Three Essays on Energy Economics

by

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Abstract

This dissertation consists of three essays in applied energy economics focusing on interfuel substitution in the electric power industry, the linkages among energy consumption, emissions and economic growth, and the price linkages among biofuel, energy and food.

The first chapter estimates substitution under static and dynamic scenarios, examining changes in technology and total factor productivity from 2001 to 2008. Two-stage estimation reveals regional characteristics and underlying elements in fuel and factor choice processes. Substitution varies widely depending on the region, coal technology, capital investment, and R&D activities.

The second chapter explores the causal relationship between CO_2 emissions, hydrocarbon energy consumption, non-hydrocarbons energy consumption, and economic growth in the US for 1960-2009 with vector error correction modeling techniques, generalized impulse response, and variance decomposition in a multivariate context. The results show strong evidence for uni-directional causal relationship running from hydrocarbon consumption to investment, and weak evidence for bi-directional causality between non-hydrocarbon consumption and investment; uni-directional causality running from CO_2, hydrocarbon energy consumption, and population to non-hydrocarbon energy consumption, from hydrocarbon and non-hydrocarbon energy consumption to GDP.

The third chapter studies the price transmission system in the U.S. food-ethanol-energy links by capturing the price nonlinearities to examine the price relationships between corn, soybean, wheat, ethanol, oil and gasoline in the latest U.S. ethanol markets by using Exponential Smooth Transition VECM. The results show impacts of the ethanol industry on food prices and energy prices and provide insights for policy makers and economic agents.

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1. Introduction

Energy plays a crucial role in the global economy and will become the major economic issue of the coming century. Most recently, many policies have been initiated to promote various energy efficiency improvements and encourage development of specific energy sources. For instance, the Energy Policy Act of 2005 seeks to increase coal as an energy source while also reducing air pollution by clean coal initiatives. According to the Annual Energy Review of the Energy Information Administration (*EIA*), in 2008 the electric power sector accounted for 91 percent of all coal consumption and 29 percent of all natural gas consumption, while fossil fuels (coal, petroleum, and natural gas) accounted for 71 percent of all electricity net generation in the US. Fuel choices and factor alternatives in electricity generation are important issues in energy policy. Based on the fact that the electricity generation industry is restructuring and regulation is moving from states to regional and national levels, accurate estimates of fuel and factor use in interregional electricity generation are essential for policy makers and planners.

Several studies using various estimation models and samples have been devoted to the analyses of energy production and fuel/factor substitution in energy generation. Attention has been mostly given to national studies or international comparisons of interfuel substitution in the electric power. However, aggregate national estimates may mask regional characteristics of the electricity market and result in inappropriate policies. No previous research has estimated the regional fuel or factor substitution in electricity generation specifically for the eastern regions of the US. In addition, this is the first study to apply a two-stage model to account for both energy and non-energy inputs in electric power generation under both static and dynamic scenarios.

The focus of this study is to compare regional results from the two-stage estimation method and to reveal regional characteristics and underlying elements in fuel and factor choice processes. The results show widely-varing elasticities of substitution depending on the regions for estimation. As a by-product of this analysis, technology changes and total factor productivity are also examined to compare production efficiencies and provide policy implications for different regions so that decision makers can efficiently allocate energy resources.

The organization of the paper is as follows. Section II gives a summary of previous studies on interfuel and interfactor substitution analyses. Section III and Section IV include discussions of the theoretical model and data sources. Section V presents the empirical results.

2. Literature Review

The majority of previous studies of interfuel and interfactor substitution in the electric power industry rely on greatly aggregated data at the industry or national level. For example, Hudson and Jorgenson (1974), Atkinson and Halvorsen (1976b), Griffin (1977), Uri (1978), Mountain (1982), Söderholm (1999), Söderholm (2000) and Lee (2007) all used aggregate national data. Only two studies have used US regional data and no previous regional study has focused on the eastern part of US. Uri (1977) analyzed fuel substitution for nine US census regions. Bopp and Costello (1990) compared elasticities for five US geographic regions with national elasticities. However, the data employed in those two regional analyses were based on geographic census divisions which do not consider the regional characteristics and regulation structure of the electricity market.

Among the attempts to model the energy sector, Hudson and Jorgenson (1974) were the first to conduct an econometric study of hydrocarbon demand. They applied a translog cost model with US annual data and included the fuel prices of coal, oil, natural gas and electricity for 1947-1971. According to their results, oil demand was price elastic while coal and gas demand was inelastic. The cross elasticities suggested that the three fuels were substitutes, though coal and oil were strong substitutes (1.09) while oil and gas (0.39), and coal and gas (0.09) were weak substitutes.

Griffin (1977) incorporated a polynomial distributed lag into the translog model and applied a translog cost function to the data of 20 OECD countries for 1955, 1960, 1965, and 1969 with two separate models to estimate interfuel substitution elasticities in the European electric power industry. His results showed larger price elasticities with cross sectional data than with time series data, probably because that the time series results reflect only a partial adjustment to a new equilibrium.

Uri (1977) applied pooled time series analysis to nine US regions from 1952 to 1974. In a subsequent paper Uri (1978) did a similar study with aggregate monthly data covering 1974 to 1976. The resulting smaller elasticities led him to conclude that short run elasticities were lower than long run estimates.

Mountain (1982) included imported electricity in the translog cost function as an input. He used pooled time series data from 1964 to 1975 for two districts in Canada. The empirical results showed strong substitution between domestic and imported electricity, and strong short run substitution between coal and oil.

Bopp and Costello (1990) conducted a monthly time series analysis from 1977 to 1987 with two translog cost function models: one for five US regions, the other for the entire US. The empirical results showed that oil was own-price elastic while gas was inelastic. The latter result was expected as it is known that gas is typically a peak fuel for generators designed to run during busy times. The results also demonstrated that the price elasticities were lower in the regional model than in the aggregate.

Söderholm (1999) conducted a pooled annual aggregate national analysis for seven European countries using a translog cost function for the years 1978-1995. The results showed strong substitution between gas and oil. Söderholm (2000) employed a regulatory intensity variable as an exogenous variable and estimated a generalized Leontief cost function with the same dataset. The results showed significant interfuel substitution in European electricity production and the estimation from the perspective of regulation intensities showed that it was hard to separate the individual effects of the SO_2 regulations.

In addition to aggregate level analysis, in order to characterize the fuel choice in individual electricity generating plants or firms some research has also been devoted to firm-level or plant-level analysis. Atkinson and Halvorsen (1976a), Haimor (1981), Ko and Dahl (2001), Lee (2002), Considine and Larson (2007) and Tuthill (2008) used micro data from the US, while Tauchmann (2006) analyzed firm-level data from Germany.

Atkinson and Halvorsen (1976a) employed a translog profit function to examine the demand for hydrocarbons by US electric plants, using data on capital quantities, labor quantities, coal price, oil price, and natural gas price. They used cross sectional data for 1972. Their results showed that oil and coal were own-price elastic and cross-price elastic. By applying the same translog profit function, Atkinson and Halvorsen (1976b) compared the three hydrocarbons using a short run substitution analysis with monthly time series for the years 1972–1974. Contrary to their earlier results, the own price elasticity of natural gas was highly elastic and significant. All cross elasticities were significant and indicated substitutability.

Haimor (1981) applied a translog model to plant-level data, including capital stock and labor price as variables influencing the fuel choices of 45 plants that used all three fuels (coal, oil and gas) during the years 1970-1975. His findings showed strong substitution between coal and oil and large changes in response to unstable markets, making forecasting difficult.

Ko and Dahl (2001) employed a translog cost function to estimate interfuel substitution with monthly panel data for 185 US utilities for the year 1993. They divided the utilities into four fuel choice capability sets of coal and oil, coal and gas, gas and oil, and coal and oil and gas. Their results showed that coal was own-price elastic while oil and gas were inelastic, and that substitution was strong between coal and oil, but weak between gas and the other two fuels.

Table 1 compares the data, models and elasticities from the selected studies. A limitation of the estimation method in most of these studies arises when interfuel substitutions are estimated assuming exogenous energy aggregates. Because fuel price changes almost certainly stimulate substitution among both fuels and factors of production, ignoring this feedback effect may result in unreliable conclusions.

While the current study is the first application in the electricity sector of a two-stage translog model that incorporates feedback effects between interfactor and interfuel substitutions, this is a well-established method for determining fuel substitution elasticities in the manufacturing sector. Pindyck (1979), Andrikopoulos, Brox and Paraskevopoulos (1989), Cho (2004) and Ma, Oxley, Gibson and Kim (2008) all use this method to examine industrial interfuel substitution. A comparison of their data and main results is given by Table 2. All of those studies employing two-stage translog functions and panel data show inconclusive substitution results for different countries.

In the electric power industry, however, only two firm-level studies employed two-stage decisions. Mountain's (1982) incorporated imported electricity as an input and applied the translog cost function to firm-level data from New Brunswick and Nova Scotia in Canada. In the first stage, the optimal quantities of imported and domestic electricity were estimated, and in the second the fuel choice in domestic electricity given the exogenous quantity of domestic electricity was determined. Tauchmann (2006) applied a linear non-structural function to firm-level data from German electricity generating firms for the years 1968-1998. The author estimated optimal capacities in the first stage, and examined fuel substitution given exogenous capacities in the second.

The two-stage estimation method in the current paper differs from Tauchmann in several details: it employs instrumental variables for aggregate energy prices, it estimates interfuel and interfactor substitution with regional-level data from the eastern US, and it estimates Marshallian unconditional elasticities to capture feedback effects.

3. Model

3.1. The static model

For many years, the electricity generation industry vertically-integrated in the US has been operating as regulated monopolists. As economies of scale always exist at generation stage, the average cost of producing a unit of power is at lowest when the entire demand is supplied by monopoly rather than by many competitive producers. By selecting the low cost option at each point in time, Kaserman and Mayo (1991) found that the total costs from the input stage are minimized, and the vertical structure of the utilities is determined by this cost minimization process. To simplify the estimation process of the two-stage cost share system, cost-minimization is considered in two-stages. In the first stage, total costs are minimized in the consumption of capital, labor and aggregated energy. In the second, aggregate energy costs are also minimized in the consumption of coal, oil and natural gas. Following the approach suggested by Pindyck (1979), the two-stage cost function is specified as:

(1) $$C=f\,[P_K, P_L, P_E(P_C, P_O, P_G, t), Y, t]\ ,$$

where C denotes total cost; P_K and P_L denote factor prices of capital and labor; P_E denotes a conditional function of the prices of three fuel inputs P_C, P_O and P_G ;Y denotes output generation; t denotes time which can also capture the trend of technical change;. Equation (1) is assumed to be weakly separable.

The translog cost model introduced by Christensen, Jorgenson and Lau (1971) has been widely used to estimate energy demand elasticities as it has the advantage of reducing multicollinearity and reducing the number of parameters estimated. Under the assumption that the production function is weakly separable in factor inputs of capital, labor and energy, and that these three factors are homothetic, the first stage translog cost function is written as the logarithmic second-order Taylor expansion:

(2) $$\ln C = \alpha_0 + \sum_{i=1}^{n} \alpha_i \ln P_{it} + \alpha_{it}\, t + \alpha_{iy} \ln Y_t + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_{ij} \ln P_{it} \ln P_{jt} + \frac{1}{2} \alpha_{tt} t^2 + \frac{1}{2} \alpha_{yy} (lnY_t)^2 + \sum_{i=1}^{n} \alpha_{iy}\ lnY_t \ln P_{it}, + \sum_{i=1}^{n} \alpha_{it}\ t \ln P_{it} + \alpha_{yt}\ t \ln Y_t\ ,$$

where C denotes total cost; i and j $=$ K, L, E; P_{it} denotes the price of factor i at time t; Y_t denotes the generation output at time t; t denotes time or technical change; and α denotes parameters to be estimated.

Taking the partial derivative of (2) with respect to $\ln P_{it}$ and applying Shephard's Lemma yields the first stage cost share equation (R_i):

(3) $$R_{it}=\alpha_i + \sum_{j=1}^{n} \alpha_{ij}\ln P_{jt}+\alpha_{iy} lnY_t+\alpha_{it}t\ .$$

Assuming that the parameters are linear functions of regional dummy variables D_m and that all the coefficients are allowed to vary across regions except for the interaction forms of factor prices, then the factor cost share equation is given by:

(4) $$R_{it}=(\alpha_{io} + \sum_{i=1}^{k} \alpha_{im}D_m) + \sum_{i=1}^{n} \alpha_{ij}\ln P_{it}+(\alpha_{iy0+} \sum_{i=1}^{k} \alpha_{iym}D_m)\ lnY_t$$
$$+(\alpha_{it0+} \sum_{i=1}^{k} \alpha_{itm}D_m)\ t.$$

The imposed symmetry and homogeneity restrictions can be written as:

(5) $\alpha_{ij}=\alpha_{ji}$, for all i and j ,

(6) $$\sum_{i=1}^{n}(\alpha_{io} + \sum_{i=1}^{k} \alpha_{im}D_m)=1,$$

(7) $$\sum_{i=1}^{n} \alpha_{ij}=\sum_{i=1}^{n}(\alpha_{iy0+} \sum_{i=1}^{k} \alpha_{iym}D_m)=\sum_{i=1}^{n}(\alpha_{it0+} \sum_{i=1}^{k} \alpha_{itm}D_m)=0.$$

Hicksian cross-price elasticities, own-price elasticity for input i with respect to changes in prices of input j, and Allen partial elasticities of substitution between factor-inputs are computed as:

(8) $$\mathrm{E}_{\mathrm{ij}}^{*}=\frac{\alpha_{ij}}{R_i}+R_j,\ \ \forall \mathrm{i}\neq \mathrm{j} \text{ and } \mathrm{E}_{\mathrm{ii}}^{*}=-1+\frac{\alpha_{ij}}{R_i}+R_j,$$

(9) $$\sigma_{\mathrm{ij}}=\frac{\mathrm{E}_{\mathrm{ij}}^{*}}{R_j},\ \forall \mathrm{i}\neq \mathrm{j},\ \text{ and }\ \sigma_{\mathrm{ii}}=\frac{\mathrm{E}_{\mathrm{ii}}^{*}}{R_i}.$$

In the second stage, the homothetic aggregate energy price function is given by:

(10) $$\ln P_E = \beta_0 + \sum_{i=1}^{n} \beta_i \ln P_{it} + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} \ln P_{it} \ln P_{jt} + \sum_{i=1}^{n} \beta_{it} \ t \ln P_{it} ,$$

where P_E is the aggregate energy price; P_{it} is the fuel price at time t; and β is an estimated parameter.

Taking the partial derivative of Equation (9) with respect to $\ln P_{it}$ and imposing the same assumptions about regional dummy variables as in the factor cost share equation gives the second stage cost share equation (S_i):

(11) $$S_{it} = (\beta_{io} + \sum_{i=1}^{k} \beta_{im} D_m) + \sum_{i=1}^{n} \beta_{ij} \ln P_{it} + (\beta_{it0+} \sum_{i=1}^{k} \beta_{itm} D_m)\, t.$$

The symmetry and homogeneity restrictions are:

(12) $\beta_{ij} = \beta_{ji}$, for all i and j,

(13) $\sum_{i=1}^{n} (\beta_{io} + \sum_{i=1}^{k} \beta_{im} D_m) = 1$,

(14) $\sum_{i=1}^{n} \beta_{ij} = \sum_{i=1}^{n} (\beta_{it0+} \sum_{i=1}^{k} \beta_{itm} D_m) = 0$.

Conditional Hicksian cross-price elasticities, own-price elasticity for input i with respect to changes in prices of input j, and conditional Allen partial elasticities of substitution between factor inputs are computed as:

(15) $e^*_{ij} = \frac{\beta_{ij}}{S_i} + S_j \ \ \forall i \neq j$ and $e^*_{ii} = -1 + \frac{\beta_{ij}}{S_i} + S_j$,

(16) $\sigma_{ij} = \frac{e^*_{ij}}{S_j} \ \ \forall i \neq j$ and $\sigma_{ii} = \frac{e^*_{ii}}{S_i}$.

To examine the feedback effect between interfuel and interfactor elements, conditional Hicksian price elasticities are transformed to unconditional Marshallian price elasticities by the following equation:

(17) $$\mathrm{E_{ij}}=\mathrm{e_{ij}}+\mathrm{e_i^x}\,(1+\eta_\mathrm{p})\,S_j=\mathrm{e_{ij}^*}+\mathrm{e_i^x}\eta_\mathrm{p}S_j.$$

where $\mathrm{E_{ij}}$ denotes unconditional Marshallian price elasticities; $\mathrm{e_i^x}$ denotes the expenditure elasticity from the conditional cost function; η_p denotes the income elasticity from the total cost function. Given $\mathrm{e_i^x}=1$ by homotheticity and $\eta_\mathrm{p}=\mathrm{E_{EE}^*}$, the unconditional Marshallian price elasticities are calculated from the following equation:

(18) $$\mathrm{E_{ij}}=\mathrm{e_{ij}^*}+\mathrm{E_{EE}^*}S_j\ .$$

3.2. The dynamic translog adjustment model

In the basic static analysis, it was assumed that fuel and factor demands remain constant in the short term. However, as shown in Figures 1 and 2, the aggregate energy price and oil price increased sharply while the average payroll, coal price and gas price increased more slowly during the sample period. Since the substitution effect may not be able to adjust instantaneously, in this section an adjustment process is considered. This Partial Adjustment Model (*PAM*), presuming an underlying stationary procedure in the data, assumes that the observed cost share in period t is somewhere between the equilibrium cost share and the observed cost share in t-1. The adjustment process is described as follows:

(19) $$R_t\text{-}R_{t-1}=\gamma\,(R_t^*\text{-}R_{t-1}),\ 0<\gamma\leq 1,$$

where R_t^* denotes the equilibrium level of cost share at time t; R_t denotes the observed cost share at time t; R_{t-1} denotes the observed cost share at time t-1; γ denotes the adjustment coefficient, such that for instantaneous adjustment γ=1.

As shown by Taheri (1994), the dynamic factor cost share equation and fuel cost share equations are given by:

(20) R_{it}=$(\alpha_{io} + \sum_{i=1}^{k} \alpha_{im} D_m) + \sum_{i=1}^{n} \alpha_{ij} \ln P_{it}$

$$+(\alpha_{iy0+} \sum_{i=1}^{k} \alpha_{iym} D_m)\, lnY_t + (\alpha_{it0+} \sum_{i=1}^{k} \alpha_{itm} D_m)\, t + \ (\alpha_{ir0+} \sum_{i=1}^{k} \alpha_{irm} D_m)\, R_{t-1}$$

(21) S_{it}=$(\beta_{io} + \sum_{i=1}^{k} \beta_{im} D_m) \sum_{i=1}^{n} \beta_{ij} \ln P_{it} + (\beta_{it0+} \sum_{i=1}^{k} \beta_{itm} D_m)\, t + (\beta_{is0+} \sum_{i=1}^{k} \beta_{ism} D_m)\, S_{t-1}$

4. Data and data sources

From the perspective of US electricity market development and political factors, states are usually divided into ten major areas [1] as shown in Figure 3, according to Federal Energy Regulatory Commission (*FERC*). Since there is transmission within the *FERC* regions but very little between, interregional trade will not be discussed in this paper. Considering the location and level of electricity market growth, seven regions [2]covering 30 states [3]were chosen for this study.

