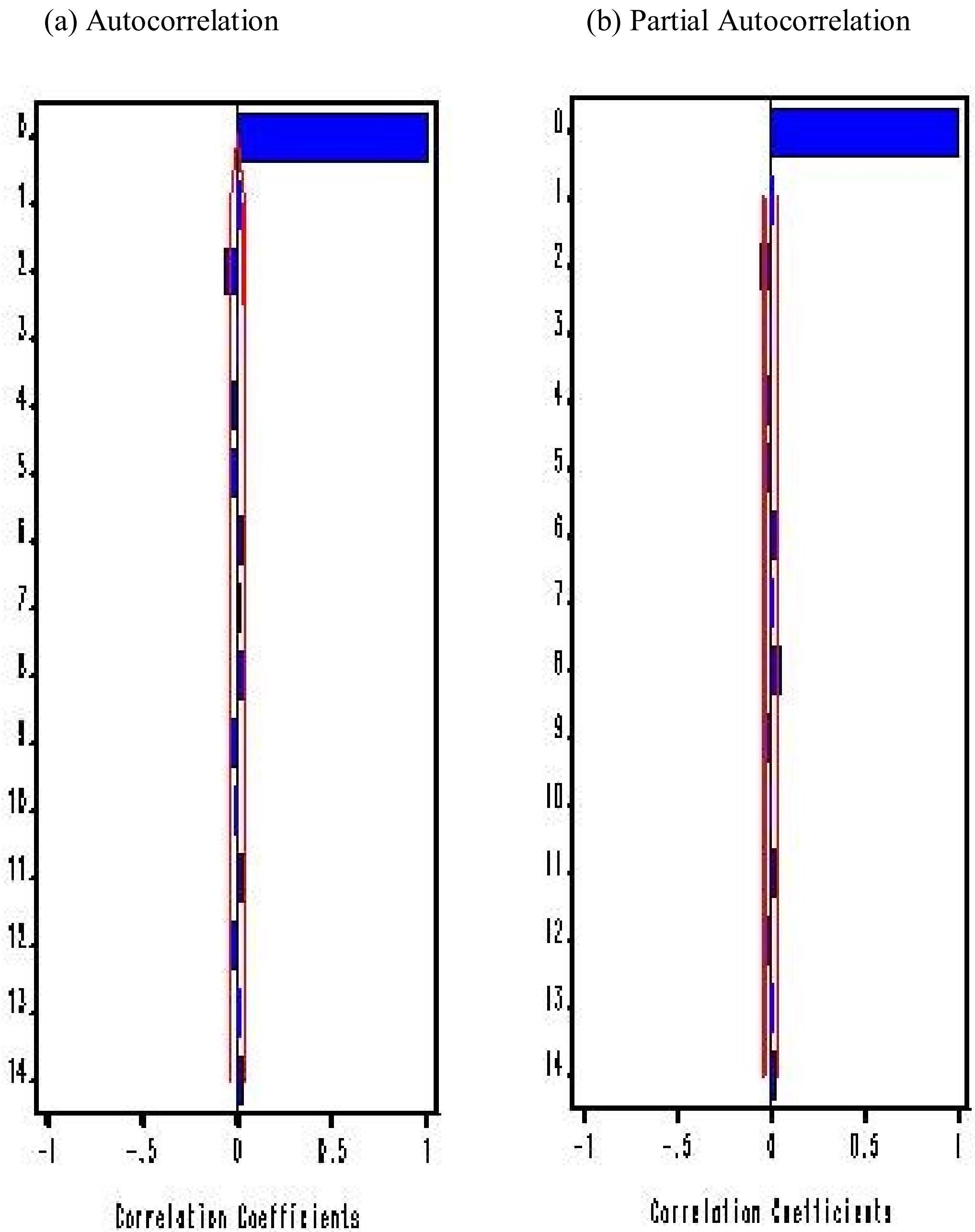


Figure 4.5 Prediction Error Autocorrelation Plots of REGSARIMA Model

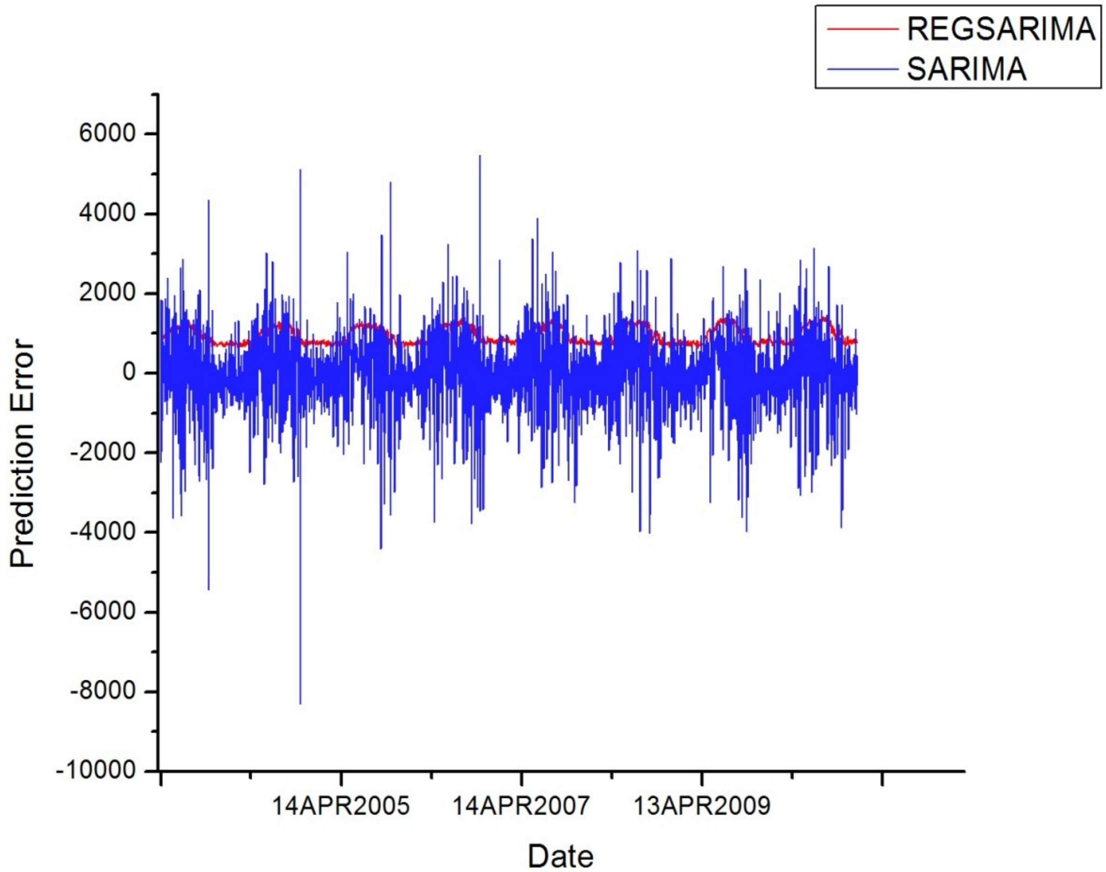


Figure 4.6 Prediction Error of SARIMA and REGSARIMA model

APPENDIX C

TABLES

Table 2.1 Data Description (4/15/2008 – 2/28/2011)

Daily 742 Observations	CP	DP	LCP	LDP
Mean	567.3787	950.8104	2.7441	2.9716
Standard Deviation	119.9545	171.6786	0.0926	0.0733
Skewness	0.4786	1.1532	-0.226	0.7497
Kurtosis	0.402	0.9103	0.3364	0.1834

Weekly 148 Observations	CP	RP	DP	LCP	LRP	LDP
Mean	567.37	950.81	2.7443	2.9716	2.7443	2.9716
Standard Deviation	119.95	171.67	0.0926	0.0733	0.0926	0.0733
Skewness	0.4786	1.1532	-0.226	0.749	-0.226	0.749
Kurtosis	0.402	0.91	0.336	0.183	0.336	0.183

Table 2.2 Long-run Relationship among Crude Oil Price, Rack Price, and Retail Price

Variable	LRP	LDP	LDP
Constant	0.56 (0.06)	0.53 (0.06)	1.004 (0.07)
LCP	0.84 (0.02)		0.71 (0.02)
LRP		0.85 (0.02)	

Note : Standard errors are in parentheses.