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[1] The ten regions include California, Midwest, New England, New York, Northwest, PJM Interconnection (PJM), Southeast, Southwest, Southwest Power Pool (SPP) and Texas.

[2] The regional division was as follows: (1) Alabama; (2) Southeast (Florida, Arkansas, Louisiana, Mississippi, Georgia, Tennessee, North Carolina, South Carolina); (3) PJM (Delaware, District of Columbia, Maryland, New Jersey, Ohio, Pennsylvania, Virginia, West Virginia); (4) New

The dataset is a panel consisting of annual region-level observations from 2001 to 2008. Annual state-level labor data are from the Quarterly Census of Employment and Wages (*QCEW*) of the Bureau of Labor Statistics (*BLS*) and include all employee numbers and total wage payments by federal, local and private owners. The average wage of labor is obtained by dividing the total payroll by its corresponding number of employees. The price of capital is obtained by estimating the production function *VA=f (rK, L, E)*, where *VA* is value-added. The price of capital is a shadow price and the nameplate capacity[4] is used as a proxy for capital.

Fuel prices (coal, oil and gas), generation data and capacity data for the 30 states come from *EIA*- 28, *FERC*-423, *EIA*-906 and *EIA*-860. The price of aggregate energy is obtained from the equation: $\ln P_E = \beta_0 + \sum_{i=1}^{n} \beta_i \ln P_{it} + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \beta_{ij} \ln P_{it} \ln P_{jt} + \sum_{i=1}^{n} \beta_{it}\, t \ln P_{it}$, where P_E is the aggregate energy price; P_{it} is the fuel price at time t; β are parameters that can be estimated from Equation (11), except for β_0 which is calculated following Pindyck (1979), so that $P_E = 1$ in 2001.

York; (5) Midwest (North Dakota, South Dakota, Nebraska, Minnesota, Iowa, Wisconsin, Illinois, Indiana, Michigan); (6) SPP (Kansas, Oklahoma); (7)Texas.

[3] Each region covers several full states and several parts of states according to *FERC*. Since the data for parts of states are inaccessible, full-state and majority-states coverage are aggregated to approximate the regions.

[4] Nameplate capacity refers to the full-load sustained output of a generator registered with authorities for classifying the power output.

5. Results

The empirical analysis starts with pretests of stationarity properties of the variables. The panel unit root test developed by Levin, Lin and Chu (2002) is employed to allow for individual effects, time effects and possibly a time trend. Lags of the dependent variable are introduced to allow for serial correlation in the errors. The test with the null hypothesis of nonstationarity, could be regarded as an Augmented Dickey-Fuller (*ADF*) test when lags are included. Panel unit root test results shown in Table 3 indicate that each variable has no unit root and is stationary.

To estimate the static translog model, the fuel cost share system in (11) is first estimated by employing Seemingly Unrelated Regression (*SUR*), imposing the symmetry and homogeneity restrictions from (12), (13) and (14) and dropping the gas cost share equation. Using the estimated parameters, the aggregate energy prices, treated as an instrumental variable in factor share equations, are computed by (10). The same *SUR* technique is used to estimate the factor cost share system given by Equation (4), dropping the capital cost share equation and imposing the symmetry and homogeneity restrictions given by Equations (5), (6) and (7).

5.1. Fuel cost share equation estimation and interfuel substitution

Table 4 present the parameter estimates for the static and dynamic translog fuel cost share equations. Both the models have good explanatory power. The R^2 is 0.99 for the coal share equation and 0.89 for the oil equation in the static model and the R^2 is 0.99 for the coal equation and 0.90 for the oil equation in the dynamic model. More than half of the parameters are statistically significant. Durbin-Watson (*DW*) values are 2.467 and 1.501 for coal and oil in the static model, implying that first order serial correlation is inconclusive. In the dynamic models, the *DW* value is 2.437 for coal, suggesting inconclusive serial correlation and 2.223 for oil with no serial correlation.

Using the parameters estimated above and the sample means of each fuel cost share for each region from Table 5, the static Hicksian conditional price elasticities of fuel demand and the Allen elasticities of substitution are calculated and reported in Table 6. The static Marshallian unconditional price elasticities are presented in Table 7.

As shown in Table 6, the results are generally larger than results from previous studies shown in Table 1. All of the own price elasticities for coal are negative except for New York and Texas. In general, the smaller the cost share the larger the own price elasticity will be. The elasticities range between -0.04 in the Midwest, where coal has the larger cost share in electricity generation, and -0.18 in SPP with a smaller coal cost share. The negative signs for New York and Texas are contrary to theory but they are plausible since coal consumption and coal cost shares are extremely low (less than 19% of shares) in these two regions. Alabama and Texas have the largest own price elasticities for oil at -8.75 and -7.79 respectively, and New York has the smallest at -1.04, which is reasonable since the first two states both have very low oil shares in their electric power sectors. Own price elasticities for natural gas vary from -0.19 in Texas to -0.75 in the Midwest.

Coal and oil appear to be substitutes only in the Southeast and PJM regions, whereas in the other five regions they are complements. The complementarity in those five regions is probably due to their much lower oil consumption and relatively low oil cost shares in the sample period.

In contrast, coal and gas are all substitutes except for New York. Coal and gas are the most substitutable (σ =0.45 and σ=0.42) in Alabama and SPP and the least substitutable (σ =0.11 and σ =0.08) in the Southeast and Texas. It is not surprising that coal and gas have substantial substitution possibilities in New York because coal consumption there is very low and hence their coal cost share is only about 6% while their gas share is about 66%. Oil and gas are all substitutes in the seven regions and the elasticities of substitution are between 1.67 in New York and 22.58 in Alabama. The Marshallian unconditional price elasticities are shown in Table 7. These incorporate the feedback effect between interfuel and interfactor and are more consistent with economic theory except for the own price elasticity of coal in New York.

The dynamic Hicksian conditional price elasticities, Allen elasticities of substitution, and dynamic Marshallian unconditional price elasticities are shown in Tables 8 and 9. These are slightly smaller than the static models, but with only slightly larger variance and in similar direction, which indicates the models are consistent with each other and with factor demand theory.

5.2. Factor cost share equation estimation and interfactor substitution

Table 10 show the parameter estimates for the static and dynamic translog factor cost share equations. Both the static and dynamic models have good explanatory power with R^2=0.99 for the capital and the labor share equation. More than half of the parameters are statistically significant. In the static model, Durbin-Watson values are 1.743 with no serial correlation for energy-input, and 1.836 for labor-input suggesting inconclusive serial correlation. In the dynamic model, DW values are 2.053 and 2.027 for labor and energy inputs showing no serial correlation problem.

Based on the parameter estimates and the means of each factor cost share for each region from Table 5, the static Hicksian price elasticities of factor demand and Allen elasticities of substitution are reported in Table 11.

The results show that all the own price elasticities have negative signs, consistent with economic theory. Own price elasticities for capital are relatively small, between -0.26 in PJM and -0.56 in SPP. Own price elasticities for labor vary from -0.75 in SPP to -1.29 in PJM. The Southeast and PJM have the largest own price elasticities for aggregate energy of -3.22 and -2.36 respectively. New York has the smallest at -1.57.

Capital and labor are substitutes with values for partial elasticities of substitution around unity in all seven regions. Capital and aggregate energy appear to be the substitutes with the largest magnitude of elasticities. They are most substitutable in the Southeast (σ =1.63) and least substitutable in New York and the Midwest (σ=1.20 and σ=1.22). Labor and aggregate energy are substitutes in all seven regions, with a range of elasticities between 2.89 in SPP and 8.17 in Southeast.

In sharp contrast, the dynamic Hicksian conditional price elasticities and dynamic Allen elasticities of substitution presented in Table 12 show different results in signs and magnitudes from the static results. Surprisingly, the own price elasticities of capital are positive. Capital and energy are substitutes under the static model, but are complements under the dynamic model based on lagged shares. The elasticities of substitution vary from 1.20 in New York to 1.63 in Southeast. Labor and energy also appear to be complementary in the dynamic model with elasticities between 2.89 in SPP and 8.17 in the Southeast. This result reflects the impact of the sharp increase in energy price during the periods of 2001 to 2005 and 2006 to 2008. When the energy price is fairly low, capital and labor could be substitutable with aggregate energy. But later, the sharply increasing energy price makes capital price and labor wage relatively cheaper than before and the substitutable relationships between capital and energy or labor and energy are no longer stable and efficient.

5.3. Technological Change and Total Factor Productivity (TFP)

To address the issue of technological change, following the methods of Binswanger (1974) and Debertin (1990), the technical changes of each fuel/factor during the sample period are captured through the following equations:

$$(22) \qquad U_i^{fuel} = \left(\frac{\partial S_i}{\partial t}\right)\left(\frac{1}{S_i}\right) = \frac{\beta_{it0} + \sum_{i=1}^{k} \beta_{itm} D_m}{S_i},$$

$$(23) \qquad U_i^{factor} = \left(\frac{\partial R_i}{\partial t}\right)\left(\frac{1}{R_i}\right) = \frac{\alpha_{it0} + \sum_{i=1}^{k} \alpha_{itm} D_m}{R_i},$$

where α, β are the parameter estimates from the static translog models, and R_i and S_i denote the factor share and fuel share of the *i*th inputs. Given that the factor/fuel shares are always positive, the technical change is progressive if U_i is positive, and regressive if negative. If U_i is close to zero, the technological change is considered neutral.

As shown in Table 13 the impact of technological change in oil is larger than in coal and gas. Technological change bias appears to be coal regressive, but oil and gas progressive in most of the regions. Table 13 also presents technological change bias in factor demand, which tends to be capital regressive, but labor and energy progressive in most of the regions.

In addition to technological change bias, total factor productivity (*TFP*) is an important index accounting for changes in total output not caused by the amount of inputs used in production. Increases in *TFP* usually result from technological improvement or innovation, efficiency and specialization. Following Avila and Evenson (1995), the least restrictive derivation is from the accounting relationship where *TFP* is the residual between output growth rate and inputs' growth rates. The derivation is as follows.

First consider that the total value of production is equal to total value of inputs:

(24) $P_{Y_t}Y_t = \sum_{i=1}^{n} P_{it}\ Q_{it}$,

where P_{Y_t} denotes the price of output i at time t; Q_{it} denotes the quantity of input i at time t. The rate of change, taking variable P_{Y_t} as an example, is defined as:

(25) $\widehat{P_{Y_t}} = \frac{\partial P_{Y_t}}{P_{Y_t}\partial t}dt.$

Equation (24) is expressed in change rate form by (26). Then divide both sides of Equation (26) by $P_{Y_t}Y_t$ and substitute R_i, the factor share of input i, for $\frac{P_{it}Q_{it}}{\sum_{i=1}^{n} P_{it}\,Q_{it}}$. The total factor productivity growth rate is expressed by Equation (27).

(26) $Y_t\frac{\partial P_{Y_t}}{\partial t}dt + P_{Y_t}\frac{\partial Y_t}{\partial t}dt = \sum_{i=1}^{n} P_{it}\ \frac{\partial Q_{it}}{\partial t}dt + \sum_{i=1}^{n} Q_{it}\frac{\partial P_{it}}{\partial t}dt.$

(27) $\widehat{TFP_t} = \widehat{Y_t} - \sum_{i=1}^{n}\ \widehat{Q_{it}}$

The indexes of *TFP* estimates from the factor-input model are shown in Table 14 and Figure 4 for each region. Labor and energy production efficiency (output per unit input) are shown in Figures 5 and 6.

Table 14 expresses the *TFP* growth rates for factor inputs from 2001 to 2008 by region, as well as the average *TFP* for each region and each year. Alabama and SPP perform worst with most of the low *TFP* in each year, which is mainly due to the low labor production efficiency in Alabama and the low energy and labor production efficiency in SPP as shown in Figures 5 and 6. However, New York and Texas, with low energy production efficiency and medium labor production efficiency, perform rather better than the other regions.

From the perspective of time period, average regional *TFP* shows the best performance in 2005 and 2008, which is probably due to the implementation of the Energy Policy Act of 2005, the Energy Independence and Security Act of 2007, and the Emergency Economic Stabilization Act of 2008. In the worst-performing regions, most experienced negative *TFP* growth rate in 2002 and 2007. Large negative *TFP* developments in Alabama and SPP pulled the average down below zero. The negative indices suggest deteriorating effects from elements other than factor inputs in the electricity industry. Those elements are likely to involve insufficient innovation or R&D, the reduction or delay in "clean" capacity investment because of the uncertainty of environmental policy, the potential cost for pollution control or tradable emissions, or the reduction of investment in hydrocarbons under policies that encourage generation from renewable sources or "green" sources. It is likely that regions with low or negative *TFP* realize less technological improvement and bear higher underlying cost from environmental regulations.

6. Conclusion and policy implication

This paper examines static and dynamic regional interfuel and interfactor substitution and measures technological change, production efficiency and total factor productivity in the eastern US electric power industry. In this study, electricity generation considers three fuel inputs (coal, oil and gas) and two factor inputs (capital and labor). A two-stage translog model is used to analyze annual data from seven regions in the eastern US.

For interfuel elasticities, the empirical results show that all the own price elasticities in the static and dynamic models are negative. Oil has the largest magnitude of own price elasticities while coal has the smallest. While complementarity exists between coal and oil, substitutability is shown between coal and gas, and between oil and gas in both the static and dynamic models, with the exceptions of New York and Texas, which have opposite signs for cross price elasticities compared to other regions. However, it also has to be taken into consideration that coal is used in baseload generators that never shut down, gas used as a peak fuel is not designed to run continuously, and switching fuels is costly or impossible except between coal and oil.

The results imply that regulations on the price of oil would be the most effective, and the least effective on the price of coal. Policy makers' use of a full array of taxes and subsidies should take into account the varying elasticities of substitution in different regions. For instance, New York and Texas might suffer from a taxation/subsidy policy that was desirable for Alabama.

For interfactor elasticities, the static and dynamic models tell different stories. In the static model, for all seven regions, the elasticities are of the same sign without exception: own price elasticities are negative, cross elasticities are positive and statistically significant. Aggregate energy has the largest magnitude of own price elasticities while capital has the smallest. The static model shows unit substitutability between capital and labor, weak substitutability between capital and energy, and strong substitutability between labor and energy.

In sharp contrast, the dynamic model shows positive own price elasticities for capital in all regions and negative cross price elasticities, with the exceptions of Alabama and the Southeast.

Capital and labor appear to be complementary in five regions. Complementarities are detected between capital and aggregate energy, and between labor and aggregate energy under the dynamic models. The results suggest that energy price has the largest response to price regulations and capital has the smallest. However, unlike the risk of making inconsistent policies for fuel inputs, government planners could be more confident in making consistent policies related to capital, labor and aggregate energy.

The technological change estimates show regional variation, but the general trend suggests movement to energy-intensive technology with higher efficiency in coal input and capital investment. The results of the total factor productivity analysis also suggest the need for more technological or R&D investments in the electricity industry, especially for regions with low or negative *TFP* such as Alabama and SPP. Energy policy authorities should consider incentivizing corresponding regulations for those regions with negative *TFP*.

In summary, these elasticity estimates are relatively high compared to other national or international studies, which is sensible considering that regional differences are lost in aggregation. These results also reveal different magnitudes and signs in regional elasticities of substitution, suggesting that energy price policy and energy tax/subsidy policy should pay more attention to regional characteristics so as to more efficiently allocate resources.

Appendix:

Table 1. Selected studies on fuel substitution in the electric power industry

Author	Country	Dataset	Estimation Techniques	Estimated Substitution Elasticities
Hudson and Jorgenson (1974)	US	state-level, 1947-1971, annual	translog cost model	e^*_{CO}=1.09 e^*_{CG}=0.09 e^*_{OG}=0.39
Atkinson and Halvorsen (1976a)	US	firm-level cross section,1972	translog normalized restricted profit function	e^*_{CC}=-0.01; e^*_{CO}=0.3 to 5.52 e^*_{OO}=0.01; e^*_{CG}=-0.79 to 0.2 e^*_{GG}=-2.55; e^*_{GO}=0.25 to 8.22
Atkinson and Halvorsen (1976b)	US	aggregate, monthly time series, 1972–1974,shortrun	translog profit function	e^*_{CC}=-0.39 to -3.9 e^*_{OO}=-0.56 to -4.12 e^*_{GG}=-0.34 to -10.5 e^*_{CO}=0.3 to 5.52 e^*_{CG}=-0.79 to 0.21 e^*_{GO}=0.25 to 8.22
Griffin (1977)	20 OECD countries	pooled data; 1955, 1960, 1965 and 1969; annual	translog cost function	e^*_{CC}=-0.66; e^*_{OO}=-3.46 e^*_{GG}=-0.9; e^*_{CO}=0.5 e^*_{CG}=0.16; e^*_{GO}=0.58
Uri (1977)	9 US regions	pooled data, 1952–1974,annual	translog cost function	e^*_{CC}=-0.38 to -4.01 e^*_{OO}=-0.34 to -3.04 e^*_{GG}=-0.55 to -2.95 σ_{CO}=1.90 to 121.93 σ_{CG}=1.72 to 3.54 σ_{OG}=1.94 to 4.06
Bopp and Costello (1990)	(1)5 US regions (2)US	short run ,monthly time series,1977–1987	two translog cost function models	e^*_{CC}=-0.52 to 0.38 e^*_{OO}=-0.39 to -1.29 e^*_{GG}=-0.25 to -0.4 e^*_{CO}=0.73; e^*_{OC}=0.57 e^*_{CG}=1.14; e^*_{OG}not reported e^*_{GC}=0.29 to 0.82 e^*_{GO}=1.15 to 1.42
Söderholm (2000)	7 Western European countries	pooled annual aggregate national data 1978-1995,shortrun	generalized Leontief cost function	e^*_{CC}=-0.08 to -0.49 e^*_{OO}=-0.23 to -2.98 e^*_{GG}=-0.22 to –8.81 e^*_{CO}=0.07 to 2.34 e^*_{OC}=0.07 to 1.04 e^*_{CG}=0.01 to 0.56 e^*_{GC}=0.02 to 0.93 e^*_{GO}=0.22 to 7.88 e^*_{OG}=0.52 to 1.94

Ko and Dahl (2001)	US	monthly panel data for 185 US utilities in 1993	translog cost function	e^*_{CC}=-0.57; e^*_{OO}=-3.05 e^*_{GG}=-1.46; e^*_{CO}=0.29 e^*_{OC}=3.21; e^*_{CG}=0.28 e^*_{GC}=1.54; e^*_{OG}=-0.15 e^*_{GO}=-0.08

Table definitions: C=coal; O=oil; G=gas.

Table 2. Selected studies on factor and fuel substitution using the two-stage translog function outside electric power industry

Author	Dataset	Inputs	Country and industry	Estimation techniques	Main Results
Pindyck(1979)	Pooled data, 1963-1973;annual	*K,L,E(C, O, G, EL)*	Ten Countries;	Two-stage translog cost function	(K:L), (E:L)=substitutes (C:O),(C:E),(C:G),(E:O)= substitutes (G:O),(G:E)=complements
Cho(2004)	Pooled data; 1981-1997; quarterly data	*K,L,E(C, O EL)*	Korea	Two-stage dynamic translog cost function	(K:L), (K,E)=substitutes (E:L)=complements (C:O)= substitutes (E:O),(C:E)=complements
Ma, Oxley, Gibson and Kim(2008)	Pooled data; 1995-2004; annual	*K,L,E(C, O, G, EL)*	Ten regions of China; Industry	Two-stage translog cost function	(K:L),(K:E),(E:L)=substitutes (C:E),(G:O),(E:O)=substitutes (C:O)=complements
Andrikopoulos, Brox and Paraskevopoulos (1989)	Pooled; 1962-1982;annual	*K,L,E(C, O,G,EL)*	Ontario; seven manufacturing industries	Two-stage translog production function; FIML	(K:L),(E:L)=substitutes (C:G),(G:O),(E:O)=substitutes (C:O)=complements
Taheri (1994)	Pooled data; 1974-1981		US; eleven 2-digit manufacturing	Dynamic two-stage translog cost function	(C:O),(E:O)=substitutes (G:O)=complements

Table definitions: *K*=capital; *L*=labor; *E*=energy; *C*=coal; *O*=oil; *G*=gas; *EL*=electricity; *NEL*=non-electricity energy;

Table 3. t-values from panel unit root test results

Fuel		*Factor*	
lnP_1	-9.58***	*lnY*	-0.01***
lnP_2	-12.27***	*lnw*	-50.22***

lnP$_3$	-2.53***	*lnr*	-4.81***
S$_1$	-6.00***[a]	*lne*	-4.00***
S$_2$	-8.04***	*R*$_1$	-7.17***
S$_3$	-3.47***	*R*$_2$	-1.1e+04***[a]
		R$_3$	-1.5e+04***[a]

Notes: The adjusted t values are obtained from Levin-Lin-Chu panel unit root tests including time trend with one lag. *LR* variance: Bartlett kernel, 6 lags average (chosen by *LLC*). H_o= Panels contain unit roots. H_a= Panels are stationary. (*), (**) and (***) denote rejection of the null hypothesis at the 10%, 5% and 1% level. [a] denotes time trend not included.

Table 4. Parameter estimates of static and dynamic translog fuel cost share equations

Static				Dynamic			
Variable	Coal	Oil	Gas	*Variable*	Coal	Oil	Gas
Intercept	0.351***	0.222***	0.427***	*Intercept*	0.21*	0.22***	0.57*
	(0.030)	(0.066)	(0.072)		(0.12)	(0.08)	(0.14)
lnp1	0.167***	-0.033*	-0.133*	*lnp1*	0.18***	-0.03*	-0.14*
	(0.018)	(0.025)	(0.031)		(0.02)	(0.03)	(0.04)
lnp2	-0.033	-0.094*	0.127	*lnp2*	-0.03*	-0.10*	0.13*
	(0.025)	(0.053)	(0.059)		(0.03)	(0.06)	(0.07)
lnp3	-0.133***	0.127***	0.006***	*lnp3*	-0.14***	0.13**	0.01**
	(0.020)	(0.045)	(0.049)		(0.03)	(0.05)	(0.06)
t	-0.001	0.003	-0.001	*t*	0.00	0.00	0.00
	(0.003)	(0.007)	(0.008)		(0.01)	(0.01)	(0.01)
d2	-0.218***	0.176***	0.042***	*d2*	-0.13	0.07	0.06
	(0.018)	(0.035)	(0.039)		(0.15)	(0.18)	(0.23)
d3	0.096***	0.082**	-0.178**	*d3*	0.39**	0.09*	-0.48*
	(0.018)	(0.035)	(0.040)		(0.17)	(0.09)	(0.19)
d4	-0.451***	0.345***	0.106***	*d4*	-0.42***	0.25***	0.17***
	(0.018)	(0.036)	(0.040)		(0.08	(0.09)	(0.12)
d5	0.239***	-0.014*	-0.225*	*d5*	0.52*	0.00	-0.52
	(0.018)	(0.035)	(0.039)		(0.26)	(0.12)	(0.29)
d6	-0.052***	-0.005*	0.057*	*d6*	0.03	0.00	-0.03
	(0.019)	(0.037)	(0.041)		(0.16)	(0.08)	(0.17)
d7	-0.344***	-0.018	0.361	*d7*	-0.26*	-0.04	0.30
	(0.018)	(0.035)	(0.040)		(0.13)	(0.11)	(0.17)
d2t	-0.002	-0.006	0.008	*d2t*	0.00	0.00	0.00
	(0.003)	(0.006)	(0.007)		(0.01)	(0.01)	(0.01)
d3t	-0.003	0.002	0.001	*d3t*	-0.01*	0.00	0.01*
	(0.003)	(0.006)	(0.007)		(0.01)	(0.01)	(0.01)
d4t	0.008**	-0.018***	0.010**	*d4t*	0.01*	-0.02**	0.01*
	(0.003)	(0.006)	(0.007)		(0.01)	(0.01)	(0.01)
d5t	0.003	0.007	-0.010	*d5t*	0.00	0.01*	-0.01
	(0.003)	(0.006)	(0.007)		(0.01)	(0.01)	(0.01)

d6t	-0.013***	0.006	0.007	*d6t*	-0.01*	0.01*	0.01*
	(0.003)	(0.006)	(0.007)		(0.01)	(0.01)	(0.01)
d7t	0.009***	0.006*	-0.014	*d7t*	0.01*	0.01*	-0.01*
	(0.003)	(0.006)	(0.007)		(0.01)	(0.01)	(0.01)
				s	0.23*	0.44	-0.67
					(0.21)	(2.06)	(2.07)
				d2s	-0.15	0.02	0.13
					(0.38)	(2.12)	(2.15)
				d3s	-0.51*	-0.27	0.78
					(0.29)	(2.08)	(2.10)
				d4s	1.03*	-0.05	-0.98
					(0.81)	(2.06)	(2.21)
				d5s	-0.43*	-0.85	1.28
					(0.36)	(3.67)	(3.69)
				d6s	-0.13	-0.70	0.84
					(0.30)	(2.58)	(2.59)
				d7s	-0.04	1.42	-1.38
					(0.46)	(7.76)	(7.77)

Notes: Numbers in parentheses are the standard errors. Parameter estimates and standard errors for gas are calculated based on homogeneity restrictions and error propagation. (*), (**) and (***) denote statistically significance at the 10%, 5% and 1% level.

Table 5. Mean fuel and factor cost share for each region

	Fuel			Factor		
	S_C	S_O	S_G	R_K	R_L	R_E
AL	0.50	0.01	0.49	0.58	0.32	0.10
SE	0.26	0.17	0.57	0.70	0.25	0.04
PJM	0.57	0.12	0.32	0.77	0.17	0.07
NY	0.06	0.28	0.67	0.69	0.18	0.13
MW	0.74	0.03	0.23	0.69	0.19	0.12
SPP	0.40	0.02	0.58	0.48	0.43	0.09
TX	0.18	0.01	0.81	0.50	0.41	0.09

Table 6. Static Hicksian conditional price elasticity and Allen elasticities of substitution for fuel inputs

	AL	*SE*	*PJM*	*NY*	*MW*	*SPP*	*TX*
e^*_{CC}	-0.17	-0.10	-0.14	1.76	-0.04	-0.18	0.10
	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)
e^*_{CO}	-0.05	0.04	0.06	-0.25	-0.01	-0.06	-0.17
	(0.11)	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.12)
e^*_{CG}	0.22	0.06	0.08	-1.49	0.05	0.25	0.07
	(0.12)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.13)

e^*_{OC}	-2.26	0.06	0.28	-0.06	-0.22	-1.30	-2.24
	(0.12)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.13)
e^*_{OO}	-8.75	-1.40	-1.70	-1.04	-3.66	-5.74	-7.79
	(0.15)	(0.12)	(0.12)	(0.12)	(0.12)	(0.13)	(0.16)
e^*_{OG}	11.01	1.34	1.42	1.12	3.88	7.04	10.03
	(0.16)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.17)
e^*_{GC}	0.23	0.03	0.15	-0.41	0.15	0.17	0.02
	(0.13)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.14)
e^*_{GO}	0.27	0.39	0.52	0.47	0.59	0.24	0.17
	(0.16)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.17)
e^*_{GG}	-0.50	-0.42	-0.66	-0.32	-0.75	-0.41	-0.19
	(0.17)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.18)
σ_{CO}	-4.52	0.23	0.49	-0.89	-0.30	-3.27	-12.39
	(0.12)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.13)
σ_{CG}	0.45	0.11	0.26	-2.22	0.20	0.42	0.08
	(0.13)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.14)
σ_{OG}	22.58	2.34	4.47	1.67	17.09	12.04	12.45
	(0.19)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.20)

Notes: Numbers in parentheses are the standard errors. Elasticities are calculated with the means of each fuel cost shares for each region as shown in Table 5.

Table 7. Static Marshallian unconditional price elasticities for fuel inputs

	AL	*SE*	*PJM*	*NY*	*MW*	*SPP*	*TX*
E_{CC}	-1.08	-0.95	-1.48	1.66	-1.24	-0.94	-0.25
E_{CO}	-0.08	-0.49	-0.22	-0.70	-0.07	-0.10	-0.20
E_{CG}	-0.67	-1.78	-0.66	-2.54	-0.33	-0.87	-1.51
E_{OC}	-3.17	-0.78	-1.06	-0.15	-1.43	-2.05	-2.59
E_{OO}	-8.77	-1.94	-1.97	-1.49	-3.72	-5.78	-7.82
E_{OG}	10.12	-0.50	0.67	0.06	3.51	5.92	8.45
E_{GC}	-0.69	-0.82	-1.19	-0.50	-1.06	-0.59	-0.34
E_{GO}	0.25	-0.15	0.24	0.03	0.54	0.20	0.14
E_{GG}	-1.39	-2.26	-1.41	-1.37	-1.12	-1.52	-1.76

Table 8. Dynamic Hicksian conditional price elasticity and Allen elasticities of substitution for fuel inputs

	AL	SE	PJM	NY	MW	SPP	TX
e^*_{CC}	-0.15	-0.07	-0.12	1.91	-0.02	-0.16	0.15
	(0.11)	(0.21)	(0.20)	(0.27)	(0.23)	(0.20)	(0.22)
e^*_{CO}	-0.05	0.04	0.06	-0.23	-0.01	-0.06	-0.16
	(0.19)	(0.31)	(0.30)	(0.360	(0.35)	(0.31)	(0.42)
e^*_{CG}	0.20	0.02	0.06	-1.66	0.03	0.22	0.01
	(0.19)	(0.32)	(0.31)	(0.36)	(0.36)	(0.32)	(0.42)

e^*_{OC}	-2.15	0.07	0.29	-0.05	-0.18	-1.23	-2.14
	(0.38)	(0.68)	(0.67)	(0.67)	(0.86)	(0.72)	(1.34)
e^*_{OO}	-8.02	-1.42	-1.72	-1.06	-3.75	-5.90	-8.02
	(0.43)	(0.75)	(0.74)	(0.73)	(0.95)	(0.80)	(1.46)
e^*_{OG}	11.16	1.35	1.43	1.12	3.93	7.13	10.16
	(0.43)	(0.76)	(0.74)	(0.74)	(0.95)	(0.80)	(1.46)
e^*_{GC}	0.21	0.01	0.11	-0.44	0.10	0.15	0.00
	(0.38)	(0.70)	(0.68)	(0.70)	(0.89)	(0.74)	(1.35)
e^*_{GO}	0.28	0.39	0.52	0.48	0.60	0.24	0.17
	(0.44)	(0.77)	(0.75)	(0.76)	(0.97)	(0.82)	(1.47)
e^*_{GG}	-0.48	-0.40	-0.64	-0.31	-0.71	-0.39	-0.18
	(0.44)	(0.77)	(0.76)	(0.76)	(0.98)	(0.82)	(1.47)
σ_{CO}	-4.29	0.26	0.51	-0.82	-0.25	-3.10	-11.84
	(0.20)	(0.33)	(0.31)	(0.37)	(0.37)	(0.32)	(0.43)
σ_{CG}	0.41	0.04	0.20	-2.48	0.14	0.38	0.01
	(0.20)	(0.33)	(0.32)	(0.38)	(0.37)	(0.33)	(0.43)
σ_{OG}	22.90	2.36	4.52	1.68	17.32	12.20	12.62
	(0.46)	(0.79)	(0.77)	(0.77)	(0.98)	(0.83)	(1.49)

Notes: Numbers in parentheses are the standard errors. Elasticities are calculated with the means of each fuel cost shares for each region as shown in Table 5.

Table 9. Dynamic Marshallian fuel price unconditional elasticity

	AL	SE	PJM	NY	MW	SPP	TX
E_{CC}	-0.93	-0.74	-1.23	1.82	-1.07	-0.8	-0.14
E_{CO}	-0.07	-0.38	-0.17	-0.62	-0.06	-0.09	-0.19
E_{CG}	-0.56	-1.45	-0.55	-2.57	-0.29	-0.73	-1.33
E_{OC}	-2.93	-0.61	-0.82	-0.14	-1.23	-1.87	-2.44
E_{OO}	-8.03	-1.85	-1.95	-1.45	-3.8	-5.93	-8.04
E_{OG}	10.4	-0.12	0.82	0.21	3.61	6.18	8.83
E_{GC}	-0.58	-0.66	-0.99	-0.53	-0.94	-0.49	-0.3
E_{GO}	0.26	-0.04	0.3	0.09	0.55	0.21	0.15
E_{GG}	-1.25	-1.88	-1.26	-1.23	-1.03	-1.34	-1.51

Table 10. Static and dynamic parameter estimates for factor share equations

Static				*Dynamic*			
Variable	Capital	Labor	Energy	*Variable*	Capital	Labor	Energy
Intercept	-6.034**	3.640*	3.393*	*Intercept*	5.51*	-7.33*	2.82*
	(2.799)	(3.243)	(4.284)		(3.80)	(5.06)	(6.32)
lnp1	0.253***	-0.183***	-0.070***	*lnp1*	0.30***	-0.22***	-0.08***
	(0.019)	(0.022)	(0.029)		(0.03)	(0.04)	(0.04)

lnp2	-0.183*** (0.022)	0.071** (0.029)	0.112** (0.037)	*lnp2*	-0.22*** (0.04)	0.09* (0.05)	0.13* (0.06)
lnp3	-0.070*** (0.007)	0.112*** (0.012)	-0.042*** (0.014)	*lnp3*	-0.08*** (0.01)	0.13*** (0.02)	-0.05*** (0.02)
lny	0.338** (0.150)	-0.153 (0.175)	-0.185 (0.230)	*lny*	-0.30* (0.20)	0.43* (0.27)	-0.13* (0.34)
t	-0.011*** (0.003)	0.010*** (0.003)	0.001*** (0.004)	*t*	0.00 (0.00)	0.00 (0.01)	0.00 (0.01)
d2	-1.492 (0.055)	0.204 (0.061)	1.288 (0.082)	*d2*	-8.59 (0.07)	5.89 (0.09)	2.70 (0.11)
d3	-4.650* (0.053)	1.138 (0.059)	3.512 (0.079)	*d3*	-1.85 (0.07)	0.84 (0.09)	1.02 (0.12)
d4	18.281*** (0.042)	-15.326*** (0.049)	-2.955*** (0.064)	*d4*	2.71 (0.05)	-2.16 (0.07)	-0.56 (0.08)
d5	8.594* (0.073)	-6.917 (0.081)	-1.676 (0.109)	*d5*	28.17** (0.11)	-29.02** (0.14)	0.85** (0.18)
d6	-8.503* (0.045)	5.561* (0.050)	2.942* (0.068)	*d6*	-9.09* (0.05)	7.75 (0.07)	1.33 (0.08)
d7	-8.492* (0.080)	13.906* (0.088)	-5.414* (0.118)	*d7*	-15.42* (0.09)	22.72* (0.12)	-7.30* (0.16)
d2y	0.039 (0.027)	0.007 (0.030)	-0.046 (0.040)	*d2y*	0.45 (0.03)	-0.32 (0.04)	-0.13 (0.06)
d3y	0.203 (0.027)	-0.046 (0.029)	-0.157 (0.040)	*d3y*	0.11 (0.04)	-0.07 (0.05)	-0.03 (0.06)
d4y	-0.988*** (0.023)	0.823*** (0.026)	0.165*** (0.034)	*d4y*	-0.15 (0.03)	0.13 (0.04)	0.03 (0.05)
d5y	-0.453* (0.036)	0.352 (0.040)	0.101 (0.054)	*d5y*	-1.39*** (0.05)	1.40** (0.07)	0.00 (0.09)
d6y	0.461* (0.025)	-0.299 (0.027)	-0.162 (0.037)	*d6y*	0.49* (0.03)	-0.40 (0.04)	-0.09 (0.05)
d7y	0.400* (0.040)	-0.684* (0.045)	0.284* (0.060)	*d7y*	0.80* (0.05)	-1.16* (0.06)	0.36 (0.08)
d2t	0.000 (0.004)	0.000 (0.004)	-0.001 (0.006)	*d2t*	-0.01 (0.01)	0.01 (0.01)	0.00 (0.01)
d3t	0.002 (0.004)	-0.003 (0.004)	0.001 (0.006)	*d3t*	-0.01 (0.00)	0.00 (0.01)	0.00 (0.01)
d4t	0.013*** (0.003)	-0.011*** (0.003)	-0.002*** (0.004)	*d4t*	0.00 (0.00)	0.00 (0.01)	0.00 (0.01)
d5t	0.013*** (0.005)	-0.011** (0.005)	-0.001** (0.007)	*d5t*	0.02*** (0.01)	-0.02** (0.01)	0.00 (0.01)

d6t	-0.022***	0.017**	0.005**	*d6t*	-0.01	0.01	0.00
	(0.007)	(0.008)	(0.010)		(0.01)	(0.01)	(0.01)
d7t	0.005	-0.001	-0.003	*d7t*	-0.01*	0.01*	0.00
	(0.005)	(0.006)	(0.008)		(0.01)	(0.01)	(0.01)
				S	0.47***	0.46***	-0.93***
					(0.08)	(0.12)	(0.14)
				d2s	-0.30	-0.26	0.56
					(0.20)	(0.23)	(0.30)
				d3s	0.10	0.08	-0.18
					(0.21)	(0.27)	(0.34)
				d4s	-0.21	-0.17	0.38
					(0.19)	(0.21)	(0.29)
				d5s	0.57*	0.54	-1.11
					(0.31)	(0.42)	(0.52)
				d6s	-0.34***	-0.37**	0.71**
					(0.12)	(0.16)	(0.20)
				d7s	-0.29**	-0.27*	0.56*
					(0.13)	(0.17)	(0.21)

Notes: Numbers in parentheses are the standard errors. Parameter estimates and standard errors for capital are calculated based on homogeneity restrictions and error propagation. (*), (**) and (***) denote statistically significance at the 10%, 5% and 1% level.