Table 2.3 Estimation Results of ECM Model for Weekly Data

Upstream(Rack price)			Downstream(Retail Price)		
	Coefficient	Standard Error		Coefficient	Standard Error
PLCP	0.4715	0.0904	PLRP	0.0002	0.0328
NLCP	0.4631	0.0947	NLRP	0.024	0.0351
PLCP(-1)	0.12	0.0902	PLRP(-1)	0.1224	0.0491
NLCP(-1)	0.029	0.1099	NLRP(-1)	-0.0048	0.0048
PLRP(-1)	0.0658	0.1267	PLRP(-2)	0.0634	0.0452
NLRP(-1)	0.0189	0.1572	NLRP(-2)	0.2872	0.0475
PECT(-1)	-0.1588	0.0698	PLDP(-1)	0.3768	0.068
NECT(-1)	-0.0707	0.0702	NLDP(-1)	0.3185	0.0636
			PECT(-1)	-0.1275	0.0421
			NECT(-1)	-0.1829	0.0478
R-square		0.4328	R-square		0.8485

Note : A negative number in parentheses indicates the order of lag.

Table 2.4 Results for Price Asymmetry Tests

Upstream(Rack price)			Downstream(Retail Price)		
H_0	*F* statics	*p*-value	H_0	*F* statics	*p*-value
PLCP = NLCP	0.00	0.9540	PLRP = NLRP	0.92	0.3375
PLCP(-1) = NLCP(-1)	0.58	0.4448	PLRP(-1) = NLRP(-1)	0.77	0.3816
PLRP(-1) = NLRP(-1)	0.16	0.6915	PLRP(-2) = NLRP(-2)	6.03	0.0141
PECT(-1) = NECT(-1)	5.17	0.0230	PLDP(-1) = NLDP(-1)	218.89	<.0001
			PECT(-1) = NECT(-1)	0.00	0.9540

Note : A negative number in parentheses indicates the order of lag.

Table 2. 5 Estimation Results of ECM Model for Retail Prices Responding to Crude Oil Prices (Weekly)

	Retail Price	
	Coefficient	Standard Error
PLCP	-0.0631	0.0267
NLCP	0.0552	0.0276
PLCP(-1)	0.2443	0.028
NLCP(-1)	0.0568	0.0322
PLCP(-2)	0.132	0.026
NLCP(-2)	0.1333	0.0328
PLDP(-1)	0.546	0.0686
NLDP(-1)	0.3982	0.0752
PECT(-1)	-0.073	0.0234
NECT(-1)	0.0016	0.0216
R-squared	0.8338	

Note : A negative number in parentheses indicates the order of lag.

Table 2. 6 Test Results for ARCH and Normality on OLS Residuals

Normality Test		ARCH Test				
H_0	$\mu = 0$	Order	Q Statics	Pr > Q	LM Statics	Pr > Q
t Statics	-0.507	1	10.84	0.001	9.82	0.0017
p-value	0.61	2	12.83	0.0016	9.9	0.007
		3	13.26	0.0041	9.9	0.0194
		4	13.3	0.0099	9.95	0.0412
		5	13.72	0.0175	10.15	0.0709
		6	16.1	0.0132	11.4	0.0766
		7	19.08	0.0079	12.11	0.0969
		8	26.69	0.0008	15.43	0.0512
		9	31.74	0.0002	16.11	0.0645
		10	43.78	<.0001	22.03	0.0149
		11	44.44	<.0001	22.71	0.0194
		12	47.23	<.0001	24.57	0.017

Note : A negative number in parentheses indicates the order of lag.