Table 11. Static Hicksian price elasticities and Allen elasticities of substitution for factor inputs

	AL	SE	PJM	NY	MW	SPP	TX
E^*_{KK}	-0.45	-0.32	-0.26	-0.34	-0.34	-0.56	-0.54
	(0.24)	(0.26)	(0.26)	(0.25)	(0.28)	(0.26)	(0.28)
E^*_{KL}	0.32	0.25	0.17	0.18	0.19	0.43	0.41
	(0.26)	(0.28)	(0.28)	(0.27)	(0.30)	(0.27)	(0.30)
E^*_{KE}	0.13	0.07	0.09	0.16	0.15	0.13	0.13
	(0.31)	(0.33)	(0.33)	(0.32)	(0.35)	(0.32)	(0.36)
E^*_{LK}	0.58	0.71	0.77	0.69	0.69	0.48	0.50
	(0.27)	(0.29)	(0.29)	(0.28)	(0.31)	(0.28)	(0.31)
E^*_{LL}	-0.92	-1.05	-1.29	-1.26	-1.22	-0.75	-0.78
	(0.29)	(0.31)	(0.31)	(0.30)	(0.32)	(0.30)	(0.33)
E^*_{LE}	0.34	0.34	0.52	0.57	0.53	0.27	0.28
	(0.33)	(0.36)	(0.35)	(0.35)	(0.37)	(0.35)	(0.38)
E^*_{EK}	0.76	1.15	1.04	0.80	0.84	0.68	0.70
	(0.34)	(0.37)	(0.36)	(0.36)	(0.39)	(0.36)	(0.40)
E^*_{EL}	1.07	2.08	1.31	0.74	0.80	1.23	1.25
	(0.35)	(0.38)	(0.38	(0.37)	(0.40)	(0.37)	(0.41)
E^*_{EE}	-1.83	-3.22	-2.36	-1.57	-1.64	-1.91	-1.95
	(0.39)	(0.42)	(0.42)	(0.41)	(0.45)	(0.41)	(0.46)

σ_{KK}	-0.78	-0.46	-0.34	-0.49	-0.49	-1.17	-1.08
	(0.29)	(0.31)	(0.31)	(0.30)	(0.33)	(0.30)	(0.33)
σ_{KL}	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	(0.30)	(0.33)	(0.32)	(0.32)	(0.34)	(0.32)	(0.35)
σ_{KE}	1.31	1.63	1.36	1.20	1.22	1.41	1.41
	(0.34)	(0.37)	(0.37)	(0.36)	(0.39)	(0.36)	(0.40)
σ_{LL}	-2.88	-4.11	-7.75	-7.21	-6.48	-1.77	-1.89
	(0.34)	(0.36)	(0.36)	(0.35)	(0.38)	(0.36)	(0.39)
σ_{LE}	3.34	8.17	7.87	4.24	4.26	2.89	3.05
	(0.37)	(0.40)	(0.40)	(0.39)	(0.42)	(0.40)	(0.43)
σ_{EE}	-17.97	-77.32	-35.43	-11.72	-13.19	-20.26	-21.62
	(0.45)	(0.49)	(0.49)	(0.48)	(0.52)	(0.48)	(0.53)

Notes: Numbers in parentheses are the standard errors. Elasticities are calculated with the means of each factor-input cost shares for each region as shown in Table 5.

Table 12. Dynamic Hicksian price elasticity and Allen elasticities of substitution for factor inputs

	AL	SE	PJM	NY	MW	SPP	TX
E^*_{KK}	0.03	0.07	0.11	0.07	0.06	0.02	0.02
	(0.37)	(0.86)	(0.02)	(0.73)	(1.34)	(0.69)	(1.05)
E^*_{KL}	0.08	0.06	-0.01	-0.02	-0.01	0.14	0.14
	(0.43)	(0.95)	(0.03)	(0.82)	(1.51)	(0.77)	(1.19)
E^*_{KE}	-0.11	-0.13	-0.09	-0.04	-0.05	-0.16	-0.15
	(0.49)	(1.08)	(0.03)	(0.93)	(1.69)	(0.88)	(1.34)
E^*_{LK}	0.15	0.16	-0.06	-0.09	-0.04	0.16	0.16
	(0.47)	(1.09)	(0.03)	(0.92)	(1.85)	(0.88)	(1.41)
E^*_{LL}	-0.84	-0.95	-1.15	-1.12	-1.09	-0.7	-0.72
	(0.52)	(1.17)	(0.03)	(1.00)	(2.00)	(0.95)	(1.53)
E^*_{LE}	0.7	0.79	1.2	1.22	1.13	0.54	0.55
	(0.58)	(1.29)	(0.04)	(1.11)	(2.16)	(1.05)	(1.67)
E^*_{EK}	-0.62	-2.22	-1.07	-0.01	-0.3	-0.82	-0.85
	(0.58)	(1.43)	(0.03)	(1.20)	(2.46)	(1.13)	(1.85)
E^*_{EL}	2.18	4.8	3.02	1.59	1.72	2.44	2.51
	(0.63)	(1.50)	(0.03)	(1.26)	(2.58)	(1.20)	(1.95)
E^*_{EE}	-1.56	-2.58	-1.95	-1.37	-1.42	-1.62	-1.66
	(0.68)	(1.60)	(0.03)	(1.36)	(2.73)	(1.28)	(2.07)
	0.03	0.07	0.11	0.07	0.06	0.02	0.02
σ_{KK}	(0.43)	(0.97)	(0.02)	(0.83)	(1.49)	(0.79)	(1.18)
	0.08	0.06	-0.01	-0.02	-0.01	0.14	0.14
σ_{KL}	(0.48)	(1.06)	(0.03)	(0.91)	(1.65)	(0.86)	(1.30)
	-0.11	-0.13	-0.09	-0.04	-0.05	-0.16	-0.15
σ_{KE}	(0.54)	(1.18)	(0.03)	(1.02)	(1.81)	(0.96)	(1.44)
	0.15	0.16	-0.06	-0.09	-0.04	0.16	0.16
σ_{LL}	(0.61)	(1.31)	(0.04)	(1.13)	(2.18)	(1.08)	(1.69)
	-0.84	-0.95	-1.15	-1.12	-1.09	-0.7	-0.72
σ_{LE}							

	(0.66)	(1.42)	(0.04)	(1.22)	(2.33)	(1.16)	(1.82)
σ_{EE}	0.7	0.79	1.2	1.22	1.13	0.54	0.55
	(0.78)	(1.77)	(0.04)	(1.51)	(2.94)	(1.43)	(2.26)

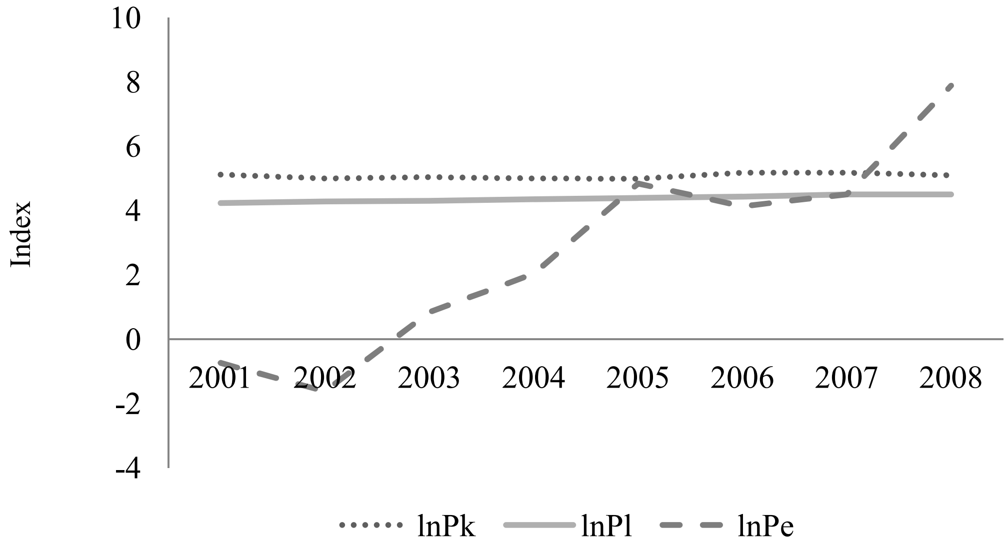
Notes: Numbers in parentheses are the standard errors. Elasticities are calculated with the means of each factor-input cost shares for each region as shown in Table 5.

Table 13. Technological change in fuel and factor demand

	Fuel			Factor		
	Coal	Oil	Gas	Capital	Labor	Energy
AL	0.00	0.22	0.00	-0.02	0.03	0.01
SE	-0.01	-0.02	0.01	-0.02	0.04	0.02
PJM	-0.01	0.04	0.00	-0.01	0.04	0.04
NY	0.10	-0.05	0.01	0.00	-0.01	-0.01
MW	0.00	0.29	-0.05	0.00	-0.01	0.00
SPP	-0.04	0.44	0.01	-0.07	0.06	0.07
TX	0.04	0.61	-0.02	-0.01	0.02	-0.02

Table 14. Total factor productivity growth rates for factor-input model

	2002	2003	2004	2005	2006	2007	2008	Average
AL	-0.23	0.00	-0.44	0.07	-0.18	-0.12	0.05	-0.12
SE	-0.18	0.00	0.00	0.30	-0.05	-0.04	0.05	0.01
PJM	0.06	-0.15	0.03	0.10	0.08	-0.09	0.00	0.00
NY	0.03	0.04	0.02	-0.13	0.11	-0.06	0.20	0.03
MW	-0.07	0.13	0.06	-0.07	0.06	-0.05	-0.01	0.01
SPP	0.01	-0.12	-0.06	-0.10	-0.06	0.00	-0.01	-0.05
TX	-0.08	0.07	0.15	0.06	0.08	0.00	0.01	0.04
Average	-0.07	0.00	-0.04	0.03	0.01	-0.05	0.04	-0.01


10
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Index
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Figure 1. Indices of average factor prices for the electric power industry in the eastern US

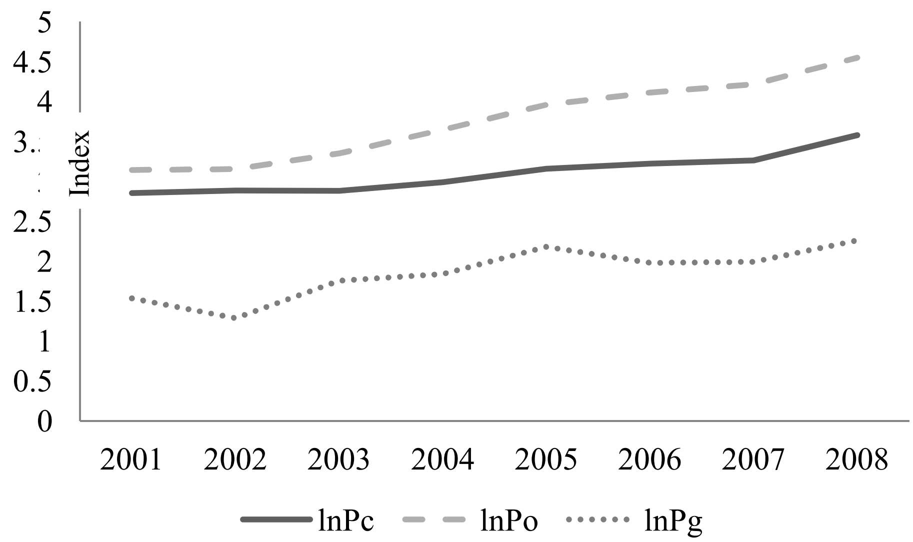

Figure 2. Indices of average fuel prices for the electric power industry in the eastern US

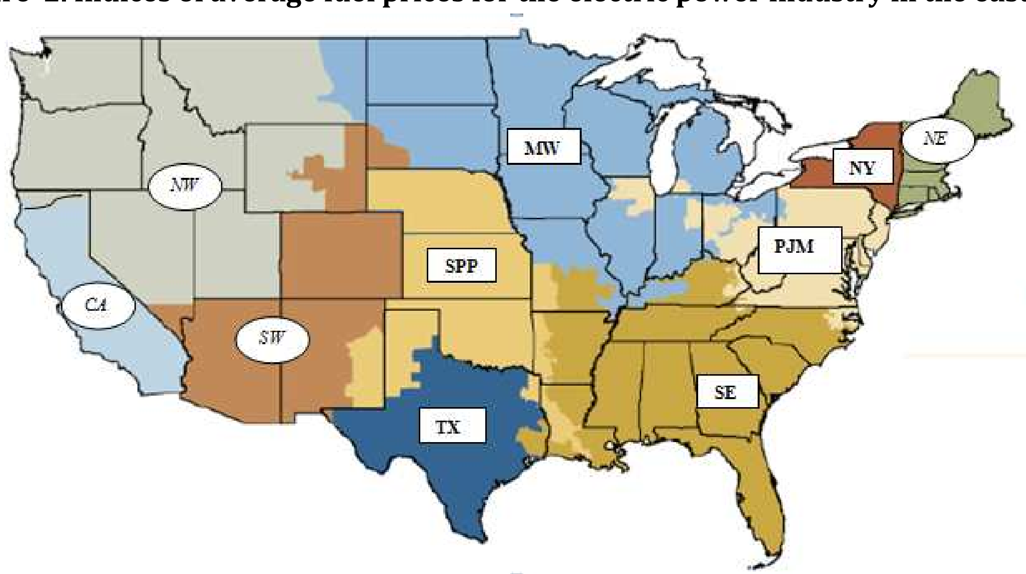

Figure 3. The electric regions in US

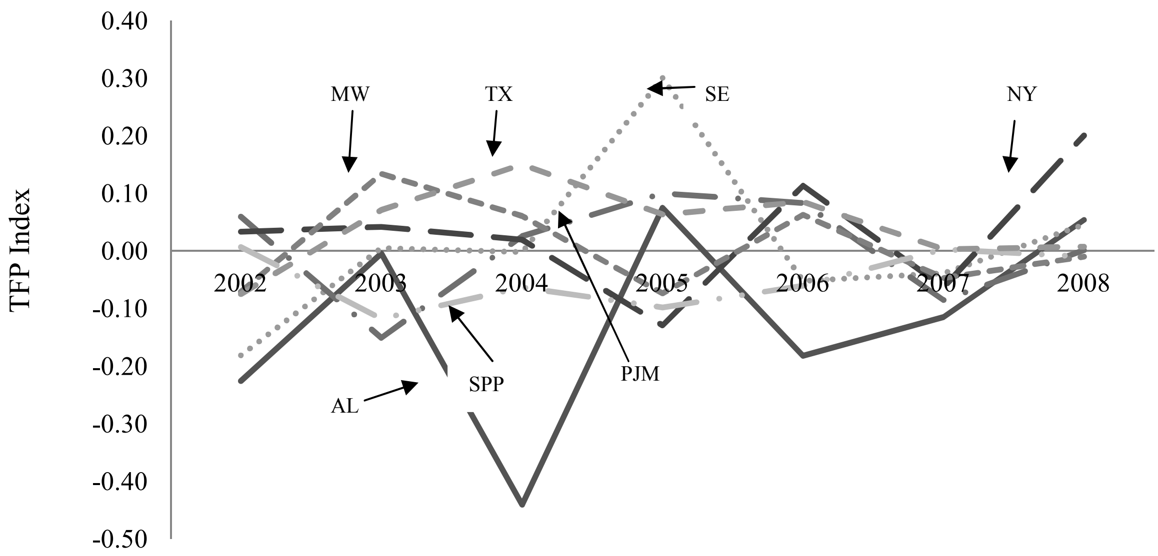

Figure 4. Total factor productivity growth rates by regions for factor-input model

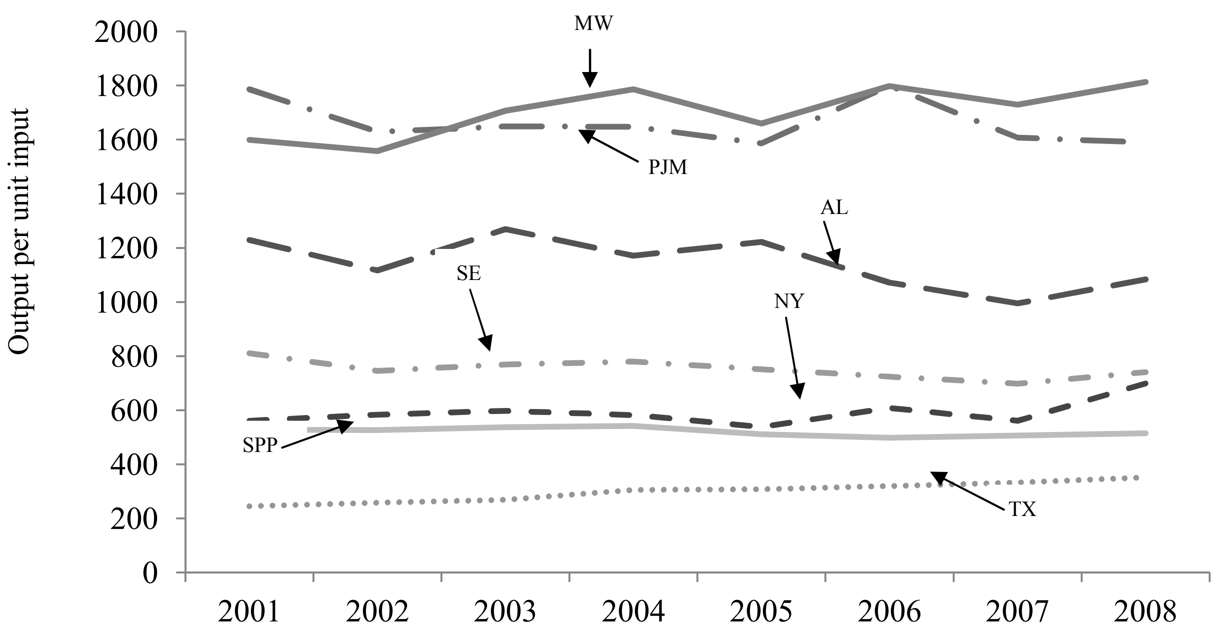

Figure 5. Energy production efficiency by region

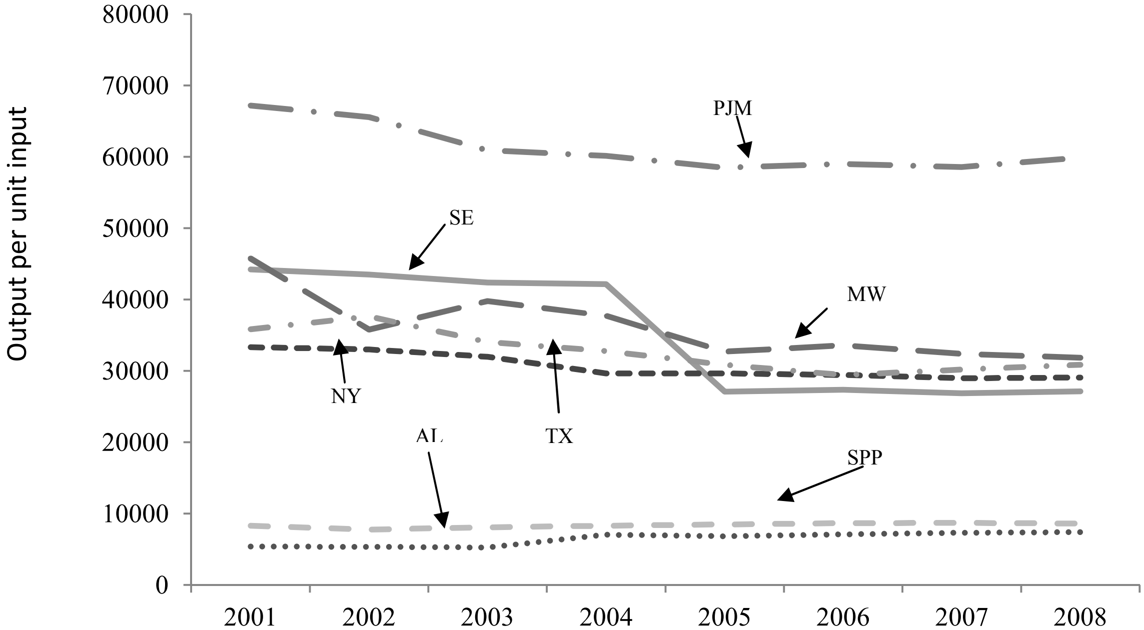

Figure 6. Labor production efficiency by region

Chapter 2: CO_2 Emissions, Non-Hydro Energy Consumption and Economic Growth: A US Study Based on Cointegration and Error-correction

1. Introduction

The objective of this paper is to examine the causal relationships between CO_2 emissions, hydrocarbon energy consumption, non-hydrocarbon energy consumption, and real GDP growth in the US from 1960 to 2009.

The most critical environmental problem of the time is global warming, which is exacerbated by continuously increasing greenhouse gas emissions. Carbon dioxide emissions accounted for more than 98% of greenhouse gas emissions in the last two decades according to World Bank World Development Indicators. Considering that the majority of emissions are caused by combustion of hydrocarbons, environmental policies mainly focus on improving energy efficiency, reducing energy consumption and switching fuel choices, all of which affect economic development.

Efficient and timely measures to jointly improve the condition of the environment and economic development are important for the US because it is one of the largest energy consumers and energy-related CO_2 emitters. The portion of hydrocarbon energy consumption in the US has decreased from 96% in 1960 to 83% in 2009, as non-hydrocarbon consumption has increased. The nexus of energy-environment-economics is an important issue that takes into account the dependence of the US on fuel consumption and the potential economic sacrifices to reduce CO_2 emissions.

The prime issue objective of this paper is to test whether hydrocarbon energy consumption, GDP growth, investment and population growth affect CO_2 emissions; in addition, whether the latter affects the former. The organization of this paper is as follows: Section 2 gives reviews of recent literature. Theoretic models and methodologies are illustrated in section 3. Section 4 describes the data and data sources. The empirical results are discussed in section 5. Section 6 concludes with policy implications.

2. Literature Review

There are three branches of recent studies exploring causal relationships between pollutant emissions, energy consumption, and economic development. The first branch focuses on the link between energy consumption and economic growth. More energy consumption is required as the economy develops, therefore as energy consumption grows, the economy develops correspondingly. Earlier studies employing Granger causality and cointegration techniques in bivariate models following Kraft and Kraft (1978) failed to reach a unanimous conclusion, probably due to the omitted variables bias and the substitution effects between energy and other inputs. Stern (1993) concluded that energy consumption Granger-causes GDP by applying a multivariate model with energy, consumption, GDP, capital, and labor force in the US. Various multivariate studies have examined the causality between energy and economic growth but still produce conflicting results, such as Masih and Masih (1998), Stern (2000), Asafu-Adjaye (2000), Glasure (2002), Soytas and Sari (2003), Oh and Lee (2004), Altinay and Laragol (2004), Wolde-Rufael (2004), Ghali and Elsakka (2004), and Lee (2006).

The second branch studies the relationship between emissions and economic growth, which initially relies on the environmental Kuznets curve (EKC) hypothesis indicating an inverted U-shaped connection between environmental degradation and economic development. The empirical results of Unruh and Moomaw (1998), Heil and Selden (1999), Taskin and Zaim (2000), Friedl and Getzner (2003), Coondoo and Dinda (2008), and Managi and Jena (2008) are controversial and are criticized for lack of feedback from emissions to GDP (see Hill and

Magnani 2002, Stern 2004). Chontanawat et al. (2008), Aslanidis and Iranzo (2009), Payne (2010) and Ozturk (2010) implemented extended research on the environmental Kuznets curve, the results of which are inconclusive as well.

The third, and newest, branch associates the first two branches and explores the nexus in environmental pollution, energy consumption, and economic development within a multivariate system. A series of econometric techniques has been applied and the results have been varied based on the variables involved, sample length and different countries. Their data, methods, and results of causal relationship are compared with the present study in Table 6.

Soytas et al. (2007) using the TY procedure [5] and a Vector autoregression (*VAR)* model, found energy consumption Granger-causes carbon emissions but found no causal relationship between GDP and emissions, or between energy consumption and GDP after controlling for the capital stock and labor from 1960 to 2004 for the US.

Ang (2008) applied multivariate cointegration as well as an error-correction model (ECM), and showed that GDP Granger-causes energy consumption and CO_2 emissions weakly Granger-cause GDP in Malaysia during the period 1971-1999.

Soytas and Sari (2009) investigated the Granger causality link between economic growth, CO_2 emissions and energy consumption controlling for the capital stock and labor in Turkey for the period 1960-2000 again using the TY procedure and VAR models. They found no link between GDP and emissions, and CO_2 emissions uni-directionally Granger cause energy consumption.

[5] TY procedure is an augmented VAR approach proposed by Toda and Yamamoto (1995) and can be applied for any arbitrary level of integration.

Beside emissions, energy consumption and GDP, Halicioglu (2009) added the variable of foreign trade and investigated the causal relationship between the four covariates in Turkey for the period 1960-2005 with cointegration and ECM. The findings show a bi-directional Granger causality between emissions and GDP.

Zhang and Cheng (2009) employed the TY procedure and VAR model of economic growth, energy use, CO_2 emissions, capital and urban population in China from 1960 to 2009. Results suggest a uni-directional Granger causality running from GDP to energy consumption and from energy consumption to CO_2 emissions.

Menyah and Wolde (2010) examined the causal relationship between nuclear energy consumption, renewable energy consumption, and CO_2 emissions in the US for the period 1960-2007 by applying the TY procedure and found uni-directional causality from nuclear energy consumption to CO_2 emissions, and no causality between renewable energy consumption and CO_2.

Pereira and Pereira (2010) extended the literature to estimate the impact of shocks to the demand for specific types of energy by employing cointegration. The results show strong evidence for Portugal from 1977 to 2003 that energy consumption has a significant impact on economic performance.

To my knowledge, this paper is the first to estimate causal relationship between CO_2 emission, hydrocarbon energy consumption, non-hydrocarbon energy consumption, and economic development after controlling for investment and total population. Hydrocarbon energy and non-hydrocarbon energy are separated because emissions are mainly caused by the combustion of hydrocarbons energy sources. Beside the policy implications from causal relationships between emissions, energy consumption and economics, contributions to fuel-choice and fuel-switching policy are expected.

3. Model and methodology

3.1 Model

To explore the long-run nexus between carbon dioxide emissions, energy consumption and economic development, the general model can be specified as follows:

$$C_t = f\ (F_t,\ N_t,\ Y_t,\ K_t,\ P_t), \tag{1}$$

where C_t denotes carbon dioxide emission, F_t denotes hydrocarbon energy consumption, N_t denotes non-hydrocarbon energy consumption, Y_t denotes real GDP, K_t denotes investment, and P_t denotes total population.

According to previous studies, the choice of linear or quadratic models depends on the dataset and the relationship between C and Y. To estimate the relationship between CO_2 emission, energy consumption, and economic growth, in the studies of Halicioglu (2009) for Turkey, and Apergis and Payne (2009) for the Commonwealth of Independent States, quadratic form models are applied. However, linear models are generally employed in most of the studies, such as Glasure and Lee (1997) for South Korea and Singapore, Soytas, Sari and Ewing (2007), and Ang (2008) for Malaysia, Soytas and Sari (2009) for the US, Zhang and Cheng (2009) for China, Menyah and Rufael (2010), and Pereira and Pereira (2010) for Portugal.

3.2 Unit root, cointegration and long-run causality

Cointegration refers to a linear combination of nonstationary variables. To apply this methodology, unit root hypothesis tests and integration analysis are necessary before proceeding to cointegration and error correction. Augmented Dickey-Fuller (ADF) t-tests (Dickey and Fuller, 1979) and Phillips-Perron (PP) tests (Perron, 1988) are conducted to test the null hypothesis of a unit root in the different variables including 1974 and 1978 dummies. The optimal lag form is selected using the BIC[6].

Two or more variables are cointegrated if they are integrated of the same order and their linear combination is stationary (Engle and Granger 1987). Cointegrated variables show a long term equilibrium relationship and share common stochastic trends, thus there must exist at least one unidirectional or bidirectional causality in the Granger sense. Moreover, if the variables are detected to be cointegrated, spurious problems would be ruled out.

The multivariate cointegration method is well developed by Johansen and Juselius (1990). The multivariate system constitutes a first-order vector autoregression (VAR) and all the variables are supposed to be endogenous as follows:

$$y_t = \square + \sum_1^m \Gamma_j \, y_{t-j} + v_t \quad , \tag{2}$$

where y_t denotes vector of endogenous I(1) variables, that is $C_t, F_t,\ N_t,\ Y_t,\ K_t$ and P_t; m denotes lag length which is determined by a mixed criterion of AIC, BIC and likelihood ratio; Γ_j denotes the coefficient matrix; $\square$ denotes a vector of constant terms; and v_t denotes the residual matrix. The number of cointegrating vectors, i.e. the cointegrating rank, can be detected by maximal eigenvalue and trace tests.

3.3 Vector error-correction modeling (VECM) and short-run causality

According to Engle and Granger (1987), cointegrated variables must have an error correction representation. Short-run dynamics of cointegrated variables, influenced by the deviation from the long-run relationship, can be examined by the Vector Error Correction Model (VECM), which implies that changes in the endogenous variables are functions of changes in

[6] BIC: Bayesian information criterion

exogenous variables and the level of disequilibrium captured by error correction terms in the cointegrating relationship. This technique allows for a causal linkage between variables and reintroduces the information lost in the differencing process.

Since the nexus between CO_2 emission, non-hydrocarbon energy consumption and economic growth are of primary concern, a trivariate VECM can be specified as follows assuming one cointegrated relationship.

$$\Delta \ln C_t = \alpha_1 + \sum_{i=1}^{l} \xi_{1i}\, ECT_{t-1} + \sum_{i=1}^{l} \gamma_{1i} \Delta lnC_{t-\mathrm{i}} + \sum_{i=1}^{l} \delta_{1i}\, \Delta lnF_{t-\mathrm{i}} + \sum_{i=1}^{l} \theta_{1i}\, \Delta lnN_{t-\mathrm{i}} + \sum_{i=1}^{l} \sigma_{1i}\, \Delta lnY_{t-\mathrm{i}} + \sum_{i=1}^{l} \tau_{1i}\, \Delta lnK_{t-\mathrm{i}} + \sum_{i=1}^{l} \varphi_{1i}\, \Delta lnP_{t-\mathrm{i}} + \varepsilon_{1t} \quad , \tag{3}$$

$$\Delta \ln \mathrm{N}_t = \alpha_2 + \sum_{i=1}^{l} \xi_{2i}\, ECT_{t-1} + \sum_{i=1}^{l} \gamma_{2i} \Delta lnC_{t-\mathrm{i}} + \sum_{i=1}^{l} \delta_{2i}\, \Delta lnF_{t-\mathrm{i}} + \sum_{i=1}^{l} \theta_{2i}\, \Delta lnN_{t-\mathrm{i}} + \sum_{i=1}^{l} \sigma_{2i}\, \Delta lnY_{t-\mathrm{i}} + \sum_{i=1}^{l} \tau_{2i}\, \Delta lK_{t-\mathrm{i}} + \sum_{i=1}^{l} \varphi_{2i}\, \Delta lnP_{t-\mathrm{i}} + \varepsilon_{2t} \quad , \tag{4}$$

$$\Delta \ln \mathrm{Y}_t = \alpha_1 + \sum_{i=1}^{l} \xi_{3i}\, ECT_{t-1} + \sum_{i=1}^{l} \gamma_{3i} \Delta lnC_{t-\mathrm{i}} + \sum_{i=1}^{l} \delta_{3i}\, \Delta lnF_{t-\mathrm{i}} + \sum_{i=1}^{l} \theta_{3i}\, \Delta lnN_{t-\mathrm{i}} + \sum_{i=1}^{l} \sigma_{3i}\, \Delta lnY_{t-\mathrm{i}} + \sum_{i=1}^{l} \tau_{3i}\, \Delta lnK_{t-\mathrm{i}} + \sum_{i=1}^{l} \varphi_{3i}\, \Delta lnP_{t-\mathrm{i}} + \varepsilon_{3t} \quad , \tag{5}$$

where Δ denotes the first-difference operator; l denotes the lag length set at one based on the SIC [7]criterion; ECT_{t-1} denotes the error-correction term and is the residual in period t-1 obtained from the long-run cointegrating relationship; ξ denotes the speed of adjustment parameter; and ε_t denotes a serially uncorrelated error term with mean zero.

4. Data

The dataset consists of annual national level observations in the US from 1960 to 2009. Data on carbon dioxide emissions (C) (in kt), real GDP (Y) (in constant 2000 US$), gross fixed capital formation (K) (in constant 2000 US$) and total population (P) are from World Bank

[7] *SIC*: Schwarz information criterion

World Development Indicators. Hydrocarbon energy consumption (F) and non-hydrocarbon energy consumption (N) (both in kt of oil equivalent) are from the US Energy Information Administration (EIA). According to the Annual Energy Review (AER) of the EIA, hydrocarbon energy includes coal, net import of coal coke, natural gas only (excludes supplemental gaseous fuels) and petroleum. Non hydrocarbon energy includes nuclear electric power and renewable energy[8]. As Friedl and Getzner (2003) pointed out, since the Kyoto Protocol advocates reducing the proportion of emissions, total data rather than per capita data should be employed. Follo,ing Lee (2005), and Soytas and Sari (2009). gross fixed capital formation[9] is considered a dependable proxy for investment since shifts of investment always approach shifts of capital stock with constant depreciation rate.

All data are annual and their trends before taking natural logarithms are shown in Figure 1, in which 1960 is taken as the base year so as to deliver the data series in the same scale. Figure 1 implies that C, F, Y, K and P generally stay together. It is also obvious that C and F move very closely suggesting a likely interaction between them for the following tests and discussion. G and P increase steadily over the period while K appears to grow faster from 1991. Hydrocarbon consumption (F) as well as CO_2 emissions (C) both experienced a slight decrease in 1974 due to the energy crisis and a sharp decrease in 1978due to the Public Utilities Regulatory Policies Act which was approved by Congress in 1978 to encourage electricity generation from renewable sources. However, non hydrocarbon consumption seems to increase throughout the sample with

[8] Renewable energy includes: hydro electric power, geothermal, solar/PV, wind, and biomass (EIA 2009)

[9]"Gross fixed capital formation, a flow value, measures the value of net additions to fixed assets and excludes financial assets, stocks of inventories, other operating costs and land sales and purchases. It is called "gross" because the measure does not make any adjustments to exclude the depreciation of fixed assets. "(from UNSNA and IMF Balance of Payments system)

a sharp growth rate from 1970 to 1977. Figure 1 also shows an approximately linear relationship between C and Y, which suggests a linear model rather than a quadratic model.

Figure 1

5. Empirical Results

5.1 Tests of unit root hypothesis

All the variables are examined with ADF and PP unit root tests. The ADF tests with intercept and trend give better results showing that all the variables appear to have a unit root in levels but are stationary in first differences, implying that they are all integrated at order one, that is I(1). The tests results are reported in Table 1.

Table 1

5.2 Tests for multivariate cointegration

Table 2 presents results of Johansen cointegration tests based on the trace statistic and maximum eigenvalue statistic. This paper focuses on the single cointegrating equation at 0.05 indicated by the eigenvalue test rather than the three equations indicated by the trace test, for the reason that the optimal rank of one is constant in the eigenvalue test but inconstant in the trace test if different maximum lags are allowed to be included in the underlying VAR model. Results of Lagrange-multiplier tests (LM) are also reported in Table 2 indicating no evidence of serial correlation in the residual at lag one. The two dummy variables applied to explain macroeconomic shocks are found to be statistically insignificant and thus are not included in the following analyses.

Table 2

5.3 Error-correction model and short-run causality

The optimal lag is determined to be one by the SIC criteria in the ECM. The expected directions of the error correction coefficients are positive for dlnF and dlnP, and negative for dlnC, dlnN, dlnY and dlnK. That is to say, when the carbon dioxide emission level exceeds the long-run equilibrium level, hydrocarbon energy consumption and population should rise, non-hydrocarbons consumption, real GDP and capital stock should fall, and if permitting of CO_2 emissions or environment policy is stabilizing, carbon dioxide emissions should fall.

The error-correction models and short-run causality are reported in Table 3, in which the expected signs are found, with two exceptions. The sign is as expected for the statistically significant coefficients (capital stock).

The error correction term, estimating the speed of adjustment back to the long-run equilibrium, is statistically significant with expected sign, and large in magnitude for the capital stock equation, which suggests an error correction system. When the capital stock is above or below the equilibrium, it adjusts extremely quickly (by 109% in the first year), or it takes about 11 months to converge to the long-run balance in the case of any shock to the capital equation.

Table 3 also implies that only lnN is econometrically exogenous, which cannot be explained by other variables over the lagged changes. Furthermore, strong clues are provided that there exists a two-way short-run linkage between carbon dioxide emissions and hydrocarbon energy consumption, between real GDP and population, and between capital stock and population. Additionally, there also exists uni-directional causality from changes of hydrocarbon energy consumption to changes of capital stock.