Table 2. 7 Estimation and Test Results of ECM Model with PGARCH (Weekly)

ECM Model with PGARCH			Asymmetry Test(Wald)		
Mean Equation			H_0	Statics	*p*-value
	Coefficient	St. Error	PLCP =NLCP	39.48	<.0001
PLCP	0.036	0.021			
NLCP	0.0669	0.014	PLCP(-1) =NLCP(-1)	0.07	0.796
PLCP(-1)	0.2448	0.023			
NLCP(-1)	0.1029	0.021	PLCP(-2) =NLCP(-2)	29.60	<.0001
PLDP(-1)	0.5084	0.071			
NLDP(-1)	0.4456	0.071	PLDP(-1) =NLDP(-1)	54.88	<.0001
PECT(-1)	-0.0401	0.016			
NECT(-1)	-0.001624	0.015	PECT(-1)=NECT(-1)	0.01	0.9146
Variance Equation					
	Coefficient	St. Error			
ARCH_0	2.81E-06	<.0001			
ARCHA_1	1.0603	0.565			
ARCHB_1	-0.0185	0.155			
PGARCH_1	0.0422	0.098			
LAMBDA	1.0032	0.77			
R-Squared		0.7962			
Log Likelihood		629.98			

Note : A negative number in parentheses indicates the order of lag.

Table 2. 8 Estimation and Test Results for Daily Retail Prices

	ECM Model		ECM Model with QGARCH	
Variable	Coefficient	St. Error	Coefficient	St. Error
PLCP	0.0235	0.0099	0.0054	0.0047
NLCP	-0.0154	0.0099	-0.0015	0.0049
PLCP(-1)	0.0236	0.0104	0.0034	0.0049
NLCP(-1)	0.0009	0.0105	-0.0009	0.0052
PLCP(-2)	0.0044	0.0105	0.0007	0.0052
NLCP(-2)	0.008	0.0106	0.0054	0.0055
PLCP(-3)	0.0063	0.0094	0.0132	0.005
NLCP(-3)	0.0109	0.0104	0.011	0.0052
PLCP(-4)	-0.0009	0.0094	0.013	0.0045
NLCP(-4)	0.0155	0.0103	0.0072	0.0055
PLCP(-5)	0.0188	0.0094	0.0182	0.005
NLCP(-5)	-0.0036	0.0103	0.0166	0.0054
PLCP(-6)	0.0305	0.0094	0.0218	0.005
NLCP(-6)	0.0261	0.0103	0.0347	0.0051
PLCP(-7)	0.0009	0.0095	0.0081	0.0049
NLCP(-7)	0.0545	0.0102	0.0329	0.0052
PLCP(-8)	0.0335	0.0095	0.0276	0.005
NLCP(-8)	0.0192	0.0105	0.0122	0.0055
PLCP(-9)	0.0201	0.0095	0.024	0.0051
NLCP(-9)	0.0369	0.0104	0.0137	0.0061
PLCP(-10)	0.0091	0.0094	0.0089	0.0052
NLCP(-10)	0.0224	0.0103	0.0079	0.0059
PLRP(-1)	0.5349	0.0682	0.5531	0.0586
NLRP(-1)	0.1469	0.0484	0.1697	0.0708
PLRP(-2)	0.0279	0.0789	0.1492	0.0659
NLRP(-2)	0.1468	0.0472	0.1669	0.0705
PECT(-1)	-0.0171	0.004	-0.0153	0.0018
NECT(-1)	-0.0001	0.0036	-0.0043	0.0014
Variance Equation(QGARCH)				
ARCHA_0			3.39E-14	0
ARCHA_1			0.3406	0.0753
ARCHA_2			0.1966	0.0929
ARCHB_1			-0.0001	<.0001
ARCHB_2			0.0001	<.0001
QGARCH_1			0.6119	0.0369
R-Squared		0.5615		0.5365
Log Likelihood		3644.8124		4124.3352

Note : A negative number in parentheses indicates the order of lag.

Table 2. 9 Test Results for ARCH and Normality on OLS Residuals (Daily)

Normality Test		ARCH Test				
H_0	$\mu = 0$	Order	Q Statics	Pr > Q	LM Statics	Pr > LM
t Statics	-0.472	1	11.0079	0.0009	10.9653	0.0009
p-value	0.63	2	11.4364	0.0033	11.0277	0.004
		3	11.6575	0.0087	11.1586	0.0109
		4	11.7702	0.0191	11.2101	0.0243
		5	12.794	0.0254	12.078	0.0337
		6	12.8626	0.0453	12.0781	0.0602
		7	12.886	0.0749	12.0848	0.0978
		8	12.8887	0.1157	12.0849	0.1475
		9	12.9167	0.1664	12.1043	0.2075
		10	13.1346	0.2162	12.2556	0.2683
		11	13.1349	0.2846	12.2749	0.3433
		12	14.2366	0.2859	13.3601	0.3434

Table 2. 10 Results for Asymmetry Test to Daily Retail Prices (Wald Test)

	ECM Model		ECM Model with QGARCH	
H_0	Statics	p-value	Statics	p-value
PLCP=NLCP	6.31	0.012	0.52	0.4722
PLCP(-1)=NLCP (-1)	1.66	0.1973	0.07	0.7977
PLCP (-2)=NLCP (-2)	0.45	0.5028	1.09	0.2966
PLCP (-3)=NLCP (-3)	0.03	0.8529	0.1	0.7527
PLCP (-4)=NLCP (-4)	0.68	0.4101	2.3	0.1297
PLCP (-5)=NLCP (-5)	2.19	0.1388	0.57	0.4499
PLCP (-6)=NLCP (-6)	0.02	0.8814	12.74	0.0004
PLCP (-7)=NLCP (-7)	11.28	0.0008	4.73	0.0297
PLCP (-8)=NLCP (-8)	0.86	0.3538	1.26	0.0611
PLCP (-9)=NLCP(-9)	0.92	0.3375	1.41	0.0524
PLCP (-10)=NFCP(-10)	0.85	0.357	86.88	<.0001
PLDP (-1)=NLDP(-1)	20.24	<.0001	0.05	0.0097
PLDP (-2)=NFDP(-2)	0.03	0.8741	6.69	0.8186
PECT(-1)=NECT(-1)	6.98	0.0082	8.6	0.0034

Note : A negative number in parentheses indicates the order of lag.

Table 3.1 Summary of Data on Diesel, Crude Oil, Soybean Oil Price and Supply and Demand of Diesel in Korea

	Diesel Price	**Crude oil Price**	**Soybean Price**	**Production**	**Import**	**Export**
Mean	1450.2	528.6	851.5	3465513.6	9020.2	1644980.4
StDev	189.1	138.1	224.1	277102.3	13177.7	300262.56
Min	1164.3	311	438.7	2900878.4	0.00	1033485.6
Median	1445.4	540.1	855	3449560.1	4687.5	1649302.5
Max	1919.2	843.2	1242.6	3940243.3	68962.6	2284028.6
Skewness	0.60	0.47	-0.08	-0.23	2.73	0.14
Kurtosis	-0.16	-0.51	-0.80	-0.80	8.31	-0.57
	Industry	**Transport**	**Resident**	**Public**		**Stock**
Mean	259618.7	1412726.9	70117.2	51875.5		1568750.8
StDev	56294.8	134439.9	12701.9	20039		265093.9
Min	145711.3	1048422.2	37182.6	20815.9		1185552.9
Median	256385.1	1429782.2	67850.3	47034.4		1519084.0
Max	363086.5	1707857.2	100265.9	108369.8		2597220.5
Skewness	0.04	-0.37	0.18	1.15		1.83
Kurtosis	-0.75	-0.02	0.06	1.37		4.60

Table 3.2 Estimators from Multiple Regression Results

Dependent Variable				Independent Variables
Supply of diesel	Intercept	Diesel price	Supply t-1	Trend
Coefficient	12447.433	592.325	0.251	-29.583
Standard error	3413.212	410.318	0.154	33.24
Domestic Consumption	Intercept	Diesel price	Domestic Consumption t-1	GDP
Coefficient	13202.265	-123.532	0.2	-0.002
Standard error	3498.097	560.334	0.187	0.012
Export	Intercept	Diesel price	Export t-1	
Coefficient	2632.088	-370.829	0.39	
Standard error	1266.517	346.831	0.161	
Stock	Intercept	Diesel price	Stock t-1	
Coefficient	1264.662	-26.824	0.672	
Standard error	365.649	30.102	0.1	
Diesel price	Intercept	Crude oil price		
Coefficient	3.034	0.0383		
Standard error		0.002		

Table 3.3 Regression Results for Diesel, Soybean Oil and Blended Diesel Price

Dependent Variable		**Diesel Price**	
		Intercept	Crude oil Price
Coefficient		739.303	1.345
Standard error		18.545	0.034
Dependent Variable		**Soybean Oil Price**	
		Intercept	Crude oil Price
Coefficient		110.496	1.409
Standard error		53.964	0.098
Dependent Variable		**Blended Diesel Price**	
	Intercept	Crude oil Price	Soybean oil Price
Coefficient	732.510	1.258	0.061
Standard error	19.073	0.072	0.045