Table 3

Based on the proven existence of causality in the cointegrating relationships and some ambiguous insignificant coefficients, it is necessary to carry out the Granger causality tests to specify the directions of causal links. Results presented in Table 4 show that more than one-third of parameters are significant.

Table 4

Table 4 indicates that hydrocarbon consumption Granger-causes carbon dioxide emissions, which is expected because the leading source of carbon dioxide emissions is the combustion of hydrocarbons. Considering the contemporaneous effects caused by a lag, the causality is manifested one year later.

CO_2 emissions, hydrocarbons energy consumption and population uni-directionally Granger cause non-hydrocarbon energy consumption. That is, under the control of environmental or energy regulations, non-hydrocarbon consumption is probably stimulated by the high level of CO_2 emission or by the substitution effect from decreased consumption of hydrocarbon energy. To mitigate the conflict between limited resources and unlimited demand as the population grows, the consumption of renewable energy and green energy are critical for sustainable economic growth.

Hydrocarbon and non-hydrocarbon energy consumption uni-directionally Granger cause real GDP, which is consistent with the previous studies, but the reverse does not hold. Hydrocarbon energy consumption and real GDP uni-directionally Granger cause capital stock.

Table 4 also reveals three bi-directional causal relationships between non-hydrocarbon energy consumption and capital stock, real GDP and population, and capital stock and population.

5.4 Generalized impulse response and variance decompositions

The Granger causality tests show several causal relationships within the sample period other than the trend in the future. To supplement the causality tests beyond the sample periods and examine how variables in general respond to innovations in other variables, the generalized impulse response method is employed following Pesaran and Shinv (1998) and the forecast error variances of all variables are decomposed into their percentage attributed to shocks in all variables in the system.

Figure 2 demonstrates the generalized impulse response results which give some support for Granger causality test results. CO_2 emissions do not respond to Y, F, N, K and P initially, respond negatively to Y during the first eight periods, and respond positively to F, N, K and P thereafter. Shocks to C have positive and significantly larger initial impacts on itself, which lasts longer. Hydrocarbons energy consumption appears to have a positive initial response only to C and itself. Non-hydrocarbon energy consumption has a slight positive response to F but significant response to itself, verifying the exogeneity observed in the error correction model. Moreover, C, F and N have positive and significant initial impacts on real GDP. Initially, capital positively responds to all variables except P, while population only slightly responds to K and itself.

Figure 2

The generalized variance decomposition reported in Table 5 is generally consistent with the error-correction process. The results indicate that the forecast error variance of hydrocarbon energy consumption explains around 11.8% of the error variance of carbon dioxide emissions while the latter explains more than 64% of the former. Likewise, the error variance of population accounts for more than 20% of the error variance of capital stock and the latter explains around

27% of the former, both of which imply bi-directional causality. Moreover, around 30% of the forecast error variance of real GDP is explained by the variance of carbon dioxide emissions and another 30% by hydrocarbon energy consumption, plus about 15% by population. Hydrocarbons consumption accounts for more than 30% of the variance in capital stock.

Table 5

6. Conclusion and Policy Implications

This paper explores the causal relationships between CO_2 emission, hydrocarbon energy consumption, non-hydrocarbon energy consumption, and economic growth for the US in the period 1960-2009 by employing the cointegration procedure, generalized impulse response, and variance decomposition in a multivariate model including the capital stock and total population.

Taking into account all the results above, the synthetic conclusion seems to be reasonable and as expected. Table 6 compares the causal relationship in the study with related previous studies in different contexts.

Table 6

Most importantly, strong evidence shows that hydrocarbon consumption uni-directionally causes investment. In other words, an increase of hydrocarbons consumption results in an increase of CO_2 emissions, which is followed by subsidies.

Furthermore, according to the results hydrocarbon consumption also positively affects GDP growth, as the substitution effects between hydrocarbons and non-hydrocarbons are relatively lower in GDP growth than in CO_2 emissions. That is to say, the benefit of lower CO_2 emissions surpasses the sacrifices of a lower GDP. An appropriate and efficient way to balance the increase of GDP and the decrease of carbon emissions in the US is to substitute hydrocarbon with non-hydrocarbon energy consumption. This result is consistent with results showing that total energy consumption affects CO_2 emissions from Soytas, et.al.(2007) for the US, and from Zhang and Cheng (2009) for China, given that hydrocarbon accounts for the overwhelming majority of energy consumption.

As there is no causal effect on CO_2 emissions detected from non-hydrocarbons energy consumption in the empirical results, the policy to reduce hydrocarbon energy consumption or switch to non-hydrocarbon energy is more appropriate than the one raised by previous studies which suggested reducing total energy consumption, and which would adversely affect economic growth.

Weak evidence indicates a uni-directional causal relationship running from CO_2 emissions, hydrocarbon consumption, and population to non-hydrocarbon consumption. Fuel-switching from hydrocarbons to non-hydrocarbons could be expensive but effective for the co-ordination of emissions, hydrocarbons, and non hydrocarbon energy if induced by mandates and subsidies, since the cost differences are very high.

Hydrocarbon and non-hydrocarbon energy consumption causes economic growth, but not vice versa, which is in line with results for Portugal in Pereira and Pereira (2010) but opposite to the results in Zhang and Cheng (2010) for China, and Ang (2008) for Malaysia. This result implies that inappropriate energy policies may impede economic growth and that authorities should be cautious to balance the energy regulations and economic development.

In addition, the results imply a bi-directional causal link between non-hydrocarbon energy consumption and investment. The gap between increasing energy demand and decreasing emission calls for a huge sum of investments to produce non-hydrocarbon energy. For instance, the investment to build a nuclear electricity generator or a high-power hydroelectric power facility is substantial but advisable.

Table 1 Unit root test results

	ADF tests		PP tests	
	levels	First differences	levels	First differences
Intercept				
C	-3.27**(0)	-4.05***(0)	-3.02**	-3.99***
F	-3.35**(1)	-3.35**(0)	-3.49**	-3.35**
N	-2.26(0)	-3.78***(0)	-1.62	-3.66***
Y	-2.19(0)	-4.38***(0)	-2.44	-4.04***
K	-1.35(2)	-4.33***(2)	-1.45	-2.99***
P	-0.69(2)	-3.13**(2)	-1.67	-3.13**
Intercept and Trend				
C	-1.77(0)	-4.69***(0)	-1.87	-4.74***
F	-2.46(1)	-4.14**(0)	-1.88	-4.14**
N	0.16(0)	-4.25***(0)	-0.50	-4.25***
Y	-2.97(1)	-4.77***(0)	-1.40	-4.36***
K	-3.14(1)	-4.40***(1)	-1.86	-3.14
P	-2.28(2)	-3.14 (1)	-3.09	-2.95

Notes: All variables are in natural logs. Max lag length is set to 10. Optimal lag lengths are determined by *SIC* and are in parentheses. The bandwidth is selected using the Newey-West method. Barlett-Kernel is chosen as the spectral estimation method. H_0=the series has a unit root. (*), (**) and (***) denote rejection of the null hypothesis at the 10%, 5% and 1% level.

Table 2 Johansen cointegration tests

Hypothesized Cointegration Rank	Trace statistic		Maximum eigenvalue statistic		LM test statistic[a]
	λ_{trace}	0.05 critical value	λ_{max}	0.05 critical value	
$r = 0$	132.03***	95.75	48.40***	40.08	---
$r \leq 1$	83.62***	69.82	30.47	33.88	32.97
$r \leq 2$	53.15**	47.86	27.41*	27.584	---
$r \leq 3$	25.74	29.80	13.36	21.13	37.75

[a] H_0: no autocorrelation at lag order. Johansen normalization restrictions are imposed. Optimal lag length=1 by SIC. (*), (**) and (***) denote rejection of the null hypothesis at the 10%, 5% and 1% level.

Table 3 Short-run causality from error-correction models

Equations	Coefficients of EC_{-1}	D_C	D_F	D_N	D_Y	D_K	D_P	C
D_c	0.09 (0.53)	-0.85** (-2.39)	1.43*** (3.59)	0.05 (0.51)	-0.64 (-0.98)	0.11 (0.56)	2.55 (0.99)	-0.01 (-0.24)
D_F	0.10 (0.58)	-0.64** (-1.82)	1.16*** (2.94)	0.10 (1.11)	-0.44 (-0.68)	0.04 (0.17)	4.37* (1.72)	-0.03 (-0.96)
D_N	0.16 (0.64)	-0.21 (-0.41)	0.35 (0.59)	0.49*** (3.53)	-0.33 (-0.34)	-0.02 (-0.06)	-3.80 (-1.00)	0.07 (1.37)
D_Y	-0.18 (-1.39)	-0.20 (-0.75)	0.47 (1.57)	0.05 (0.68)	-0.09 (-0.19)	0.06 (0.38)	3.47** (1.81)	-0.01 (-0.45)
D_K	-1.09*** (-3.50)	-0.52 (-0.79)	1.47** (1.98)	0.07 (0.42)	0.29 (0.24)	0.03 (0.07)	14.25*** (2.98)	-0.15 (-2.23)
D_P	0.01 (1.48)	-0.004 (-0.36)	0.01 (0.95)	0.001 (0.37)	-0.05** (-2.43)	0.01* (1.94)	0.73*** (9.51)	0.003*** (3.38)

Notes: EC_{-1} is error correction term. D denotes the first difference operator. The chi-squared statistics are in parentheses. Optimal lag length=1 by *SIC*. (*), (**) and (***) denote rejection of the null hypothesis at the 10%, 5% and 1% level.

Table 4 Granger causality test results

Dependent Variable	*C*	*F*	*N*	*Y*	*K*	*P*
C	---	17.32***	2.97	3.65	3.12	0.27
F	3.85	---	0.95	1.66	0.61	0.63
N	6.35**	5.20*	---	0.65	5.12*	9.94***
Y	1.04	6.55**	5.49*	---	1.99	12.76***
K	3.93	13.18***	5.09*	11.52***	---	21.28***
P	0.44	1.83	0.25	19.67***	10.04***	---

Notes: The statistics are chi-square statistics given by Granger causality Wald tests. (*), (**) and (***) denote significance at the 10%, 5% and 1% level indicating that the column variable Granger causes the row variable. The optimal lag length is 1 and is based on SIC.

Table 5 Generalized forecast error variance decomposition

Dependent variable	Horizon	D_C	D_F	D_N	D_Y	D_K	D_P
D_C	1	100.00	0.00	0.00	0.00	0.00	0.00
	5	82.40	11.80	1.35	1.02	1.32	2.11
	10	78.72	11.87	2.01	0.35	2.91	4.16
	15	76.11	11.84	2.10	0.18	4.03	5.74
D_F	1	79.95	20.05	0.00	0.00	0.00	0.00
	5	64.56	28.16	2.67	0.67	1.19	2.76
	10	64.82	24.00	3.30	0.23	2.80	4.87
	15	64.11	22.03	3.25	0.17	3.95	6.49
D_N	1	0.01	1.05	98.94	0.00	0.00	0.00
	5	0.36	0.78	95.81	0.36	0.55	2.15
	10	2.08	1.25	89.18	1.68	1.21	4.59
	15	2.97	1.53	86.42	2.25	1.43	5.41
D_Y	1	40.41	21.14	2.99	35.46	0.00	0.00
	5	34.19	40.09	7.01	9.20	2.16	7.35
	10	31.75	37.25	8.73	4.73	4.56	12.98
	15	31.97	34.91	8.62	3.29	5.84	15.38
D_K	1	32.26	25.60	3.45	25.63	13.05	0.00
	5	15.98	43.96	4.58	5.82	14.89	14.77
	10	9.29	36.53	5.47	5.61	19.59	23.51
	15	7.78	33.57	5.43	5.24	21.26	26.72
D_P	1	0.18	0.19	1.24	0.63	11.76	86.00
	5	0.29	0.09	1.05	4.32	24.39	69.86
	10	2.49	0.21	0.67	3.41	26.60	66.62
	15	4.96	0.53	0.44	2.61	27.17	64.28

Notes*:* *D* denotes the first difference operator.

Table 6 Causality test results comparisons with related studies

Author	Period	country	Method	Variables	Results
Soytas, et.al.(2007)	1960-2004	US	*TY, VAR*	Y,K, E,C,P^{l}	$E \rightarrow C$
Ang(2008)	1971-1999	Malaysia	*CI, ECM*	Y^{*},E^{*},C^{*}	$G \rightarrow E$, $C \rightarrow G^{\#}$

Zhang and Cheng(2009)	1960-2007	China[10]	*TY, VAR*	Y,K,E,C,P^{2}	$G \rightarrow E$ $E \rightarrow C$
Soytas and Sari(2009)	1960-2000	Turkey	*TY. VAR*	Y,K,E,C,P^{1}	$C \rightarrow E$
Halicioglu (2009)	1960-2005	Turkey	*CI, ECM*	Y,E,C,T	$G \leftrightarrow C$
Menyah and Rufael(2010)	1960-2007	US	*TY, VAR*	$Y,E(Nu,R)$	$E(Nu) \rightarrow C$
Pereira, Pereira(2010)	1977-2003	Portugal	*CI, VAR*	Y,K^{4},E,C,P^{1}	$E \rightarrow G$
Gao	1960-2009	US	*CI, ECM*	$Y,K,E(F,N),C,P^{3}$	$E(F) \rightarrow C$ $C \rightarrow E(N)^{\#}$ $E(F,N) \rightarrow G$ $^{\#}E(F) \rightarrow E(N)^{\#}$

Notes: Y, K, E (Nu, R, F and N), C, T and P denote real GDP, capital stock, total energy consumption (nuclear energy consumption, renewable energy consumption, hydrocarbons consumption and non-hydrocarbons energy consumption), CO_2 emissions, foreign trade and population.[1] total labor force, [2]urban population, [3]total population, [4] private investment, [*]per capita. [#] denotes weak causality. → denotes uni-directional causality running from the left variable to the right one. ↔ denotes bi-directional causality.

[10] China (excluding Hong Kong, Macao, Taiwan)

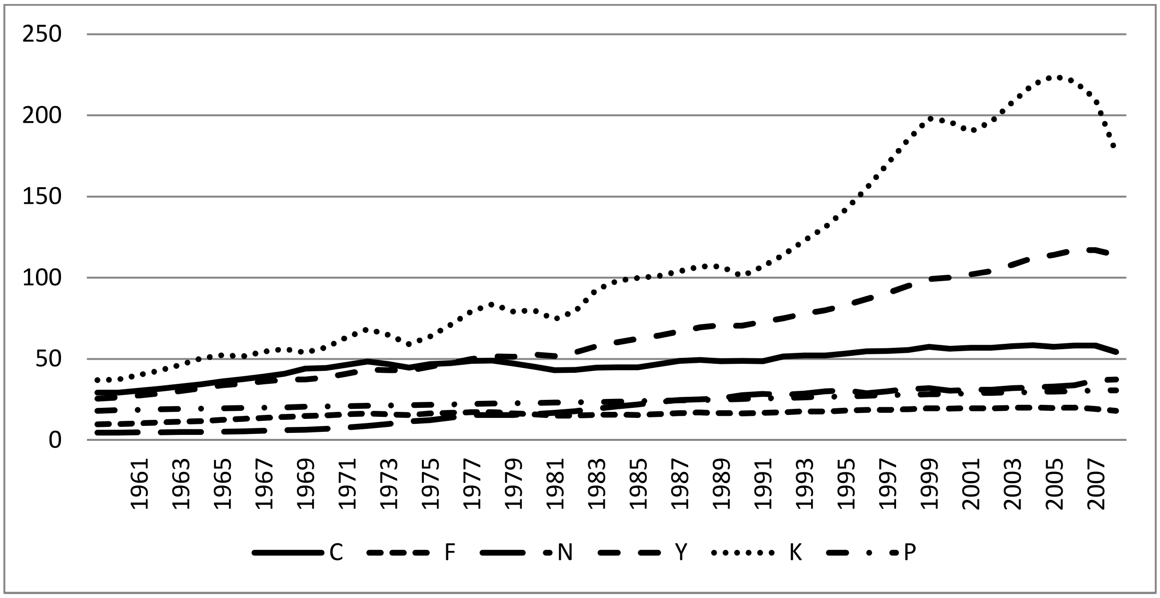

Figure 1 Trends of the variables (before taking logarithms)

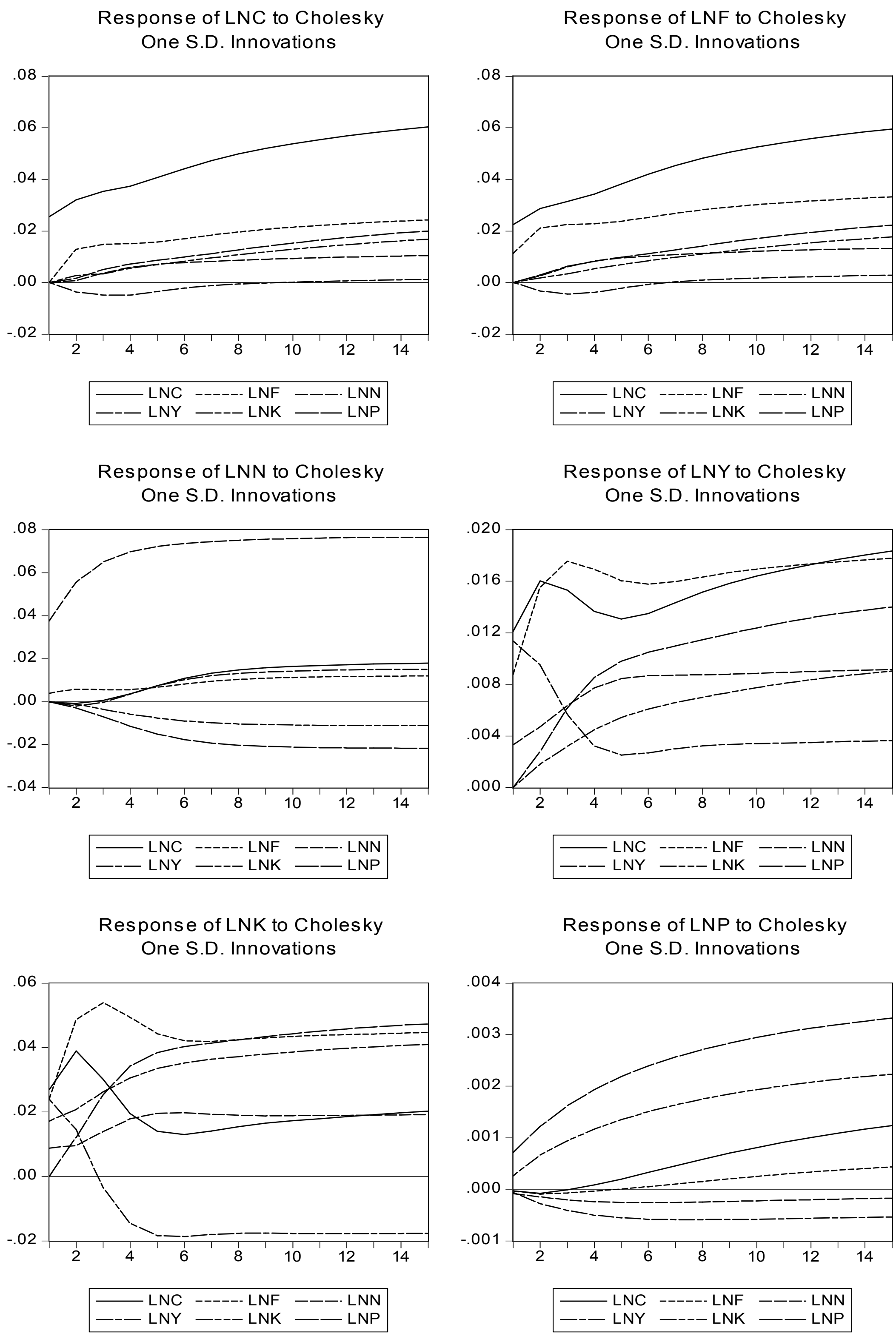

Figure 2 Generalized impulse responses

Chapter 3: Price Discovery in the Food-Ethanol-Fuel System in Ethanol Markets: An Exponential Smooth Transition VECM Perspective

1. Introduction

In the United States, the most important and widely used type of biofuel as fuel additives currently is ethanol, which is mainly produced from corn. As a renewable and domestically available resource, the use of ethanol helps to reduce harmful greenhouse gas and pollution. The production of ethanol in the United States was near 14 billion gallons in 2011 with a rapid increase compared to 10.75 billion gallons in 2009. Global Ethanol Production reached 88.7 billion litres in 2011.

The rapidly expanding production and demand for ethanol bears directly and indirectly upon the related markets. The spreading use of ethanol decreases the world's reliance on crude oil. There have been debates about the effectiveness of ethanol in replacing gasoline. Considering the large acres of land required for crops, the production and the use of ethanol tend to increase food prices. There is a dispute concerning whether corn based ethanol produces more greenhouse gases and less usable energy than soybean based biodiesel. There is an increasing acceptance of wheat ethanol in Europe but it is still a very small proportion in the U.S.

The price of corn, the main input in ethanol production, as well as the prices of soybean and wheat, doubled during the last three decades and are closely associated with the price of ethanol in recent years. Based on the high production cost of US corn-ethanol, corn subsidies are always required to implement ethanol policies. Increased domestic production of corn is a likely consequence of policies. Using corn for ethanol decreases the amounts of corn available for other uses such as food industry uses and animal feed. The corn used for ethanol purchased within a limited area and not sold for exports commands a higher price. The net effect of increased ethanol production increases the price of animal feed.

Ethanol and biofuel policies have had considerable effects on ethanol and corn production, as well as the price links among the related markets. The Energy Policy Act of 1992, one of the first Federal programs for the implementation of bioenergy was followed by another major legislative initiative, the Energy Policy Act of 2005, which assigned more power to Congress in regulating this industry. In 2006, the ban on the use of MTBE[11], which was found to contaminate groundwater, promoted further expansion of the ethanol market. Nowadays, various new laws and regulations, including the Energy Independence and Security Act of 2007 (EISA), have created mandates for increased use of, and subsidies for, ethanol. The EISA mandates an increase in biofuels from the 2007 level of 4.7 billion gallons to a total of 36 billion gallons by 2022. The EISA also specifies that at least one billion gallons of the new fuels come from biodiesel, and 16 million from other non-cornstarch sources, such as sugar, cellulosic ethanol, or waste products. In July of 2011, legislation to extend the tax credits and tariff was defeated in the United States Senate.

The main purpose of this chapter is to identify the price relationships among fuel, ethanol and agricultural commodities and to test the nonlinearity characteristics of price adjustment and the instability of regimes in ethanol markets. The organization of the paper is as follows: Section 2 reviews recent studies and Section 3 illustrates the

[11] MTBE: Methyl tert-butyl ether is a gasoline additive and can be used as an oxygenate.

theoretical models and methodologies applied. Section 4 describes data and data sources. Section 5 discusses the empirical results, and Section 6 concludes.

2. Literature Review

Considerable research has assessed the price nexus among fuel, ethanol and food by linear methodologies. The most popular methodologies have been structural vector autoregression (SVAR), vector error correction models (VECM), cointegration, and multivariate generalized autoregressive conditional heteroskedascity models (MGARCH), etc. Zhang et al. (2007) employed a SVAR model to test the hypothesis that limit pricing on MTBE refiners explained the lack of ethanol entry, and to estimate the price relationships in ethanol, corn and gasoline. Their research found that ethanol prices were subject to various shocks and have been driven by supply changes. Zhang et al. (2009) assessed the price nexus among ethanol, corn and soybean by using cointegration, vector error correction and MGARCH models. They found no long-run price links between agricultural commodities and fuel energy.

Nonlinearities of price adjustments in the ethanol market have been explored only recently. The well accepted methodology is Threshold Vector Error Correction Model (TVECM), which can be accessed by Logistic Smooth Transition VECM or Exponential Smooth Transition VECM. Rapsomanikis (2006) employed a TVECM to test for the nonlinearity in the price adjustment of ethanol, sugar and oil in Brazil. The results suggested strong threshold nonlinearity in the ethanol price system but no causal relationship between oil and ethanol. The results also indicated that sugar and ethanol can be linearly cointegrated. Balcombe (2008) estimated the price equilibrium relationships among ethanol, oil and suger in Brazil by using several bivariate error correction models including Bayesian MCMC[12] algorithms and model selection methods. The author found that there exists a long-run price relationship between sugar and oil in Brazil. The study also revealed nonlinearities in the price transition of sugar, ethanol and oil but linearity between ethanol and sugar. Serra et al. (2011) applied a smooth transition vector error correction model to examine price links among corn, oil, gasoline and ethanol prices. In contrast to Zhang et al. (2009), they found strong long-run price relationships between corn and fuel. In addition, their results revealed that an increase in corn price can generate an increase in the price of ethanol and therefore an increase in gasoline prices.

This paper is the first to assess the price relationships among gasoline, oil, ethanol, corn, soybean and wheat in the United States and only the second to employ the Exponential Smooth Transition VECM method in the ethanol market.

3. Methodology

3.1 Cointegration and Linear Vector Error Correction Model (VECM)

Unit root hypothesis tests and integration analysis are necessary before proceeding to cointegration and error correction. Augmented Dickey-Fuller (ADF) t-tests (see Dickey and Fuller, 1979) are conducted to test the null hypothesis of a unit root in the different variables. The optimal lag form is selected using the AIC[13] and SIC[14].

Cointegration refers to a linear combination of nonstationary variables. Two or more variables are cointegrated if they are integrated of the same order and their linear combination is stationary (Engle and Granger, 1987). Cointegrated variables show a long

[12] MCMC: Monte Carlo Markov Chain
[13] AIC: Akaike information criterion
[14] SIC: Schwarz information criterion

term equilibrium relationship and share common stochastic trends, thus there must exist at least one unidirectional or bidirectional causality in the Granger sense.

Cointegrated variables must have an error correction representation, according to Engle and Granger (1987). Short-run dynamics of cointegrated variables, influenced by the deviation from the long-run relationship, can be examined by the Vector Error Correction Model (VECM), which implies that changes in the endogenous variables are functions of changes in exogenous variables and the level of disequilibrium captured by error correction terms in the cointegrating relationship. This technique allows for a causal linkage between variables and reintroduces the information lost in the differencing process. Assuming one cointegrated relationship, the trivariate VECM can be specified as follows.

$$\mathrm{dlnP_{Et}} = \alpha_1 + \sum_{i=1}^{l} \xi_{1i}\, \mathrm{ECT_{t-1}} + \sum_{i=1}^{l} \gamma_{1i} \mathrm{dlnP_{E(t-i)}} + \sum_{i=1}^{l} \delta_{1i}\, \mathrm{dlnP_{G(t-i)}} +$$

$$\sum_{i=1}^{l} \theta_{1i}\, \mathrm{dlnP_{O(t-i)}} + \sum_{i=1}^{l} \sigma_{1i}\, \mathrm{dlnP_{C(t-i)}} + \sum_{i=1}^{l} \tau_{1i}\, \mathrm{dlnP_{S(t-i)}} + \sum_{i=1}^{l} \varphi_{1i}\, \mathrm{dlnP_{w(t-i)}} + \varepsilon_{Et}, \quad (1)$$

where $\mathrm{ECT_{t-1}}$ denotes the error-correction term and is the residual in period t-1 obtained from the long-run cointegrating relationship; ξ denotes the speed of adjustment parameter; ε_t denotes a serially uncorrelated error term with mean zero; d denotes the first-difference operator; l denotes the lag length (set at 3 based on AIC and SIC criteria, and the LM autocorrelation test).

3.2 Exponential Smooth Transition Vector Error Correction Model (ESTVECM)

Most of the previous studies used linear estimation methods to estimate the price relationships in ethanol markets. However, based on the fact that the ethanol market in the U.S is policy-oriented, many factors can drive the price system in ethanol market to nonlinear adjustment, which is defined as threshold-type nonlinear price behavior following Serra (2011) and Rapsomanikis and Hallam (2006). These factors include mandates of subsidies and tax credits, adjustment costs, transaction costs, and any potential risk arising from the related industries.

The threshold vector error correction model (TVECM) has been employed to examine the nonlinear characteristics between prices of different commodities (Rapsomanikis and Hallam, 2006). Based on the fact that the price transitions and adjustments are always continuous, a smooth transition procedure is introduced in this study to replace the discrete regime changes by the exponential smooth transition vector error correction model (ESTVECM) following Rothman et al. (2001).

A six-dimensional STVECM is specified to estimate the price linkages among ethanol, gasoline, oil, corn, soybean and wheat as

$$\mathrm{dlnP_t} = \left(\beta_1 + \lambda_1 z_{t-1} + \sum_{j=1}^{p-1} \theta_{1,j} \mathrm{dlnP}_{t-j}\right)\left(1 - G(s_{t-d};\gamma, c)\right) + \left(\beta_2 + \lambda_2 z_{t-1} + \sum_{j=1}^{p-1} \theta_{2,j} \mathrm{dP}_{t-j}\right)\left(G(s_{t-d};\gamma, c)\right) + \varepsilon \quad (2)$$

where P_t =(P_{Et}, P_{Gt}, P_{Ot}, P_{Ct}, P_{St}, P_{Wt}) denotes a (6*1) vector of prices at time t; β_i is a 6*1 vector and $\theta_{i,j}$ is a 6*6 matrix, both of which denote the short run dynamics, i=1,2 and j=1,…p-1; λ_i is a 4*r matrix capturing the long-run adjustment speed to disequilibrium under different regimes, i=1,2; z_{t-1} is a r*1 vector of the error correction term and r is the rank of error correction model. $G(s_{t-d};\gamma, c)$ is the smooth transition function characterized as a smooth regime switching procedure that allows two regimes to be associated continuously with extreme values, $G(s_{t-d};\gamma, c)$=0 and $G(s_{t-d};\gamma, c)$=1; s_{t-d}

is the lagged residual from the error correction term and is assumed to be the transition variable, which indicates the disequilibrium magnitude; d denotes a delay period; and parameters γ and c are combined parameters that reveal the transition speed between two regimes and the threshold between regimes. γ is set to be 0.2 as a starting value following Serra et al. (2011).

The transition between regimes depends on s_{t-d} and the corresponding value of $G(s_{t-d}; \gamma, c)$. To build the exponential smooth transition vector error correction model (ESTVECM), the exponential smooth transition function nested in the TVECM model is as follows.

$$G(s_{t-d}; \gamma, c) = 1 - exp\left\{-\frac{\gamma(s_{t-d} - c)}{\sigma^2(s_{t-d})}\right\}, \quad \gamma > 0, \tag{3}$$

where $\sigma^2(s_{t-d})$ is the variance of the transition variable.

The estimation procedure can be summarized in the following steps. After the stationary tests and multivariate cointegration tests, a linear VECM model is firstly estimated. With the optimal lags and ranks from linear VECM suggested by LM tests of residual autocorrelation and AIC and SIC , the ESTVECM model is estimated by using nonlinear least squares regression.

4. Data

This paper uses monthly national level prices on ethanol, gasoline, oil, corn, soybean and wheat from January 1982 to April 2012 in the U.S. Nominal average prices on gasoline (in dollars per gallon) and oil (in dollars per gallon) were collected from the Bureau of Labor Statistics. Ethanol average rack prices (in dollars per gallon) were collected from the government of Nebraska website.

Much research conducted to examine the role of futures markets in agricultural commodities has found that futures prices respond quickly to new information and provide unbiased forecasts of the subsequent cash price in well-designed contracts. Following Garcia and Leuthold (2004) and Carter (1999), in this paper the price proxy for corn, soybean, and wheat (all in dollars per bushel) are average monthly settlement prices for the nearby agricultural commodity futures contract and were obtained from the database of the USDA Economic Research Service.

The trends of these price series (before taking natural logarithms) are shown in Figure 1 and Figure 2. The trends in fuel prices including ethanol, gasoline and oil are relatively flat compared to the trends in agricultural commodities prices. Figure 1 indicates that the prices of ethanol, gasoline and oil generally move together. The trends were relatively flat before the 2001 recession but moved sharply upward after 2001 probably due to the economic expansion. Ethanol experienced its peak price in May 2006 while the peak prices for oil and gasoline were both in May 2008. From Figure 2 we can see that there were sizable price increases from July 2006 to June 2008 in all three agricultural commodities right after a sharp price increase in ethanol from November 2004 to May 2006.

5. Empirical Results

5.1 Unit root and cointegration

All the variables were subjected to ADF unit root tests. The results with intercept are similar to results with intercept and trend. The tests reveal that all the variables appear to have unit roots in levels but be stationary in the first differences, implying that they are all integrated at order one. Test results are reported in Table 1.

Table 1

Table 2 presents consistent results of Johansen cointegration tests based on trace statistics and maximum eigenvalue statistics. Results of Lagrange-multiplier tests (LM) are reported in the same table, suggesting that there is no residual autocorrelation at lag three. The results indicate one cointegrating equation illustrated in Table 4 at the 0.05 significance level, which is in line with Serra (2011) in that there exist long-run relations between fuel and agricultural commodities.

Table 2

5.2 VECM estimation

The expected directions of error correction coefficients are negative for all the price variables. That is to say, when the price of ethanol exceeds the long-run equilibrium level, the price of ethanol itself, as well as the prices of fuel energies including oil and gasoline, and the prices of agricultural commodities should move downward. The error-correction models and short-run causality are reported in Table 3, in which the expected signs are found with two exceptions. The optimal lag is determined to be three by AIC and SIC criteria and LM tests of residual autocorrelation in the ECM.

The error correction term, estimating the speed of adjustment back to the long-run equilibrium, is statistically significant with expected sign, and large in magnitude for prices of ethanol, gasoline, corn and soybean. When the ethanol price is above or below the equilibrium, it adjusts 3.7% in the first year, while for the prices of gasoline, corn and soybean, these speeds of adjustment are 4%, 2.1% and 2.7% respectively. Table 3 also shows that all the variables are econometrically endogenous and can be explained by at least one of the other variables over the lagged changes. Most of the signs for significant non-error-correction parameters are positive as expected, with only one exception.

Furthermore, there is strong evidence that a two-way short-run linkage exists between gasoline price and wheat price. In addition, there also exists uni-directional causality running from gasoline price to ethanol price, gasoline price to corn price, oil price to corn price and corn price to soybean price.

Table 3

Based on the proven existence of causality in cointegrating relationships and some ambiguous insignificant coefficients, it is necessary to carry out the Granger causality tests to specify the directions of causal links. Results presented in Table 4 show that more than two-thirds of parameters are statistically significant.

Table 4

Table 4 indicates that there are bi-directional Granger price causalities between ethanol and wheat, gas and oil, gas and corn, gas and soybean, gas and wheat, and oil and wheat. Oil price uni-directionally Granger causes corn and soybean prices. The fuel energies appear to have causal relationships with agricultural commodities, which is consistent with previous studies. Fuel prices can inflate prices of agricultural commodities worldwide, including those crops that have no relation to biofuels, such as rice and fish (Quaiattini, 2008). Besides, there are also uni-directional Granger causalities running from corn price to soybean price, and from wheat price to corn price and soybean price, which can be explained as substitution effects between those agricultural commodities.

5.3 STVECM estimation

In the estimation of STVECM, the optimal lags and ranks are selected based on the results from VECM estimation. The optimal lag is three according to AIC and SIC, and the results of the LM test of residual autocorrelation in VECM estimation.

Table 5 shows the estimated parameters in ESTVECM, among which the most interesting parameters in the estimation are λ_i, γ and c, which represent the adjustment speed to equilibrium, the transition speed to another regime and the threshold respectively. The statistically significant threshold parameter is -0.064 and it suggests that the system is within or around the first regime (G=0) in the neighborhood of -0.064. According to Serra (2011), the threshold variable can measure the disequilibrium magnitude if there is only one cointegration relation and error correction term. The estimation results for λ_i suggest that only ethanol price in both regimes is statistically significant. The speeds of ethanol price adjustment to the long-run equilibrium are 0.947 in regime 1 and 0.908 in regime 2. Different from the findings in Serra (2011), the oil and gasoline markets, as well as the agricultural market, do not respond to the price disequilibrium in the ethanol market. The parameter of γ is statistically significant and equal to 0.59, indicating a medium speed of transition between the two regimes.

Table 5

There is strong evidence for short run adjustments in all the prices for the two regimes, and all of the short-run dynamics parameters (β_i) are statistically significant in the two regimes. The parameters of short-run dynamics ($\theta_{i,j}$) are statistically significant at lag three for the price of gasoline, oil, corn, soybean and wheat. The results of autocorrelation tests shown in Table 5 indicate that none of the six equations have residual autocorrelation.

Figure 3 shows the time trends for the threshold variable(z_{t-1}), which varied from-0.37 to 0.56 and represented the degree of disequilibrium in the ethanol market from January 1982 to April 2012. Figure 4 shows the time series of G values (between 0 and 1) calculated from transition functions with estimated parameters. It is apparent that lower G values tend to be associated with lower deviations from the equilibrium. In that way, from both Fig.3 and Fig.4, we can find the instability of the regime caused by such factors as policy switching and growth in the economy in 1986 and in the period from Dec.2001 to Dec. 2007. In 1986, the Federal government reduced 2% of the discount rate. The US also experienced declining interest rates and a sharp drop in oil prices. (Cacy, 1987) From 2001 to 2007, the U.S economy experienced an expansion after the recession. Moreover, the Clean Air Act, the 2005 Energy Policy Act, and the 2006 ban on MTBE led to a massive expansion of the ethanol market and a large induced demand for corn.

6. Conclusion

This paper studies the price system in food-ethanol-energy links by using Exponential Smooth Transition VECM to examine the price relationships between ethanol, corn, soybean, wheat, oil and gasoline for the latest 364 months in the U.S. ethanol markets.