Table 3.4 Correlation matrix and Correlation Coefficient Test

Correlation matrix							
	Production	**Export**	**Transport**	**Industry**	**Resident**	**Public**	**Stock**
Production	1	0.31	0.30	0.24	0.26	0.20	0.16
Export		1	-0.15	0.12	0.00	0.07	-0.25
Transport			1	0.37	0.62	0.26	-0.17
Industry				1	0.64	0.64	-0.42
Resident					1	0.60	-0.34
Public						1	-0.33
Stock							1

Correlation coefficient Test							
Significance	**95%**	**t-critical**					**2.00**
	Production	**Export**	**Transport**	**Industry**	**Resident**	**Public**	**Stock**
Production		2.47	2.38	1.90	2.06	1.53	1.26
Export			1.12	0.89	0.01	0.50	1.96
Transport				3.00	5.98	2.00	1.28
Industry					6.30	6.26	3.54
Resident						5.71	2.74
Public							2.68

Table 4.1 Summary of Data on Electricity and Air Temperature

	Daily Peak Load Electricity Profile	Air Temperature
Mean	11928.59325	70.18051
StDev	2590.236391	12.77305
95 % LCI	11819.1477	69.64081
95 % UCI	12038.0388	70.72021
Min	3915.671902	29.4
Median	11258	72.9
Max	18181	92
Skewness	0.364893615	-0.64448
Kurtosis	-1.150615005	-0.55772

Table 4.2 Augmented Dickey-Fuller Unit Root Tests

Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero	0	-11.091	0.0207	-2.36	0.0179		
Mean	1	-9.2017	0.0354	-2.16	0.0296		
	2	-6.0262	0.0913	-1.75	0.0769		
Single	0	-246.21	0.0001	-11.34	<.0001	64.31	0.0010
Mean	1	-217.45	0.0001	-10.41	<.0001	54.19	0.0010
	2	-149.74	0.0001	-8.52	<.0001	36.32	0.0010
	0	-246.5	0.0001	-11.34	<.0001	64.34	0.0010
Trend	1	-217.77	0.0001	-10.41	<.0001	54.23	0.0010
	2	-149.92	0.0001	-8.52	<.0001	36.33	0.0010

Table 4.3 Estimation Results

	ARIMA		SARIMA		REGSARIMA	
Parameter	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Intercept	-0.000027	0.9508	9.35821	0.0000	0.000003	0.9919
AR(1)	0.61084	0.0000	0.86817	0.0000	0.62633	0.0000
MA(1)	0.89522	0.0000	0.05876	0.0085	0.92963	0.0000
Seasonal AR(1)			0.95483	0.0000		
Seasonal MA(7)			0.8203	0.0000	-0.1824	0.0000
Seasonal MA(14)					-0.1469	0.0000
$\boldsymbol{T_C}$					0.03465	0.0000
$\boldsymbol{T_H}$					-0.03017	0.0000

Note : A number in parentheses indicates the order of lag. AR is the autoregressive process, MA is the moving average process, T_C is air temperature for cooling, and T_H is air temperature for heating.

Table 4.4 Out -of-Sample Forecast Evaluation

Statistic of Fit	**ARIMA**	**SARIMA**	**REGSARIMA**
RMSE	1014.68889	975.552566	945.784549
MAPE	6.38868551	5.97576	5.852395
AIC	38992.6039	38789	38605
SBC	39010.4331	38819	38646

Note : RMSE is Root Mean Square Error, MAPE is Mean Absolute Percentage Error, AIC is Akaike Information Criterion, and SBC is Schwarz Bayesian Criterion.

VITA

Name: Yoon Sung Shin

Address: 600 Kimbrough Blvd.,
309 Agricultural and Life Sciences Bldg.,
2124 TAMU
College Station, TX 77843-2124
USA

Email Address: zenithshin@gmail.com

Education: B.A., Economics, Pusan National University, 2000
M.A., Economics, The State University of New York at Buffalo, 2006