The empirical results indicate one cointegration relationship among all the prices, which are all endogenous for long-run cointegration. The results also indicate strong short-run and long-run relationships between the prices of fuels and agricultural commodities. Specifically, there exist strong two-way causalities between the prices of gasoline and wheat, ethanol and wheat, gasoline and corn, gasoline and soybean, and oil and wheat, as well as one-way causalities running from gasoline to ethanol, gasoline to soybean , oil to corn, oil to soybean, corn to soybean, wheat to corn, and wheat to soybean. Among the previous studies on the price relationships between food and fuel, few took into account the price of wheat. However, since 2008, the U.S started producing to considerable wheat based ethanol and therefore wheat price should be included. An increase in the price of fuel or agricultural commodities will probably cause an increase in another fuel or agricultural commodities. That is to say, the use of food crops for ethanol causes food prices to rise. In addition, an increase in gasoline price will also raise the price of corn and ethanol. Rising corn price was a leading factor causing the boom in ethanol prices in the last two decades, since corn-based ethanol dominated the biofuel supply.

The results of the estimation from the smooth transition VECM model with a nested exponential function suggest that only in the long-run does ethanol price make significant adjustments towards equilibrium, while in the short-run dynamic analysis the other prices of gasoline, oil, corn, soybean and wheat make significant adjustments. The estimated threshold value shows a fairly low disequilibrium magnitude in ethanol market. The fuel market and the agricultural commodity market insignificantly respond to price disequilibrium in the ethanol market. The speed of transition between the two regimes is at a medium level.

Future prospects for corn ethanol mainly depend on the fuel price, corn price and Federal ethanol and biofuels policies. The government should balance food price and fuel price by fixing a market-policy-oriented ethanol price. One way to do this is to promote second generation biofuels which are made mostly from biomass, woody crops, agricultural residues or waste. Future research should also consider the cost of livestock feed and the environmental externalities, as well as changes in land use over time to get a comprehensive picture of the entire ethanol price system.

Table 1 Unit root test results

ADF tests	*Intercept* levels	First differences	*Intercept and Trend* levels	First differences
$P_{Ethanol}$	-2.479(2)	-14.303***(1)	-3.230*(2)	-14.305***(1)
P_{Gas}	-0.559(2)	-10.447***(4)	-2.853(2)	-10.565***(4)
P_{Oil}	-0.453(1)	-13.440***(0)	-2.421(1)	-13.520***(0)
P_{Corn}	-1.998(1)	-14.146***(0)	-2.664(1)	-14.163***(0)
$P_{Soybean}$	-1.885(1)	-14.474***(0)	-2.595(1)	-14.493***(0)
P_{Wheat}	-2.120(1)	-14.535***(0)	-3.016(1)	-14.534***(0)

Notes: All variables are in natural logs. Maximum lag length is set to ten. Optimal lag lengths are determined by *SIC* and are in parentheses. The bandwidth is selected using the Newey-West method. Barlett-Kernel is the spectral estimation method. H_0=the series has a unit root. (*), (**) and (***) denote rejection of the null hypothesis at the 10%, 5% and 1% level respectively.

Table 2 Johansen cointegration tests

Hypothesized Cointegration Rank	Trace statistic		Maximum eigenvalue statistic		Lagrange-multiplier test[a]	
	λ_{trace}	0.05 critical value	λ_{max}	0.05 critical value	lag	chi2
$r = 0$	130.744***	95.754	65.434***	0.078	1	82.036***
$r \leq 1$	65.310	69.819	23.283	33.877	2	74.966***
$r \leq 2$	42.027	47.856	17.797	27.584	3	44.382
$r \leq 3$	24.230	29.797	15.146	21.132	4	56.9491**

Cointegration relationship (standard error in parentheses)

$$P_E + \underset{(0.348)}{2.905} P_G - \underset{(0.295)}{2.839} P_O - \underset{(0.257)}{0.676} P_C + \underset{(0.258)}{0.869} P_S - \underset{(0.250)}{0.231} P_W - 1.434 = 0$$

[a] H_0: no autocorrelation at lag order. Johansen normalization restrictions are imposed. Optimal lag length=1 by SIC. (*), (**) and (***) denote rejection of the null hypothesis at the 10%, 5% and 1% level respectively.

Table 3 Error-correction models

Equations	EC-1	$P_{Ethanol}$	P_{Gas}	P_{Oil}	P_{Corn}	$P_{Soybean}$	P_{Wheat}	C
$P_{Ethanol}$	-0.037***	0.248***	0.203**	-0.087	0.032	0.085	0.105	0.001
	(-0.014)	(0.057)	(0.094)	(0.093)	(0.085)	(0.085)	(0.076)	(0.004)
P_{Gas}	-0.04***	0.046	0.432***	0.055	0.041	0.025	0.075*	0.001
	(0.008)	(0.034)	(0.057)	(0.056)	(0.051)	(0.051)	(0.046)	(0.002)
P_{Oil}	0.026***	-0.016	-0.001	0.321***	0.022	0.042	0.047	0.002
	(0.008)	(0.036)	(0.059)	(0.058)	(0.053)	(0.053)	(0.048)	(0.002)
P_{Corn}	-0.021*	0.002	-0.216***	0.178**	0.201***	0.051	0.087	0.001
	(0.012)	(0.049)	(0.081)	(0.08)	(0.073)	(0.073)	(0.066)	(0.003)
$P_{Soybean}$	-0.027**	-0.063	0.064	0.017	0.12***	0.161**	-0.001	0.001
	(0.011)	(0.045)	(0.074)	(0.073)	(0.066)	(0.066)	(0.06)	(0.003)
P_{Wheat}	0.011	0.033	-0.13*	0.077	-0.038	0.048	0.259***	0.001
	(0.011)	(0.045)	(0.075)	(0.074)	(0.067)	(0.067)	(0.061)	(0.003)

Notes: EC_{-1} is error correction term. *D* denotes the first difference operator. The chi-squared statistics are in parentheses. Optimal lag length=1 by *SIC*. (*), (**) and (***) denote rejection of the null hypothesis at the 10%, 5% and 1% level respectively. Standard errors are in parentheses.

Table 4 Granger causality test results

Dependent Variable	$P_{Ethanol}$	P_{Gas}	P_{Oil}	P_{Corn}	$P_{Soybean}$	P_{Wheat}
$P_{Ethanol}$	---	10.89***	13.03***	7.64***	7.40***	10.60***
P_{Gas}	1.314	----	10.60***	8.21***	5.310***	5.57***
P_{Oil}	0.17	6.20***	----	0.69	1.35	3.03*
P_{Corn}	1.84	5.92***	4.83***	----	1.40	12.7***
$P_{Soybean}$	1.66	2.39*	3.86***	4.08**	----	8.19***
P_{Wheat}	6.20***	3.9**	2.95*	0.64	0.19	----

Notes: The statistics are chi-square statistics given by Granger causality Wald tests, (*), (**) and (***) denote significance at the 10%, 5% and 1% level respectively indicating that the column variable Granger causes the row variable. The optimal lag length is 1 and is based on *SIC*.

Table 5 ESTVECM parameter estimates

	Regime	Ethanol		Gas		Oil		Corn		Soybean		Wheat	
		Parameter estimate	Standard error	Parameter estimate	Standard error	Parameter estimate	Standard error	Parameter estimate	Standard error	Parameter estimate	Standar d error	Parameter estimate	Standard error
β_i	G=1 (i=2)	0.383***	0.014	0.410***	0.021	0.306***	0.028	1.008***	0.016	1.898***	0.015	1.367***	0.016
	G=0 (i=1)	0.365***	0.014	0.377***	0.022	0.253***	0.026	1.028***	0.019	1.908***	0.017	1.370***	0.018
λ_i	G=1 (i=2)	0.947***	0.099	-0.070	0.139	0.088	0.174	0.014	0.110	0.031	0.098	0.003	0.108
	G=0 (i=1)	0.908***	0.096	-0.032	0.121	0.017	0.140	0.010	0.112	0.025	0.099	-0.002	0.109
$\theta_{i,t-1}$	G=1 (i=2)	-0.010	0.309	0.026	0.878	0.090	1.018	-0.189	0.425	-0.120	0.413	-0.187	0.459
	G=0 (i=1)	0.067	0.303	0.052	0.754	-0.036	0.830	-0.150	0.432	-0.032	0.415	-0.118	0.462
$\theta_{i,t-2}$	G=1 (i=2)	-0.034	0.308	-0.428	0.878	-1.158	1.249	-0.249	0.425	-0.131	0.412	-0.101	0.460
	G=0 (i=1)	-0.135	0.295	-0.525	0.775	-0.478	0.820	-0.194	0.434	-0.198	0.414	-0.177	0.460
$\theta_{i,t-3}$	G=1 (i=2)	0.173	0.192	1.091**	0.477	1.747**	0.730	0.899***	0.261	0.761***	0.256	0.707**	0.285
	G=0 (i=1)	0.181	0.182	1.049**	0.423	1.135**	0.501	0.860***	0.266	0.799***	0.257	0.754***	0.285
Autocorrelation LM test[a]		Chi2	0.1031		0.0009		0.0417		1.483		0.0042		0.0644
		P value	0.748		0.976		0.838		0.342		0.948		0.799
Speed of transition γ				Parameter estimate		0.590**				Standard error		0.021	
Threshold variable c				Parameter estimate		-0.064***				Standard error		-0.007	

[a] Ho: no residual autocorrelation

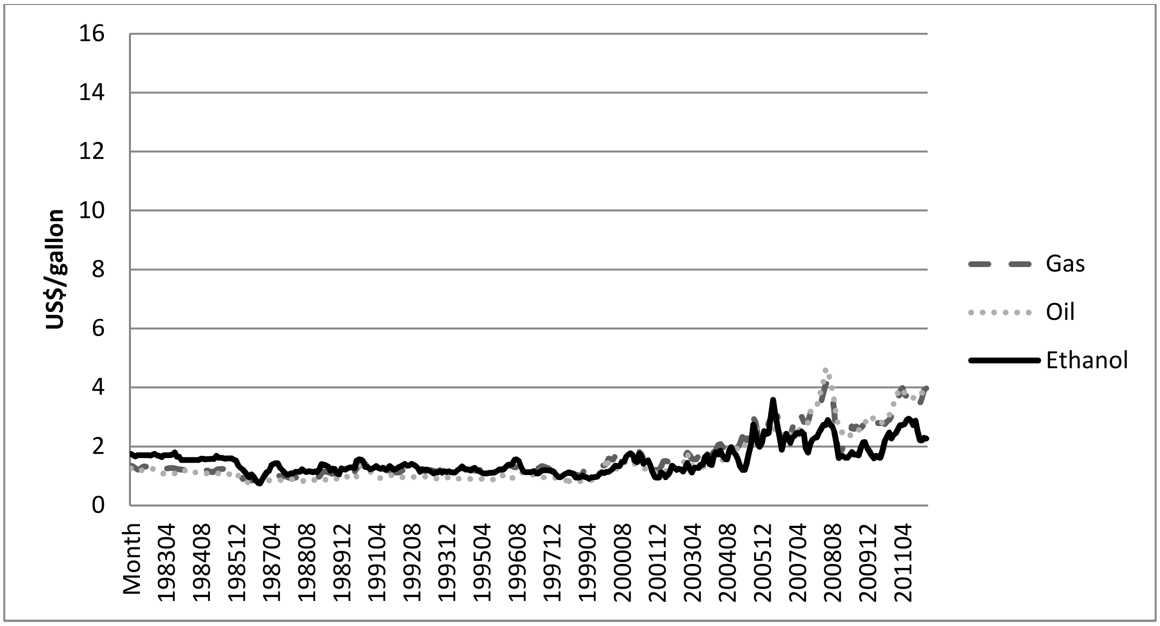

Figure 1. Price series on ethanol and fuels

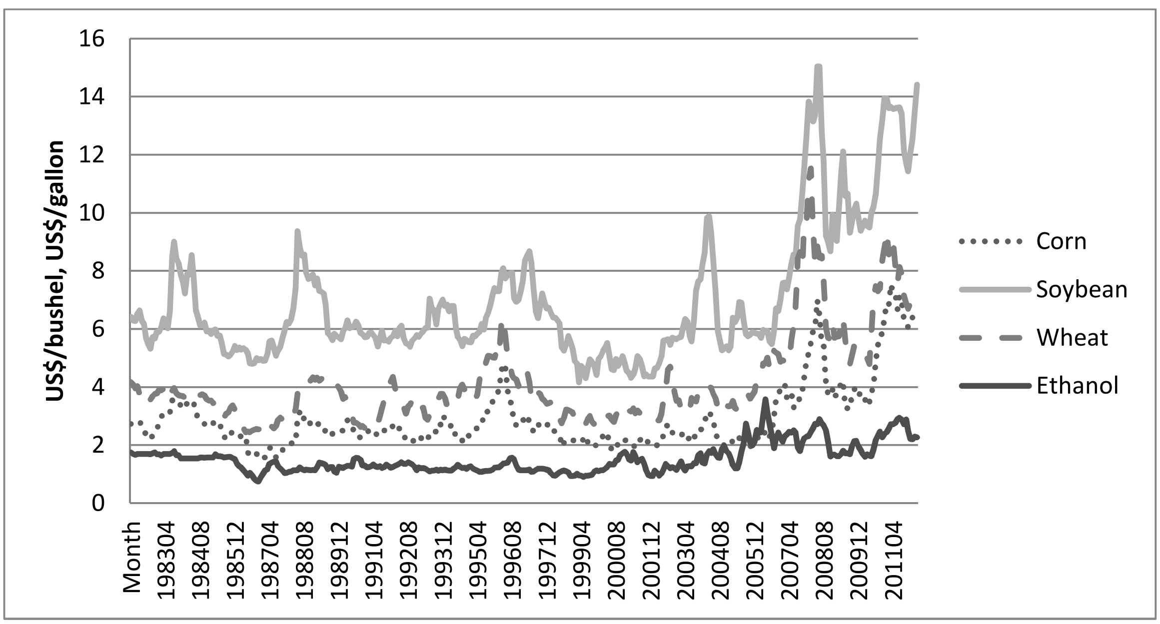

Figure 2. Price series on ethanol and agricultural commodities

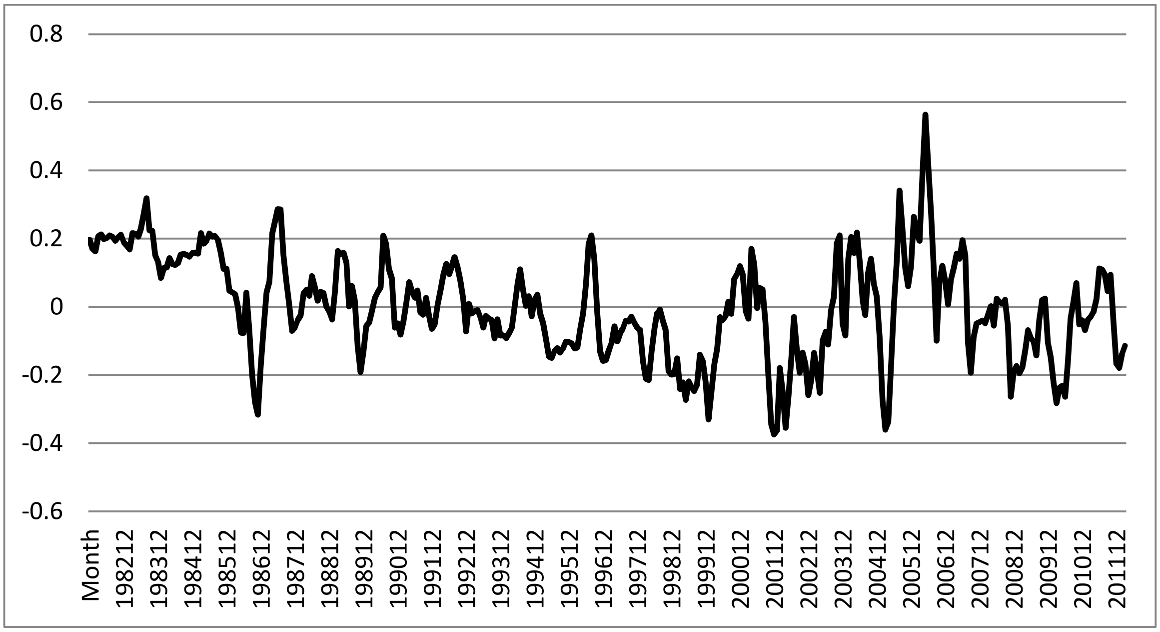

Figure 3 Threshold variable series (ECT)

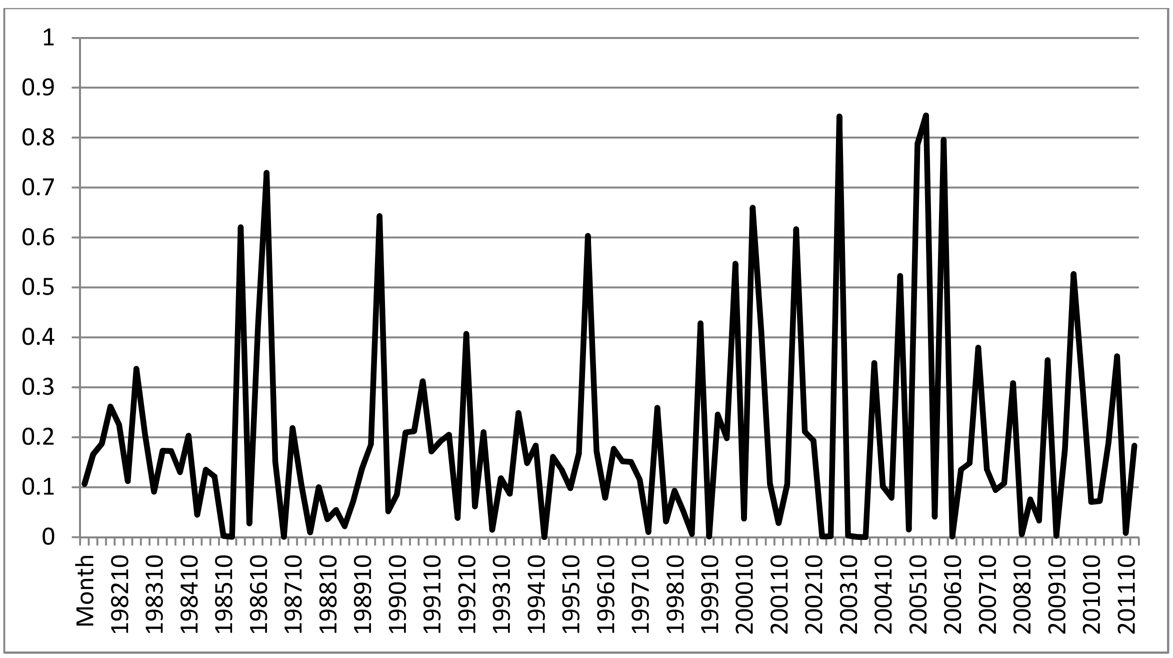

Figure 4 Transition function (G) series

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